Multi-Resolution Technique for Disaggregation of Thermal Image Using Vegetation Index

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January, 2008
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by

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Thesis submitted to the International Institute for Geo-information Science and Earth Observation in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation, Specialisation: Geoinformatics.

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Dedicated To My Parents
Abstract

Finer resolution thermal imagery is required for various applications like estimation of surface energy budget, assessment of evapotranspiration and drought prediction, exploring urban heat island effect, and monitoring volcanic eruptive activity. Currently the availability of fine spatial resolution (FR) thermal data (<100m) are very limited and its temporal resolution is low. While coarse resolution (CR) thermal data (1000m) are free and routinely available, but not suitable for many applications due to their coarse spatial resolution. DisTrad and TsHARP algorithms have been used to increase the spatial resolution of thermal image from coarse spatial resolution to fine spatial resolution by building linear relationship between NDVI derived from finer resolution and land surface temperature of CR. In order to validate the applicability these algorithms, this research modelled the relationship over a heterogeneous landscape in India using ASTER and MODIS data. Thermal data of ASTER at 90 m was used as a validation dataset. The relationship was first built between simulated ASTER thermal data at 1km resolution and its own NDVI data at 90m. The study analysed the use of linear and polynomial modelling the relationship. The nature of the relationship and the resultant sharpened thermal product at various resolutions were studied, analysed and validated. It was found that the slope and intercept of the relationship was constant up to 270 m, but changes abruptly beyond 270 m. The relationship built at 1km was utilised to predict the temperature at finer resolution using NDVI data at respective resolution. The residual error at 1km is carried forward to the finer resolution. In this way, simulated thermal data at 1km resolution was sharpened to 810 m, 630 m, 450 m, 270 m and 90 m spatial resolution. It has been found that sharpening is suitable up to 270 m, with a RMSE of 2.15° K, and beyond which the error increases sharply. The technique was tested in various landcover classes and found that within the homogeneous agricultural fields the RMSE is 1.14 K at 810 m, 1.27 K at 630 m, 1.38 K at 450 m, 1.70 K at 270 m and 3.10 K at 90 m spatial resolution.

Earlier studies assumed a constant residual error at various finer resolutions. But it is found here that the residual error was not constant over the resolution. If the residual error is kept constant then it causes discontinuous spatial representation and a clustered pixelated effect at the finer resolution, hence affecting the visual quality of the sharpened thermal data. A new approach called Modified TsHARP is proposed in which the NDVI at finer resolution have been regressed with the NDVI of coarse resolution to derive the adjusted NDVI. Then new relation was built between the adjusted NDVI and LST at coarse resolution. This approach provided a spatially and visually appealing sharpened thermal image with the RMSE of 1.89 K at 270 m. The study has also analysed the relationship between NDVI and LST at contextual level using convolution based approach. This approach has reduced the error in the heterogeneous region and has enhanced the local linearity in the relationship to derive better sharpened thermal data with the RMSE of 1.70 K.
The above said tested methods were then applied over MODIS thermal data for sharpening from 1km to 250 m resolution with RMSE of 1.98 K.

(KEYWORDS: Land Surface Temperature; NDVI; Sharpening; Spatial resolution; Thermal remote sensing, MODIS, ASTER)
Acknowledgements

I take this opportunity towards my sincere thanks to Dr. V.K. Dadhwal, Dean, IIRS, for all the necessary support during the course work and for all the facilities in IIRS. I am also thankful to Mr. P.L.N. Raju, I/C, Geoinformatics Division for his moral support, encouragement, suggestions and guidance for improvement during the research work.

Words are inadequate to convey the gratitude to my IIRS supervisor, Dr. C.Jeganathan, Geoinformatics Division. It is my proud privilege to express my deep sense of gratitude to him for his timely advice, support, comments, guidance and encouragement throughout my research period.

I am grateful to my ITC supervisor, Dr. Nicholas Hamm for his ever enthusiastic spirit, constant support, valuable guidance and critical comments rendered for the improvement, which has contributed to the successful completion of this thesis.

I am specially thankful to Mr. G. Parodi of ITC water resource division for his help and valuable suggestion. I am also thankful to Mr. Rishiraj Dutta for his guidance.

I am thankful to Mr. Ram Mohan Rao, Dr. Yogesh Kant and Ms. Sangeeta for all the help provided by them. I am also thankful to Mr. Bhaskar, Mr. Avdesh and Mr. Monaj for the help and assistance.

I am also thankful to IIRS library staff for their kind co-operation during the research period. My sincere thanks goes to my classmate for their help and pleasant stay at IIRS during my whole course period.

Last but not least, I am indebted to my Father and Mother for taking care of me and for giving me constant encouragement and support without which I would not have been able to come this far. I would also like to express my gratitude to my elder brother Mr. Sudipta Mukherjee for the guidance and moral support provided by him.
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1. Introduction

1.1. Background:
Requirements of thermal imagery have increased very rapidly because of its potential applications in environmental monitoring. Land Surface Temperature (LST) is important for global change studies and acts as a controlling variable in climatic models. It forms the basis for the application of evapotranspiration and water and energy balance modelling (Griend et al. 1993). Monitoring of vegetation health to identify the stress or favourable environmental condition on ecosystem requires thermal data (Karnieli et al. 2006). Climatic variability affects the crop growth. In order to interpret the effect of climatic variability on crop growth surface temperature information is essential.

One of the applications of thermal data would be in the field of “phenological studies” (Badeck et al. 2004). Phenological studies focus about the change in plant species physical growth. Continuous change of vegetation cover is considered as phenological change. The requirements of vegetation index and temperature are important for such studies.

Burned area estimation and active fire identification is another important applications of thermal remote sensing (Ichoku et al. 2003) It requires the daily thermal and visible satellite data to build up the composite index using NDVI and Land Surface Temperature.

Continuous spatial measurement of Land Surface Temperature is only possible using remote sensing. Thermal infrared sensors measure the emittance of the land surface from which the temperature is derived. Usually the spatial resolution of thermal sensor is low in comparison with visible sensor. The amount of energy emitted by the land surface in thermal infrared bands is very low in compare to reflected energy of the visible bands. The incoming solar radiation is reflected back from the Earth surface is measure by the visible sensor and after absorption the emitted energy reached to the thermal sensor. The amount of reflected energy is high in comparison with emitted energy (depend on the characteristics of the surface material). Hence it is difficult for the sensor radiometer to catch the emitted energy. Because of this reason the spatial resolution of thermal imagery has been kept coarse, so that the sensor get sensitize by the receiving the emitted energy.

Currently the availability of fine spatial resolution thermal data (<100 m) are very limited and its temporal resolution is low. While coarser resolution thermal data (1000 m) are free and routinely
available, but not suitable for many applications due to their coarse spatial information content. Because of that it is desirable to make use of such coarse resolution free data for environmental monitoring purpose.

The thermal data is useful for:

I. Estimation of surface energy budget (Muramatsu et al. 2006).
II. Assessment of evapotranspiration and drought prediction (Sobrino et al. 2007).
III. Exploring urban heat island effect (Chen et al. 2006)
IV. Land surface temperature estimation for wildlife habitat suitability (Alexandre et al. 1999).
V. Detecting the condition conductive to wildfire (Pinol et al. 2005).
VI. Monitoring volcanic eruptive activity (Wright et al. 2002).
VII. Detection of the coal fire (Zhang et al. 1997).

Different national projects are taking place in the different parts of India on the basis of high resolution thermal data. Like for instance, the land surface temperature estimation for urban heat island effect. Assessment of evapotranspiration ($ET$) down to seals of individual agricultural fields and evaporative losses along canals and riparian corridors project in western U.S (Agam et al. 2007).

### 1.2. Problem definition & motivation:

- The thermal imageries currently available are having moderate to coarse spatial resolution, like Landsat ETM+ 60 m, ASTER 90 m, Landsat-5 TM 120 m, MODIS 1000 m, NOAA-AVHRR 1000 m. But one needs Moderate to fine spatial resolution thermal image for different purposes.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Satellite</th>
<th>Visible/NIR</th>
<th>Spatial resolution of Thermal Band</th>
<th>Revisit time</th>
<th>Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>ETM+</td>
<td>Landsat 7</td>
<td>30 m</td>
<td>60 m</td>
<td>16 days</td>
<td>not operational</td>
</tr>
<tr>
<td>ASTER</td>
<td>Terra</td>
<td>15 m</td>
<td>90 m</td>
<td>On demand</td>
<td>operational</td>
</tr>
<tr>
<td>TM</td>
<td>Landsat 5</td>
<td>30 m</td>
<td>120 m</td>
<td>16 days</td>
<td>operational</td>
</tr>
<tr>
<td>MODIS</td>
<td>Aqua/ Terra</td>
<td>1 km</td>
<td>1000 m</td>
<td>1 days</td>
<td>operational</td>
</tr>
<tr>
<td>AVHRR</td>
<td>NOAA</td>
<td>1 km</td>
<td>1000 m</td>
<td>1-2 days</td>
<td>operational</td>
</tr>
</tbody>
</table>

- Since May 31, 2003, the technical difficulties in scan line of Landsat 7 (60 m spatial resolution in thermal band) results the stripping in thermal imagery. Thus it is difficult to use thermal data of Landsat ETM+ sensor for research and operational applications (Agam et al. 2007).
Landsat 5 (120 m spatial resolution in thermal band) has been operating for last 22 years and its life time is uncertain. Hence, it is necessary to look for alternative thermal data sets for long time monitoring of environmental phenomena.

Many applications, such as surface energy budget estimation and ET monitoring required routine basis thermal data with 250 m to 500 m spatial resolution (Kustas et. al. 2003). Fine spatial resolution thermal sensors which are currently available have low temporal resolution. In contrast, coarse spatial resolution thermal sensors have high temporal resolution (MODIS, NOAA-AVHRR). It is important to build-up a trade-off link between two.

Indian Polar Orbiting RS satellites do not have only thermal band.

Because of all these reasons, it can be said that some technique is needed to convert from coarse spatial resolution thermal imagery to moderate spatial resolution thermal imagery, so that people can use the freely available thermal data for their application.

For many landscapes, variability in LST is driven primarily by variation in amount of vegetation cover. It has been demonstrated by previous researchers that surface temperature is closely related to vegetation cover (Badeck et al. 2004, Running et. al. 1995). An inverse relationship is present between vegetation index and temperature of the surface as well as the degree of relationship varies according to climatic condition and landcover type (Karnieli et al 2006).

It is a challenging task to disaggregate the coarse spatial resolution of the thermal image into finer spatial resolution image. Attempts have been made to disaggregate of the Landsat ETM+ and aircraft thermal data using vegetation index and fractional vegetation cover transformation (Kustas et al. 2003, Agam et al. 2007, Anderson et al. 2004). **DisTrad** (Kustas et al. 2003) and **TsHARP** (Agam et al. 2007) algorithms have been used to increase the spatial resolution of thermal image by building linear relationship between NDVI and land surface temperature. But lot of study need to be done in Indian climatic and landcover condition to validate the applicability these algorithms. The current study has attempted to see the NDVI-LST relationship over a heterogeneous landscape in Harayana state, India, using ASTER and MODIS data.

1.3. **Main objective:**

- Increasing the spatial resolution of thermal images from Low or Coarse spatial resolution to fine spatial resolution.
1.3.1. Sub objectives:

- Identify and establish a relation between NDVI and thermal data.
- Derive finer resolution thermal data using NDVI from multi-sensor & multi-resolution datasets.

1.4. Research questions:

- What kind of relationship exists between temperature and NDVI?
- How can the multi-sensor multi-resolution NDVI and temperature be modeled?
- What level of accuracy can be achieved when disaggregating the thermal imagery using NDVI?
- How far the disaggregation can be done on thermal image using NDVI?
- How can the error be mapped spatially?

1.5. Structure of the thesis:

The present thesis is elaborated in six chapters.

- **Chapter 1** deals with the background of the study, problem definition and motivation, research objective and research questions.
- **Chapter 2** contains the theoretical background of Land Surface Temperature, NDVI and fractional vegetation cover \((f_c)\), relationship between NDVI and LST and temperature sharpening related literature review.
- **Chapter 3** contains the selection and description of the study area as well as data and material used in this research.
- **Chapter 4** discusses the methodology used in this research. This includes derivation of LST and NDVI, establishment of NDVI and LST relationship & different approaches for temperature sharpening and validation,
- **Chapter 5** contains the analysis part of the research as well as result of the work and discussion.
- **Chapter 6** describes the conclusion and further recommendation.
2. Background and Literature Survey

2.1. Land surface temperature:
Any object having temperature above absolute zero (-273 °C or 0 K), emit energy in both day and night time. Thermal imagery is usually obtained at 8-14 μm wavelengths, due to the atmospheric scattering and absorption at other wavelengths. Thermal sensor (radiometer) of remote sensing satellite detects the remote object by detecting the amount of energy emitted from the various surfaces.

Thermal sensor (radiometer) records the emitted energy and converts it to digital number. In order to get the Land Surface Temperature (LST) from this digital number several steps need to be followed. First, DN has to be converted into radiance using the calibration coefficient (gain and offset). The radiance of the surface converts into temperature using the Planck’s blackbody law. This temperature is called ‘brightness temperature’ or temperature at the top of the atmosphere (Liang, 2004). By applying atmospheric correction on brightness temperature we get the surface brightness temperature. The surface brightness temperature represents the temperature of the blackbody and as the Earth is not a perfect black body; the emissivity of the earth surface material is less than 1, emissivity correction need to be applied on the surface brightness temperature to retrieve the Land Surface Temperature. The terminology LST and kinetic temperature (T_k) is same, which results due to the molecular motion within the object. LST reflects the contact temperature at the surface of any material, in other words if we set a radiometer at the surface of any material the recorded temperature is known as LST.

The present study is concentrated on sharpening of land surface temperature using the Normalized Difference Vegetation Index (NDVI). The major input variables for this study are LST and NDVI. Two thermal data were considered (i) MODIS thermal imagery (band 31 and 32) and (ii) ASTER kinetic temperature product.

2.2. Algorithm to derive LST
Previous researchers have made efforts to establish of methodology to retrieve the LST from thermal data. LST can be derive using two way, use of Radiative Transfer Model (FASCODE / MODTRAN) to simulate the atmosphere or use of presently establish atmospheric and emissivity correction algorithm. Split-window technique is another commonly used method to retrieve the LST from MODIS thermal data (Mao et al 2005, Mito et al 2006). The Split-window algorithm takes into account water vapour column (WVC) and non unitary surface emissivity (Mito et al. 2006) in order to reduce the atmospheric effect from the thermal data. Mao et al. (2005) considered the atmospheric
transmittance and emissivity for retrieval of LST from MODIS thermal data by applying the split-window algorithm on band (31 and 32).

Use of the Temperature Emissivity Separation algorithm (TES) is common practice to retrieve the LST from ASTER thermal data. A new Temperature Emissivity Separation (TES) was proposed by Gillespie et al. (1998) for Terra-ASTER. ASTER has 14 spectral bands, out of which 5 thermal bands (10-14) operate between 8-12 μm. TES algorithm produces five emissivity image and one surface temperature image. It takes into account of up-welling, down welling radiance and transmissivity of the atmosphere.

2.3. NDVI and fractional vegetation cover (fc):

Amount of vegetation cover present within a pixel can be quantified in terms of vegetation index. Vegetation index can be of different form like:

- Normalize Differential Vegetation Index (NDVI) = \( \frac{NIR - R}{NIR + R} \),

- Transformed Vegetation Index (TVI) = \( \left( \frac{NIR - R}{NIR + R} + 0.5 \right)^{\frac{1}{2}} \times 100 \) (Lillesand and Kiefer, 1994)

- Vegetation Condition Index (VCI) = \( \frac{NDVI - NDVI_{\text{min}}}{NDVI_{\text{max}} - NDVI_{\text{min}}} \) (Karnieli et al. 2006)

Another form of vegetation index is fraction vegetation cover (fc), which indicates the vegetation fraction within a pixel. Fractional vegetation cover could be computed using different way:

\[ NDVI^* = \frac{NDVI - NDVI_0}{NDVI_\alpha - NDVI_0} \]

Where \( NDVI_0 \) = NDVI value of soil pixel and \( NDVI_\alpha \) = NDVI value of Vegetation Pixel (Gutman. et al. 1998)

\[ \text{FVC} = NDVI^*^2 \]

Where \( NDVI_0 = 0.13/0.08 \) and \( NDVI_\alpha = 0.80/0.98 \) (Carlson et al. 1997).

The most suitable technique (Agam et al. 2007) for fc calculation is given by Choudhury and Amhed.

\[ fc = 1 - \left( \frac{NDVI_{\text{max}} - NDVI_{\text{min}}}{NDVI_{\text{max}} - NDVI_{\text{min}}} \right)^{0.625} \] (Choudhury et al. 1994).

By this method \( fc \) can be compute using only NDVI.

The present study has taken into account the NDVI and \( fc \) for sharpening of thermal image.
2.4. **NDVI and LST relationship:**

Empirically it has been found that as the vegetation cover increases, temperature decreases. Hope *et al.* (2005) found that the relationship between surface temperature and NDVI is linear and negative. The study also found that due to warm vegetation and cold soil this relationship is positive in artic tundra ecosystem. This inverse relationship of NDVI and LST has been validated in different ecosystem (Taiga, High mountain, Forest steppe, Steppe, Desert Steppe and Desert ecosystem) in order to compute the vegetation health index which rely on strong inverse correlation between NDVI and LST (Karnieli *et al.* 2006). NDVI–LST relationship has also been studied considering urban land cover classes and the relationship is found to be linear and negative in all the land cover classes except water bodies (Yue *et al.* 2007). The study concluded that LST and NDVI have a significant linear inverse correlation.

Agam *et al.* (2007) also found that NDVI and LST is inversely correlated. The study has been done in the corn and sayabin field during the growing period and mentioned about the linearity of the NDVI-LST relationship.

2.5. **Sharpening related literature:**

Sharpening of thermal data is the motto of the present study. Attempts have been made by the previous researchers for temperature sharpening. *DisTard* procedure has been applied for disaggregation of radiometric surface temperature (Kustas *et al.* 2003). The basis of the *DisTard* algorithm is the unique relationship between NDVI and LST. Least-square polynomial regression relationship was established at coarse resolution and applied to the finer resolution NDVI pixels to predict the temperature. Later this *DisTard* algorithm was modified to *TsHARP* algorithm (Agam *et al.* 2007). The *TsHARP* technique was tested over an extensive corn / saybin field of central Iowa during the crop growing period (Agam *et al.* 2007). The study explored the relationship between land surface temperature and fractional vegetation cover. *TsHARP* was also applied on aggregated Landsat dataset.

It is important to validate this technique in heterogeneous landscapes to assess the broader applicability of the technique.

3. **Study Area and Data Preparation**

The present study is concentrated on sharpening of Land Surface Temperature in order to validate the applicability of *TsHARP* algorithm over a heterogeneous landscape in Indian climatic condition. The
previous (Agam et al. 2007) study recommended that the performance of TsHARP algorithm should be examined over the different climatic and landcover characteristics.

3.1. Location and extent:
Study area is located within the Harayana state of India. Geographically the area is situated from 27°59’30.88” N to 30°0’19” N and 75°55’19.81” E to 77°59’30.88” E. The east-west extent of the study area is 57 km and north-south extent 213 km. The total area is 12130 sq km. The study area is spread over the 12 districts of Harayana.

![Figure 3-1: Study area](image)

3.2. Description of the study area:
The climatic condition of this area is suitable for agriculture. The average temperature is about 30°C in the summers, though it gets really chilly in the winters. The humidity level ranges from 72 to 85 % in the monsoon and from 29 to 50 % in the summers. The average annual rainfall is about 800 mm. 70% of the total rainfall occur during the month July to September and 30%rainfall occurs during December to February. The area is suitable for the agriculture. The major crops of this region are rice, wheat, vegetable, mustard, rice, maize oilseeds, cotton and sugar cane.

The cropping pattern and vegetation of this two study area is almost same. The cropping pattern of the study areas is following:
From the crop calendar it is visible that September is the growing period of rice, maize, Pigeon Pea, cotton and sugarcane and February months is the growing period of wheat, mustard, potato and sugarcane. The most dominated crop of this region in the September month is rice and sugarcane.

### 3.3. Data used:

ASTER and MODIS both the data were used in the current study. At first, the algorithm has been tested on ASTER aggregated thermal data (1000 m resolution) and then applied on MODIS thermal (1000 m resolution) data sets. Both images (ASTER and MODIS) were acquired on 30th September 2006. Detail of the data sets is given below:

#### 3.3.1. ASTER data:

Four ASTER scenes from the same path were mosaiced in order to get a larger heterogeneous area. ASTER sensor has 14 bands; within this band no. 2 and band no. 3 are useful for NDVI generation. Spatial resolution of ASTER visible and NIR band is 15 m. Band 10 to band 14 are the thermal infrared bands. Spectral range of thermal inferred band is 8 to 12 \( \mu \text{m} \) and spatial resolution is 90 m.

ASTER data products are also available. In the present study ASTER surface kinetic temperature product, surface reflectance product and emissivity product were used for Land Surface Temperature (LST) and Normalize Difference Vegetation Index (NDVI) generation. ASTER L1B calibrated radiance data was used for FCC preparation in order to visual identification of landcover class and digital landcover classification.
### 3.3.2. MODIS data:

The MODIS image was taken on 30 September 2006 has been used in the present study. MODIS L1B calibrated radiance was downloaded from the website [LAADSWEB](http://laadsweb). Three different data products were taken; 1000 m resolution thermal band (band 31 and 32), aggregated 1000 m resolution visible and NIR band, 500 m resolution and 250 m resolution visible and NIR band. MODIS atmospheric and emissivity product were used for generation of Land Surface Temperature using Split-Window method. MODIS LST product also taken into account for validation LST derived using Split-Window technique.
## Table 3-2: Details of the MODIS data

<table>
<thead>
<tr>
<th>MODIS-Terra</th>
<th>30.10.2006</th>
<th>MOD011A1</th>
<th>Emissivity product</th>
<th>Atmospheric correction</th>
</tr>
</thead>
</table>

### 3.4. Preparation of ASTER data:

The ASTER surface kinetic temperature, reflectance and emissivity product was downloaded from the EOS Data gateway website (NASA). The data was initially in EOS HDF (Hierarchical Data Format) format which is imported into ERDAS imagine (.img) format. Initially the data set was projected into Geographic (Latitude / Longitude) which has been reprojected to Universal Transverse Mercator Projection (UTM) zone no. 43. Four ASTER scenes were mosaic in order to take a bigger heterogeneous landscape for this study.

### 3.5. Land Surface Temperature (LST) generation:

In the present study surface kinetic temperature product of Terra ASTER sensor has been taken. The raw temperature band was processed by the ASTER data agency using the Temperature Emissivity Separation (TES) algorithm (Gillespie et al. 1998). This algorithm takes into account the upwelling radiance, downwelling radiance and transmissivity of the atmosphere for retrieval of LST. TES algorithm takes into account of 5 ASTER thermal bands (B10-B14) as well as the above mentioned atmospheric data, in order to reduce the atmospheric effect and produce one surface kinetic temperature product or land surface temperature and emissivity for each band. The range of the temperature within this study area is 298.1 K to 329.7 K. It has been found that the temperature over the urban land cover area is high in compare to vegetated and agricultural land [Figure: 3.4 (d) & (f)].

### 3.6. Computation of NDVI:

ASTER surface reflectance product of band 2 (red) and band 3 (NIR) has been taken for generation of normalize differential vegetation index (NDVI).

$$\text{NDVI} = \frac{\text{NIR} - R}{\text{NIR} + R}$$

The range of NDVI within the study area is -0.07719 to 0.774851 respectively. Initial NDVI was derived at 15 m resolution that has been aggregated to 90 m resolution by taking the 6x6 pixels in order to make same resolution of LST.
3.7. **Derivation of fractional vegetation cover \((fc)\):**

Fractional vegetation cover \((fc)\) was calculated from NDVI image using the algorithm suggested by Chowdhury *et al.* (1994)

\[
fc = 1 - \left( \frac{NDVI_{\text{max}} - NDVI_{\text{obs}}}{NDVI_{\text{max}} - NDVI_{\text{min}}} \right)^{0.625}
\]

The advantage of this algorithm is computation of NDVI value for pure soil pixel and pure vegetated pixels is not required (in which the field measurement is required). In this algorithm NDVI\(_{\text{min}}\) and NDVI\(_{\text{max}}\) can be determined by excluding the 3% upper and lower NDVI range. Total 6% of upper and lower tails of NDVI distribution is considered as outliers. NDVI pixels having the value outside this limit are reset to max and min limit value. The range of the \(fc\) at 990 m resolution within the study area is 0 to 1. \(fc\) represents fraction of vegetation amount present within a pixel.

3.8. **Preparation of MODIS data:**

MODIS L1B 1km, 500 m and 250 m data was initially projected into Geographic (Latitude / Longitude). All the data sets were imported into .img format and reprojected to UTM zone No. 43 and datum were set to WGS 84.

3.8.1. **Geometric correction:**

There was a mismatch among the 1000 m, 500 m and 250 m MODIS dataset that has been reduced by the geometric correction with reference ASTER data. The accuracy achieve at geometric correction is less than 1 pixel in all datasets.

3.8.2. **Radiometric calibration of thermal and visible band:**

**Thermal data:**

Raw thermal band of MODIS data (31 and 32) has been converted to radiance value using the radiance gain and offset, available in the header file. The gain and offset of band 31 and 32 are following

<table>
<thead>
<tr>
<th>Band</th>
<th>Radiance gain</th>
<th>Radiance offset</th>
<th>Central wavelength ((\mu\text{m}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 31</td>
<td>0.000840022</td>
<td>1577.3397</td>
<td>11.03</td>
</tr>
<tr>
<td>Band 32</td>
<td>0.00072969758</td>
<td>1658.2212</td>
<td>12.02</td>
</tr>
</tbody>
</table>

*Table 3-3: Gain and offset of MODIS thermal band*

The equation has been used for radiance conversion is \(L = gain \times (DN - offset)\)


Unit of the radiance value is W m\(^{-2}\) mm\(^{-1}\) sr\(^{-1}\)

The radiance image was converted the brightness temperature using Plank’s law considering the Earth surface as a black body.
\[ T_{\text{bb}} = \ln\left( \frac{c_1}{\lambda L_2 10^6 + 1} \right) \]

The brightness temperature was converted to land surface temperature using Modified Split-Window model suggested by Mito et al. (2006).

The following algorithm adopted to retrieve the LST

\[ T_s = T_{s'} + 58.87(1 - \bar{\varepsilon}) - 119.59\delta\varepsilon + 46.13\left[(1 - \bar{\varepsilon}) - (0.5\delta\varepsilon)^2\right] \]

This algorithm takes into account of water vapour concentration (column water vapour) and emissivity. The values used were \( H_1 = 58.87, H_2 = -119.59 \text{ and } H_3 = 46.13 \), can vary with water vapour content of the atmosphere. If the water vapour concentration is less than 3 g cm\(^{-2}\) then the effect of water vapour on atmospheric absorption is very less and it can be ignore.

In this condition the above mentioned coefficient can be used. If the water vapour is above 3 g cm\(^{-2}\) the constant will change according to:

\[
\begin{align*}
H_1 &= -7.61w + 82.69 \\
H_2 &= 24.35w + 182.22 \\
H_3 &= -4.81w + 65.12 \\
\end{align*}
\]

Where \( w \) = water vapour concentration

In the present study water vapour concentration has been taken into account with respect to MODIS water vapour product (MOD11). \( H_1, H_2, H_3 \) coefficient has been derived with respect to 1 km pixel for LST retrieval.

Another aspect of this algorithm is mean emissivity of band thermal band. Emissivity image of MODIS data for band-31 and band-32 were taken for calculation of mean emissivity. But due to the cloud cover some pixels of emissivity image was having null value which can be considered as error. In order to correct it the emissivity image correction was applied.

3.8.3. Landcover based emissivity correction:

MODIS FCC has been classified into four major landcover classes (Urban, Agricultural, Fallow, and mixed class). The mean emissivity value of each landcover classes was derived by overlaid the emissivity image and landcover classified image. The null value pixel of emissivity image within the each landcover type was replaced by the mean emissivity value of this class. The operation was carried out for both emissivity images. Mean emissivity was retrieved by averaging both the emissivity bands.
The average emissivity and water vapour constant was given as input to the split-window algorithm to retrieve the Land Surface Temperature. Range of the LST is 301.633 K to 321.437 K at 1000 m resolution.

The land surface temperature was validated with respect to MODIS LST product with the RMSE of 1.5 K.

**Visible / NIR Band:**

Red and NIR band of MODIS data was calibrated to reflectance. The algorithm of the reflectance conversion is:

\[ R = \frac{gain \times DN}{E_0 \times \cos \theta} \]  

(Liang, 2004)

Reflectance is the ratio of incoming and outgoing solar radiation. In case of MODIS image we need to multiply DN value by the reflectance gain considering two correction factor, Earth-Sun distance correction \(E_0\) and solar zenith angle correction \(\cos \theta\).

### 3.8.4. Earth-Sun distance correction:

Earth-Sun distance correction factor is \(E_0\). The equation for computation of \(E_0\) correction factor is following:

\[ E_0 = 1 + 0.033 \times \cos \left( \frac{2 \times d_n}{365} \right) \]

Where \(d_n\) is the Julian day of the year. 30 September 2006 \((d_n = 273)\)
3.8.5. Solar zenith angle correction:

\[ \cos \theta = \sin \phi \sin \delta + \cos \phi \cos \delta \cos \omega \]

where

\( \phi \) is latitude of the observer, \( \delta \) the solar declination and \( \omega \) is Hour angle.

\[ w = 15 \times (Lat - 12) \times \pi / 180 \]

\( LAT \) is local standard time.

\[ LAT = UTC + 4 \times Lc / 60 + Et / 160 \]

3.8.6. NDVI and FC computation from MODIS data:

NDVI and FC has been derived from reflectance red and NIR data at 1000 m, 500 m and 250 m resolution. The range of the NDVI of different resolutions is following:

<table>
<thead>
<tr>
<th>Resolution</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000 m</td>
<td>0.107904</td>
<td>0.652672</td>
</tr>
<tr>
<td>500 m</td>
<td>0.0522201</td>
<td>0.681048</td>
</tr>
<tr>
<td>250 m</td>
<td>-0.0624329</td>
<td>0.704727</td>
</tr>
</tbody>
</table>

Table 3-4: Specification of MODIS NDVI

3.9. Landuse landcover classification:

ASTER FCC has been classified into landcover classes at 990 m resolution. High resolution spectral band were aggregated to coarse resolution. Coarse resolution FCC has been classified into 10 classes using Isodata classification method (Jensen, 2000). The classified image has been aggregated into 3 major landcover classes, agriculture, fallow and mixed class. Because at 990 m resolution only the major landcover classes are visible and segregating the classes is very difficult. Due to this reason only three land cover classes were taken and Isodata classification method was used. The Figure: (a) and (b) shows the FCC and classified image.
Figure 3-4: (a) ASTER (990m) FCC (Band 3,2,1), (b) Landcover classified image, (c) ASTER FCC (90m), (d) ASTER Thermal (90m), (e) MODIS FCC (1000m), (f) MODIS thermal (1000m).
4. Methodology:

Kustas et al. (2003) has applied the DisTard algorithm for sharpening the thermal image. The algorithm was based on the assumption that LST is inversely correlated with NDVI. Agam et al. (2007) has modified the DisTard algorithm and tested a new algorithm, named as TsHARP. These previous studies were carried out over a homogeneous crop field of central Iowa, USA, during a period of rapid crop growth. They explored the linear and polynomial regression model to establish the relation between LST and NDVI.

The current study has researched various possible types of relationship between LST & NDVI, validated the applicability these algorithms over a heterogeneous landscape in India using ASTER and MODIS data. The methodology is given in the flow chart (Fig. 4-1)

![Figure 4-1: General methodology](image)

Major steps carried out in the study for applying sharpening algorithm is as below:

**Step 1**: Aggregation of NDVI and LST for bringing them to same resolution.

**Step 2**: Relationship establishment between NDVI and LST.

**Step 3**: Sharpening process.
4.1. Image aggregation procedure:

LST was aggregated using the procedure suggested by Agam et al. (2007). In the procedure, thermal product (temperature image) of ASTER (90 m) was converted to radiance image using Stephan-Boltzmann law. Finer resolution radiance image was then aggregated into coarser resolution radiance image by taking spatial mean. Finally, it was converted back to coarser resolution thermal image.

According to Stephan-Boltzmann law, \( R = \varepsilon \sigma T^4 \)

where \( R \) = radiance, \( \varepsilon \) = emissivity, \( \sigma \) = Stephan Boltzmann Constant and \( T \) = LST

The derived ASTER NDVI (90 m) data was aggregated further to coarse resolution (i.e., 990, 810, 630, 450, 270, 180 m). Two approaches were followed to obtain NDVI at the coarse resolution.

a) Areal averaged NDVI: In this process, at first NDVI is generated using normal NDVI equation and then aggregated to the coarse resolution by taking the areal average different multiplies of 90 m pixels (i.e., 2x2, 3x3, 5x5, 7x7, 9x9 and 11x11)

b) Reflectance based NDVI: In this process, the DN value in the FCC was converted to reflectance data. Then reflectance values were aggregated to the coarse resolution. Then at coarser resolution, NDVI equation was applied to derive the needed NDVI at target resolution.

Out of these approaches the “areal averaged NDVI” based approach is found to be suitable, which is explained in Chapter 5.

4.2. NDVI and LST relationship establishment:

The next step in the study is to establish relationship between NDVI and LST at the coarse resolution (990 m). NDVI is considered as independent variable and LST as dependent variable. Linear and polynomial relationships were evaluated.

The equations used in these models were provided as below.

**Liner regression model:**

\( \hat{y} = \hat{a} + \hat{b}x + e \)

where \( \hat{a} \) and \( \hat{b} \) are the estimated parameter values and \( \hat{y} \) is the prediction based on these estimates, \( e \) is the error which is also called residual.
**Polynomial regression model:**  \( \hat{y} = \hat{a} + \hat{b}x + \hat{c}x^2 \)

The established relation will look like

\[ L\hat{S}_T_{CR} = a + b \times NDVI_{CR} \] \( \text{Equation 4-1} \)

where

- \( NDVI_{CR} \) refers to coarse resolution NDVI.
- \( L\hat{S}_T_{CR} \) refers to predicted LST at coarser resolution.

Residual of the relationship has been calculated by taking the difference between predicted LST and original LST.

\[ \Delta L\hat{S}_T_{CR} = LST_{Re} - L\hat{S}_T_{CR} \] \( \text{Equation 4-2} \)

### 4.2.1. Comparison of linear and polynomial model:

The ANOVA test was applied for comparison of these two regression models.

### 4.2.2. Uncertainty of relationship parameter:

To understand the uncertainty of the relationship coefficients (slope and intercept), the confidence interval on the regression parameters were calculated.

The confidence interval is given as

\[ b \pm t(1 - \frac{a}{2}; n - p) \times S(b) \]

where

- \( b \) is the coefficient that is slope or intercept.
- \( t \) is the “t” distribution.
- \( 1-a \) represent the confidence limit. For 95% confidence level \( a = 0.05 \) since \( 1-0.05 = 0.95 \)
- \( n \) = number of sample and \( p \) is the number of coefficient. For linear model \( p = 2 \) and polynomial model \( p = 3 \).
- \( S(b) \) is the standard error for the parameter.

Regression model and confidence interval were calculated using the R statistical software.

### 4.3. Sharpening process:

The sharpening process involves 2 steps as described below:
Step 1: Finer resolution NDVI \((NDVI_{FR})\) is utilised in Equation 4.1 and LST was predicted \((\hat{LST}_{FR})\).

Step 2: Here, the residual error as calculated in Equation 4.1 is added back to finer resolution predicted LST.

In other way, the overall steps can be executed through the single equation

\[
\hat{LST}_{FR} = a + b \times NDVI_{FR} + \Delta \hat{LST}_{CR} \]

Equation 4-3

Various possibilities exists while making relationship between LST and NDVI. Most of them have been analyzed in the current study as listed in the Table 4-1 and the procedure involved for analyzing the relationship is explained in this section.

<table>
<thead>
<tr>
<th>Sharpening Approaches</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approach-1</td>
<td>Whole image based linear model without considering co-efficient of variation (cv).</td>
</tr>
<tr>
<td>Approach-2</td>
<td>Whole image based polynomial model without considering cv.</td>
</tr>
<tr>
<td>Approach-3</td>
<td>Whole image based linear model considering cv.</td>
</tr>
<tr>
<td>Approach-4</td>
<td>Whole image based polynomial model considering cv.</td>
</tr>
<tr>
<td>Approach-5</td>
<td>Landcover classification based linear model considering cv.</td>
</tr>
<tr>
<td>Approach-6</td>
<td>NDVI threshold based linear model considering cv.</td>
</tr>
<tr>
<td>Approach-7</td>
<td>NDVI threshold based polynomial model considering cv.</td>
</tr>
<tr>
<td>Approach-8</td>
<td>Adjusted NDVI based linear model considering cv.</td>
</tr>
<tr>
<td>Approach-9</td>
<td>Spatial contextual regression.</td>
</tr>
</tbody>
</table>

Table 4-1: Different Approaches evaluated in the research

4.4. Description of different sharpening approaches:

4.4.1. Approaches 1 & 2 whole image based linear and polynomial model:

In approach-1 the linear model has been established between NDVI and LST at 990 m resolution considering all the pixels of the image. In the approach-2 polynomial model has been applied to establish the NDVI-LST relation at 990 m resolution considering the whole image. The residual error at 990 m resolution was calculated by taking the difference between “observed and predicted” LST.

The model established at 990 m resolution was applied on different target resolution NDVI in order to predict temperature. The residual from the 990 m model were added back to the predicted temperature at the target resolution.
Water body tend to have both low NDVI and low temperature, and do not maintain the inverse relationship of LST and NDVI as found in the vegetated pixels (Agam et al. 2007). Hence water body pixels were be eliminated before establishing the relationship.

![Diagram](image)

**Figure 4-2: Diagrammatic representation of sharpening approach 1&2**

**4.4.2. Approach 3 & 4 whole image based linear and polynomial model considering cv:**

In order to avoid the outliers in the regression model, coarse resolution NDVI pixels having uniform sub pixel variability were considered. In this regard, coefficient of variation (cv) (standard deviation divided by mean) has been computed over the 11x11 pixels of 90 m resolution NDVI and only those pixels having cv less than 0.25 (Kustas et al. 2003 and Agam et al. 2007) were selected for generating the regression model. Based on these selected pixels linear and polynomial regression models were established at coarse resolution (990 m) and the residual computed. The model was applied to the target resolution NDVI pixels to predict the temperature, then residuals of coarse resolution model was added back.

But within a heterogeneous area the NDVI-LST relationship can vary in different landcover classes. The above mentioned approach does not satisfy the class dependency criteria. Due to this reason the whole image based NDVI-LST relationship may not reflect actual the ground reality.
4.4.3. Approach-5 landcover classification based linear model considering $cv$:

In this approach the image has been classified into three major landuse classes; agricultural land, fallow and mixed class. Only three classes have been taken because at the 990m resolution other classes are not visible. Within the each land cover class NDVI-LST relationship was established at coarse resolution and respective residuals were calculated. Then this established relationship was applied to the target resolution NDVI pixels of corresponding class and residuals were added back. Finally the predicted thermal image of different class was integrated, in order to get thermal image of the whole area.

The disadvantage of this approach is that it highly relies on the accuracy of the classification. Segregating the different landcover classes in the course resolution is very difficult. The accuracy of land cover classification is not high in coarse resolution as it depends upon different factor like method of classification, ground cover information about the area, classification skill and heterogeneity of the study area.
4.4.4. Approach-6 & 7 NDVI thresholds based linear model & polynomial model with $cv$:

Classification results varies with different users and hence establishing uniform relationship for the same study area by different users will be a difficult process. Hence, in order to avoid classification accuracy problem we need to have a reproducible and repeatable procedure. In this regard, NDVI threshold based sharpening technique is attempted. In this approach, the study area was classified in 3 different NDVI classes (i.e., NDVI<0.2, 0.2<NDVI<0.5 and NDVI>0.5). Linear and polynomial regression model both were generated with respect to the different NDVI classes and applied the model to corresponding target resolution NDVI class pixels to predict the temperature. Finally they were integrated into single image.

It has been found that the linear model is suitable for all NDVI classes, but polynomial model is not suitable within “<0.2 NDVI range”. A detail of this is can be found in the Chapter 5.
### 4.4.5. Approach-8 adjusted NDVI based linear model considering \( cv \).

In this approach, finer resolution NDVI has been transformed into coarse resolution NDVI through a regression model. 990 m resolution NDVI pixels were regressed with central pixel of 11x11 block of 90 m NDVI. The relationship was applied on finer resolution NDVI. The resultant NDVI will be called “adjusted NDVI”. The “adjusted NDVI” is applied in the NDVI-LST relationship equation (i.e., [Equation 4.1](#)). The residual of 990 m was added to the predicted LST.
4.4.6. Approach-9: spatial contextual regression

In this approach a local window based spatial regression technique was utilised. In order to avoid the uncertainty in the relationship due to heterogeneous pixels, local window based regression would be useful. In this technique, linear regression model was established for every 3x3, 5x5 and 7x7 overlapping and non-overlapping pixels block, at every location spatially. In this process, 3x3, 5x5 and 7x7 mask will be moved over all the image location in an overlap and non-overlap mode and then regression coefficients (i.e., slope and intercept) images were created. Using this spatial coefficient images, LST was predicted within each 3x3, 5x5 and 7x7 pixel block. The advantage of this approach is that the spatial variability is restricted to that location only and hence not affecting the relationship at other location, and hence the resultant residual error would expected to be less.
4.5. **Validation:**

Original 90 m LST was aggregated to different target resolution, and kept as a reference dataset for validation of predicted thermal image at respective target resolution. The Root Mean Square Error (RMSE) and Mean Error (ME) were computed in order to assess the level of agreement between reference and predicted temperature. Root Mean Square Error depicts, on average, the departure of predicted value from the reference value.

\[
RMSE = \left[ \frac{1}{n} \sum_{i=1}^{n} \left( \hat{LST}_{FR} - LST_{Ref} \right)^2 \right]^{1/2}
\]  

\[\text{Equation 4-4}\]
The bias of the prediction can be estimated in terms of Mean Error.

\[ ME = \left[ n^{-1} \sum_{i=1}^{n} \left( LST_{FR} - LST_{Re} \right) \right] \] \hspace{2cm} \text{Equation 4-5}

Mean Error shows whether the measurements are consistently underestimate (negative) or overestimate (positive) the true value. It also tells us the actual deviation of predicted value from true value.

The nature of the error distribution was measured in terms of skewness. Skewness is a measure of asymmetry and shows the manner in which the items are clustered around the average. It gives a relative measure with positive sign when skewness is to the right and with negative sign when skewness is to the left (Croxton and Cowden, 1979).

The difference between the mean, median or mode provide an easy way of expressing the skewness. But the mode for most frequency distribution is only an approximation and the median may be more satisfactorily located. Therefore Skewness was calculated using the following equation:

\[ \text{skewness} = \frac{3(\bar{X} - \text{Median})}{s} \] \hspace{2cm} \text{Equation 4-6}

Where \( s \) = Standard deviation.

In order to identify the pattern of error distribution skewness was computed. It indicates that the distribution of error is systematic or random.

In order to identify the spatial pattern of error, different measures were calculated. (a)Non-Spatial: RMSE, ME and Skewness were considered. (b)Spatial: Error map of predicted LST (Observed – Predicted LST) has been classified in order to show the spatial distribution of error.

![Figure 4-9: Schematic representation of validation procedures](image-url)
5. RESULT, ANALYSIS AND DISCUSSION

5.1. NDVI aggregation results:

NDVI image (90 m) was aggregated to the coarse resolution through “areal averaged approach” and “Reflectance based approach”. Both the approaches were analysed for their effectiveness through “R-square” of the regression. R-square value in the areal based approach is 0.8445 and in the reflectance based approach is 0.7943. Fig.5.1 shows the established relationship diagram. Correlation between both the NDVIs is 0.94064, which conveys that both are highly correlated (Goodchild, 1986 as referred in Arc/Info help).

![Figure 5-1: Relation between areal averaged NDVI vs LST and reflectance based NDVI vs LST](image)

From the above analysis it is found that the difference between “Areal averaged NDVI” and “Reflectance based NDVI” is very low and “Areal averaged NDVI” gives better correlation with LST. The previous study (Agam et al. 2007) also suggested that aggregation of NDVI should be done by taking the areal average, because NDVI is relatively scale invariant (Anderson et al. 2004; De Cola, 1997; Friedl et al. 1995; Hall et al. 1992 – as referred by Agam et al. 2007). Hence, all the analysis have been done based on “Areal averaged NDVI” only.

Figure 5.2a & 5.2b shows the resultant NDVI derived through these approaches. Red shows the agricultural fields. Within the agricultural landuse, it is found that the absolute NDVI difference (Fig. 5.2 c) is very small and more in the heterogeneous areas. Standard deviation of NDVI difference (Fig. 5.2 d) reflects that deviation from mean, and this is also very low in agricultural areas. Since the
resolution was coarse (990 m), the study has considered only 3x3 just to check immediate
neighbourhood variability.

Figure 5-2: (a) areal averaged NDVI; (b) reflectance based NDVI; (c) absolute NDVI difference between (a) & (b); (d) standard deviation with 3x3 mask.

5.2. NDVI & LST relationship evaluation:

5.2.1. Linear and polynomial relationship establishment without cv:
The relationship between NDVI and LST were analysed through linear and polynomial regression models at different resolution (990, 810, 630, 450, 270, 180, 90 m). Figure-5.3 shows the linear relationship between NDVI and LST established at different resolutions. Figure 5.4 shows coefficients of linear model plotted (slope and intercept) along with upper and lower confidence interval value.
**Figure: 5.5** shows plot of R-square (c), maximum & minimum limits of residual error (b) and residual standard error (a) of linear model. The range of maximum minimum residual is increasing and R-square value is decreasing towards high resolution, which suggests that the relationship is weaker at high resolution.

![Figure 5.5](image)

**Figure 5-3:** NDVI- LST relationship at different resolution (without cv).

**Variation of regression slope**

Variation of R-Square with respect to resolution

**Variation of regression intercept**

Variation of residual standard error with respect to resolution

**Variation of residual with respect to resolution**

**Variation of R-Square with respect to resolution**

(a) (b) (c)
From the confidence interval of slope and intercept of linear and polynomial model (Figure 5.7), it is visible that the range of confidence limit is higher in polynomial model than linear model. It suggests that the uncertainty of regression model coefficients (slope and intercept) is high in polynomial model in comparison to linear model.

To identify the suitable regression model for NDVI-LST relationship establishment, comparison of linear and polynomial was carried out using ANOVA analysis. 95% confidence level was taken. In this case if the probability value (Pr(>F)) less than 0.05, then polynomial model is more significant in compare to the linear model and if it is greater than 0.05 then linear model is significant.

The result of the ANOVA analysis obtained is (Pr(>F)) <2.2e-16. Since 2.2e-16 is too small in comparison to 0.05, it can be conclude that polynomial model is more significant than linear model. But the landcover of the study area is heterogeneous. So, the regression model established without considering cv may not be correct.
Figure 5-6: Shows the polynomial relationship between NDVI and LST (without cv)

Figure 5-7: Confidence limit of model coefficient plot (a) slope (b) intercept and (c) constant
5.2.2. Linear and polynomial relationship establishment with $cv$:

In order to eliminate the heterogeneous noisy pixels while making NDVI-LST relationship, only those pixels with coefficient of variation less than 0.25 is considered in this analysis (Figure : 5.9). Because of if the subpixel variability of NDVI is present, the heterogeneous effect will affect the relationship. The previous study (Agam et al. 2007; Kustas et al. 2003) also use the coefficient of variation 0.25 for selecting the homogeneous pixels.

Range of residual (Figure: 5.14b) error at 90 m resolution is higher (-26.37 to 21.04) in polynomial model compared to linear model (Figure: 11b) (-23.59 to 21.19). R-square is also high in polynomial model (Figure: 14c) in compare to linear model (Figure: 10c). But residual standard error is high in linear model (Figure: 11a) than polynomial model (Figure: 14a). The ANOVA analysis suggests that in 95% cases the polynomial model is better than linear model since the Pr($>F$) value (<2.2e-16) is much less than 0.05.
Figure 5-9: Shows the linear relationship between NDVI and LST (with cv)

Figure 5-10: Confidence limit of linear model coefficient: (a) slope (b) intercept and (c) R-square

Figure 5-11: (a) Plot of RSE, minimum maximum residual range (b) and R-square (c)
Figure 5-12: Shows the polynomial relationship between NDVI and LST (with cv)

Figure 5-13 Confidence limit of polynomial model coefficient (a) slope (b) intercept and (c) R-square
5.2.3. Model selection within agricultural area:

In the current study, the whole image was used to establish the linear and polynomial model. But in the whole image based regression analysis, the relationship is affected by the heterogeneous effect. The previous study related to sharpening of thermal data (Agam et al. 2007) was carried out in the homogeneous agricultural landscape. Since the study area passes heterogeneous landscape, it is necessary to check whether linear or polynomial model is suitable to establish NDVI-LST relationship within homogeneous agricultural patches. In this regard, 350 samples were taken from NDVI and LST images (990 m) within pure agricultural land and checked the relationship using linear and polynomial regression model at different resolutions.
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Figure 5-17: polynomial model coefficient plot (a) slope (b) intercept and (c) R-square

![Variation of residual standard error with to resolution](image1)

(a) Resolution

![Variation of residual with respect to resolution](image2)

(b) Resolution

![Variation of R-Square with respect to resolution](image3)

(c) Resolution

Figure 5-17: (a) RSE, (b) minimum maximum residual and (c) R-square of linear model

From the confidence interval plot (Figure: 5.17) it is visible that at coarse resolution uncertainty of slope and intercept is much higher in polynomial model compare to linear model. Both the models are compared using ANOVA analysis. The Pr(>F) value in Table: 5-1 indicates that, in agricultural landscape, linear model is significant than polynomial model upto 630 m. So, in order to establish the relationship between thermal and NDVI data, having the resolution coarser than 630 m, linear model is suitable than polynomial model. Since the study will be aiming to establish sharpening of MODIS (1000 m) thermal data, linear model is more suitable than polynomial.

<table>
<thead>
<tr>
<th>Resolution</th>
<th>Pr(&gt;F) value</th>
<th>Suitable Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>990 m</td>
<td>0.5806</td>
<td>Linear</td>
</tr>
<tr>
<td>810 m</td>
<td>0.2284</td>
<td>Linear</td>
</tr>
<tr>
<td>630 m</td>
<td>0.0167</td>
<td>Linear</td>
</tr>
<tr>
<td>450 m</td>
<td>6.84E-06</td>
<td>Polynomial</td>
</tr>
<tr>
<td>270 m</td>
<td>1.21E-10</td>
<td>Polynomial</td>
</tr>
<tr>
<td>180 m</td>
<td>9.32E-11</td>
<td>Polynomial</td>
</tr>
<tr>
<td>90 m</td>
<td>2.20E-16</td>
<td>Polynomial</td>
</tr>
</tbody>
</table>

Table 5-1: Model Significance agricultural patch
5.3. Justification of Sharpening Process:

Before applying the sharpening model, it is necessary to test whether the sharpening of thermal imagery is feasible.

**Assumption**: If the prediction error of LST at 90m using NDVI & LST relationship (using 990m resolution data) is comparable to the prediction error of LST at 90m using NDVI & LST relationship made from 90m resolution data, then it can be said that the 990m data-relationship can be utilised for sharpening.

In order to test this, following steps have been carried out.

**Process 1**: Predicted the LST at 90 m resolution using the sharpening procedure (Equation 4.3) on aggregated 990 m ASTER NDVI and validated with respect to reference LST (i.e., original ASTER 90 m thermal data). The RMSE (Equation 4.4) of predicted LST using sharpening procedure was found to be 3.63 K at 90 m resolution.

**Process 2**: Next, established the relationship using 90 m resolution NDVI and LST and applied the model on 90 m NDVI to predict the temperature. The actual prediction error of temperature at 90 m resolution has been calculated by taking the difference between reference LST and predicted LST. RMSE of predicted temperature has been found 3.65 K.

From the above comparison it can be said that RMSE of predicted LST (from 990m NDIV to 90 m LST), using sharpening procedure is similar as the actual prediction error at 90 m resolution (90 m NDVI to 90 m LST). So, it can be conclude that sharpening of thermal image is feasible.

5.4. NDVI & fractional vegetation cover (fc) relationship evaluation:

Agam *et al.* (2007) suggested that fractional vegetation cover (fc) is better correlated with surface temperature than NDVI. But the present study found that relation between fc and LST is not linear. It is well defined that the NDVI is linearly co-related with LST (Karnieli *et al.* 2006, Yue *et al.* 2007). Hence, the fc should have the linear correlation with NDVI. Theoretically the range of the NDVI varies from +1 to -1 and fc varies from 0 to 1. Relation between fc and NDVI was calculate and plotted in Figure: 5.18. The plot shows that the trend is nonlinear. Within the study area of current research, the range of the NDVI varies from 0.1 to .66 (computed from MODIS data). Hence, it is necessary to check whether the trend of NDVI and fc relation is linear or not within this range. Plot in Figure: 5.19 also indicate the non linear trend. In TsHARP algorithm fc was computed using the algorithm given by Choudhury *et al.* (1994). In this algorithm upper and lower 3% tails of NDVI distribution excluded as
outliers and NDVI outside this limit replaced by this limit value. With respect to NDVI, $f_c$ is computed and plotted (Figure: 5.20). This plot also shows the non-linear trend of NDVI and $f_c$ relationship.

**Figure 5-18:** Theoretical relationship $f_c$ vs. NDVI

**Figure 5-19:** Scene specific relationship $f_c$ vs. NDVI.

**Figure 5-20:** NDVI & $f_c$ relationship after replacing the outliers.

From the above mentioned arguments it can be said that $f_c$ and LST relationship is non-linear. $f_c$ and LST relationship was also checked over MODIS and ASTER data sets at 1000 m and 990 m resolution respectively (Figure: 5.21, 5.22) and found to be non-linear.

**Figure 5-21:** $f_c$ & LST relationship based on ASTER data
Since the study area is a heterogeneous landscape, it could be possible that LST vs. fc relationship is not as expected. But, theoretical relationship is also found to be non-linear (Figure: 5.18) because of this the current study did not consider the fc for sharpening thermal imagery.

5.5. Evaluation of different sharpening approaches:

In the current study 9 different sharpening processes have been applied. The regression models established at coarser resolution NDVI and LST was applied on different target resolutions (810m, 630m, 450m, 270m, 180m, and 90m) to predict the LST (Equation-4.3). At first, difference between the predicted LST and reference LST of same resolution (Equation-4.3) was calculated, which named as “RMSE without residual”. Then residual error (i.e., observed – predicted) calculated at 990m resolution was added back to the predicted LST and difference was calculated with reference LST of same resolution, which is named as “RMSE with residual”.

The result obtained from different approaches is discusses below:

5.5.1. Approach-1: whole image based linear model without considering coefficient of variation (cv)

In this approach relationship has been generated at 990 m resolution for each pixels of the image and sharpening applied. After the validation of different target resolution predicted LST, RMSE and mean error were calculated from the error map (observed-predicted LST). Table 5-2 shows that RMSE and mean error calculated for different resolution predicted thermal images.
The RMSE shows the accuracy of the predicted temperature and mean error shows whether the prediction is biased. The RMSE curve (Figure: 5.23a) shows that as we move towards finer resolution, RMSE of predicted temperature increases. But this increasing trend is not linear and after the 180 m resolution slope of the RMSE curve is steeply increasing. It is also visible from the graph that after adding the residual of 990 m, the RMSE of predicted LST is much less in compare to without residual added predicted LST.

The curve (Figure: 5.23b) of the mean error shows that in this approach all the values are positive and hence there is an over prediction of temperature (0.4 K) in all target resolution. At the 990 m resolution the mean error is 0.41 k which increased to 0.43 K at the 90 m resolution.
Histogram of different resolution error map was computed (Figure: 5.24). It shows that towards the finer resolution, range of the error in predicted thermal image increases. In the 810 m resolution the range of the error was -6 K to 6 K. But in the 90 m resolution the range of the error is -20 K to 20 K. In the 270 m resolution the range of the error is \(-10\) K to 10 K. The histogram curve is not having normal distribution.

5.5.2. **Approach-2: whole image based polynomial model without cv.**

In this approach polynomial regression model has been applied in order to establish the NDVI-LST relationship at coarse resolution. Sharpening model has been applied on different target resolution NDVI and validated.
The RMSE curve (Figure: 5.25a) shows that initially (810 m resolution) RMSE of the predicted temperature (2.09 K) is less in compare to linear model (2.20 K). But towards the high resolution RMSE increases (4.06 K at 90 m resolution) more rapidly than linear model (4.13 K).

In case of mean error (Figure: 5.25b) there is a sudden drop in 810 m resolution to 630 m resolution. If we add the residual to the finer resolution predicted LST, under estimation of predicted temperature is -0.75 K to -0.41 K. We cannot find any meaningful interpretation about the variation of mean error, specially from 810 m to 630 m (Figure: 5.25b). It may happen because of the random effect, the previous study (Agam et al. 2007; Kustus et al. 2003) did not considered mean error in their evaluation.

<table>
<thead>
<tr>
<th>Resolution</th>
<th>RMSE without residual</th>
<th>RMSE with residual</th>
<th>Mean Error without residual</th>
<th>Mean Error with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>810 m</td>
<td>2.09</td>
<td>0.78</td>
<td>0.84</td>
<td>0.03</td>
</tr>
<tr>
<td>630 m</td>
<td>2.01</td>
<td>1.25</td>
<td>0.06</td>
<td>-0.75</td>
</tr>
<tr>
<td>450 m</td>
<td>2.20</td>
<td>1.47</td>
<td>0.10</td>
<td>-0.71</td>
</tr>
<tr>
<td>270 m</td>
<td>2.62</td>
<td>1.98</td>
<td>0.18</td>
<td>-0.63</td>
</tr>
<tr>
<td>180 m</td>
<td>3.09</td>
<td>2.56</td>
<td>0.25</td>
<td>-0.56</td>
</tr>
</tbody>
</table>

Table 5-3: RMSE & mean error table of approach-2

Figure 5-25: (a) RMSE & (b) mean error of approach 2

5.5.3. Approach-3: whole image based linear model with cv:

In this approach outliers pixel has been remove for generation of NDVI-LST relationship. The RMSE curve shows that RMSE (Figure: 5.26a) of the predicted LST is less in comparison to without cv based approach. At 270 m resolution earlier the RMSE achieved is 2.74 K which became 2.73 K in this approach. The mean error shows that after adding the residual the mean error at each resolution is very less (0.02 K).
5.5.4. Approach 4: whole image based polynomial model considering \(cv\).

In this approach polynomial regression was applied considering the \(cv\). Predicted temperature of different target resolution was validated and calculation of RMSE and mean error were done. The RMSE curve (Figure 5.27a) suggests that at 810 m resolution, RMSE of the predicted temperature is 0.82 K which increase to 3.65 K at 90 m resolution after adding the residual. After 270 m resolution RMSE increases more rapidly.

The mean error shows (Figure 5.27b) that over estimation of LST at 810 m resolution is 0.03 K which is decreases to -0.51 K at 630 m resolution and the reduced continuously. In the 90 m resolution mean error has been found to be -0.13 K.

### Table 5-4: RMSE & mean error table of approach -3

<table>
<thead>
<tr>
<th>Resolution</th>
<th>RMSE without residual</th>
<th>RMSE with residual</th>
<th>Mean Error without residual</th>
<th>Mean Error with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>810 m</td>
<td>2.03</td>
<td>0.83</td>
<td>0.12</td>
<td>0.01</td>
</tr>
<tr>
<td>630 m</td>
<td>2.14</td>
<td>1.00</td>
<td>0.12</td>
<td>0.00</td>
</tr>
<tr>
<td>450 m</td>
<td>2.32</td>
<td>1.30</td>
<td>0.12</td>
<td>0.01</td>
</tr>
<tr>
<td>270 m</td>
<td>2.73</td>
<td>1.91</td>
<td>0.13</td>
<td>0.01</td>
</tr>
<tr>
<td>180 m</td>
<td>3.20</td>
<td>2.53</td>
<td>0.13</td>
<td>0.02</td>
</tr>
<tr>
<td>90 m</td>
<td>4.14</td>
<td>3.65</td>
<td>0.17</td>
<td>0.14</td>
</tr>
</tbody>
</table>

(a) RMSE Curve of Approach 3

(b) ME Curve of Approach 3

Figure 5.26: (a) RMSE & (b) mean error of approach 3
5.5.5. Approach 5: landuse classification based linear model with cv.

In this approach landuse based NDVI-LST relationship was applied for disaggregating the temperature. It was found that the regression model varies in different land cover class.

This relationship was applied to the different target resolution NDVI and predicted the LST. The predicted LST was validated with respect to reference LST of corresponding resolution. At first RMSE of full image was evaluated and then RMSE was calculated within the landuse class. The RMSE curve (Figure: 5.28a) is little flat in compare to approach 1 to 4.

At the 810 m resolution RMSE of predicted temperature is 0.99 K and 630 m to 180 m resolution RMSE increases slowly. After 180 m resolution RMSE increases 1.02 K (2.48-3.50).

Table 5-5: RMSE & mean error table of Approach-4

<table>
<thead>
<tr>
<th>Resolution</th>
<th>RMSE without residual</th>
<th>RMSE with residual</th>
<th>Mean Error without residual</th>
<th>Mean Error with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>810 m</td>
<td>2.02</td>
<td>0.82</td>
<td>0.66</td>
<td>0.03</td>
</tr>
<tr>
<td>630 m</td>
<td>2.02</td>
<td>1.11</td>
<td>0.13</td>
<td>-0.51</td>
</tr>
<tr>
<td>450 m</td>
<td>2.22</td>
<td>1.37</td>
<td>0.17</td>
<td>-0.46</td>
</tr>
<tr>
<td>270 m</td>
<td>2.64</td>
<td>1.94</td>
<td>0.26</td>
<td>-0.37</td>
</tr>
<tr>
<td>180 m</td>
<td>3.13</td>
<td>2.54</td>
<td>0.34</td>
<td>-0.29</td>
</tr>
<tr>
<td>90 m</td>
<td>4.11</td>
<td>3.65</td>
<td>0.51</td>
<td>-0.50</td>
</tr>
</tbody>
</table>

Figure 5-27: (a) RMSE & (b) mean error of approach 4
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Table 5-6: RMSE table of approach 5

<table>
<thead>
<tr>
<th>Resolution</th>
<th>RMSE without residual</th>
<th>RMSE with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full image</td>
<td>Others</td>
</tr>
<tr>
<td>810m</td>
<td>1.95</td>
<td>2.26</td>
</tr>
<tr>
<td>650m</td>
<td>2.06</td>
<td>2.39</td>
</tr>
<tr>
<td>450m</td>
<td>2.22</td>
<td>2.54</td>
</tr>
<tr>
<td>270m</td>
<td>2.60</td>
<td>2.90</td>
</tr>
<tr>
<td>180m</td>
<td>3.03</td>
<td>3.30</td>
</tr>
<tr>
<td>90m</td>
<td>3.92</td>
<td>4.13</td>
</tr>
</tbody>
</table>

Table 5-7: Mean error table of approach 5

<table>
<thead>
<tr>
<th>Resolution</th>
<th>Mean error without residual</th>
<th>Mean error with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full image</td>
<td>Others</td>
</tr>
<tr>
<td>810m</td>
<td>-0.03</td>
<td>0.41</td>
</tr>
<tr>
<td>630m</td>
<td>-0.03</td>
<td>0.39</td>
</tr>
<tr>
<td>450m</td>
<td>0.11</td>
<td>0.39</td>
</tr>
<tr>
<td>270m</td>
<td>0.12</td>
<td>0.40</td>
</tr>
<tr>
<td>180m</td>
<td>0.05</td>
<td>0.41</td>
</tr>
<tr>
<td>90m</td>
<td>0.13</td>
<td>0.39</td>
</tr>
</tbody>
</table>

Figure 5-28: (a) RMSE of the full image (b) RMSE of different landuse classes

From the class wise validation of predicted temperature (Figure: 5.29a) it can be found that agricultural area RMSE is much less in (1.70 K at 270 m resolution) compare to other land cover class. In respect fallow and other landuse class, up to 270 m resolution RMSE is less in fallow land and beyond that other landuse class having less RMSE. The mean error curve shows (Figure: 5.29b) that over the agricultural area temperature is underestimated.
Figure 5-29: (a) Mean error of full image, (b) Mean error of LST within different landuse class

5.5.6. Approach-6: NDVI threshold based linear model with cv.

In this approach NDVI-LST relationship is established at different NDVI range (0-0.2, 0.2-0.5 and >0.5) using linear regression model.

The RMSE curve shows (Figure: 5.30a) that up to 270 m resolution, RMSE of the predicted temperature is less than 2 K and after 270 m resolution RMSE increase to 3.68 K at 90 m resolution. After adding the residual to predicted LST, up to 450 m resolution mean error is less than 0.1 K.

<table>
<thead>
<tr>
<th>Resolution</th>
<th>RMSE without residual</th>
<th>RMSE with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full image</td>
<td>NDVI &lt;0.2</td>
</tr>
<tr>
<td>810m</td>
<td>1.90</td>
<td>2.39</td>
</tr>
<tr>
<td>630m</td>
<td>2.02</td>
<td>2.56</td>
</tr>
<tr>
<td>450m</td>
<td>2.21</td>
<td>2.69</td>
</tr>
<tr>
<td>270m</td>
<td>2.64</td>
<td>2.99</td>
</tr>
<tr>
<td>180m</td>
<td>3.12</td>
<td>3.26</td>
</tr>
<tr>
<td>90m</td>
<td>4.09</td>
<td>3.94</td>
</tr>
</tbody>
</table>

Table 5-8: RMSE table of NDVI thresholds with linear model

Figure: 5.30b shows different NDVI class wise RMSE plot. The area having > 0.5 NDVI value is having the least RMSE in predicted LST. At the 270 m resolution the RMSE of the predicted LST is 1.36 K.

The curve of mean error Figure: 5.30a shows that over >0.5 the NDVI range temperature is under predicted and over the NDVI range 0 to 0.2 and 0.2 to 0.5 temperature is over predicted by this
method. Only in the NDVI range 0.2 to 0.5 range (added residual), after 450 m resolution under estimation of temperature was found.

<table>
<thead>
<tr>
<th>Resolution</th>
<th>Mean error without residual</th>
<th>Mean error with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full image</td>
<td>NDVI &lt;0.2</td>
</tr>
<tr>
<td>810m</td>
<td>0.19</td>
<td>0.12</td>
</tr>
<tr>
<td>630m</td>
<td>0.22</td>
<td>0.26</td>
</tr>
<tr>
<td>450m</td>
<td>0.26</td>
<td>0.33</td>
</tr>
<tr>
<td>270m</td>
<td>0.34</td>
<td>0.59</td>
</tr>
<tr>
<td>180m</td>
<td>0.40</td>
<td>0.92</td>
</tr>
<tr>
<td>90m</td>
<td>0.53</td>
<td>1.68</td>
</tr>
</tbody>
</table>

Table 5-9: mean error table of NDVI thresholds with linear model

![Graph](attachment:graph.png)

Figure 5-30: (a) RMSE of full image and (b) RMSE of different NDVI class

![Graph](attachment:graph.png)

Figure 5-31: (a) Mean error of full image and (b) Mean error of different NDVI class

5.5.7. Approach-7 NDVI threshold based polynomial model considering cv.
In this approach NDVI threshold based sharpening model was applied to predict the LST at different target resolution. The evaluated result of this approach is shown in the Table: 5-10. The RMSE value of full image after adding the residual is 1.54 K at 810 m resolution which has been increased to 3.30 K at 270 m and 4.96 K at 90 m resolution. In this approach the RMSE error is very high (4 to 10 K) in region NDVI <0.2 range as well as the mean error is also high (2 to 8 K).

Table 5-10: RMSE table NDVI thresholds based polynomial approach

<table>
<thead>
<tr>
<th>Resolution</th>
<th>RMSE without residual</th>
<th>RMSE with added residual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full image</td>
<td>NDVI &lt;0.2</td>
</tr>
<tr>
<td>810m</td>
<td>3.00</td>
<td>10.37</td>
</tr>
<tr>
<td>650m</td>
<td>3.17</td>
<td>10.54</td>
</tr>
<tr>
<td>450m</td>
<td>3.41</td>
<td>10.64</td>
</tr>
<tr>
<td>270m</td>
<td>3.91</td>
<td>10.96</td>
</tr>
<tr>
<td>180m</td>
<td>4.47</td>
<td>11.32</td>
</tr>
<tr>
<td>90m</td>
<td>5.62</td>
<td>12.17</td>
</tr>
</tbody>
</table>

Table 5-11: Mean error table NDVI thresholds based polynomial approach

<table>
<thead>
<tr>
<th>Resolution</th>
<th>Mean error without residual</th>
<th>Mean error with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full image</td>
<td>NDVI &lt;0.2</td>
</tr>
<tr>
<td>810m</td>
<td>0.69</td>
<td>-10.09</td>
</tr>
<tr>
<td>650m</td>
<td>0.76</td>
<td>-10.23</td>
</tr>
<tr>
<td>450m</td>
<td>0.87</td>
<td>-10.30</td>
</tr>
<tr>
<td>270m</td>
<td>1.06</td>
<td>-10.56</td>
</tr>
<tr>
<td>180m</td>
<td>1.24</td>
<td>-10.88</td>
</tr>
<tr>
<td>90m</td>
<td>1.61</td>
<td>-11.64</td>
</tr>
</tbody>
</table>

Figure 5-32: (a) RMSE of full image and (b) RMSE of different NDVI class
5.5.8. Approach-8 adjusted NDVI based linear model considering cv:

Adjusted NDVI has been used for sharpening the temperature. RMSE curve (Figure 5.35) of resultant predicted temperature depicts that error is increasing towards the finer resolution. In 270 m resolution RMSE of the predicted LST is 1.89 K and in 180 m resolution RMSE is 2.46 K. The RMSE curve shows that after 270 m resolution RMSE increases rapidly. After adding the residual of 990 m resolution, the error in predicted LST is much less in compare to without residual added predicted LST. Mean error is less up to 270 m resolution (-0.11) and after that it changes dramatically.

<table>
<thead>
<tr>
<th>Resolution</th>
<th>RMSE without residual</th>
<th>RMSE with residual</th>
<th>Mean Error without residual</th>
<th>Mean Error with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>810 m</td>
<td>2.03</td>
<td>0.83</td>
<td>0.01</td>
<td>-0.10</td>
</tr>
<tr>
<td>630 m</td>
<td>2.14</td>
<td>1.00</td>
<td>0.07</td>
<td>-0.04</td>
</tr>
<tr>
<td>450 m</td>
<td>2.33</td>
<td>1.30</td>
<td>0.04</td>
<td>-0.07</td>
</tr>
<tr>
<td>270 m</td>
<td>2.72</td>
<td>1.89</td>
<td>0.00</td>
<td>-0.11</td>
</tr>
<tr>
<td>180 m</td>
<td>3.15</td>
<td>2.46</td>
<td>-0.11</td>
<td>-0.22</td>
</tr>
</tbody>
</table>

Table 5-12: RMSE & mean error table of adjusted NDVI based approach.
Figure 5-36: Location of the agricultural area

Figure 5-37: Observed LST, predicted LST and error at 270m resolution within a small subset. The Figure 5-37 shows that the pattern of observed and predicted temperature of the area is almost same. The error map shows that the error is more in the fallow landuse in comparison with agricultural land.
5.5.9. Approach-9: spatial contextual regression:

In this approach prediction of temperature at different target resolution was done using the linear regression model established in 3x3, 5x5 and 7x7 pixels mask [non-overlapping (block) and overlapping pixel (focal)]. Table 5.13 shows the RMSE and mean error of predicted LST computed using 3x3, 5x5, 7x7 non-overlapping pixel block. The predicted temperature of target resolution was validated with respect to observed temperature. The RMSE of predicted temperature at 270 m resolution for window size 3x3, 5x5 and 7x7 pixel block are 1.88 K, 1.75 K and 1.98 K (without residual) and 1.88 K, 1.70 K and 1.79 K (with residual) respectively. The curve of the mean error indicates that temperature is over predicted by this method but the amount of over prediction is very low. Mean error at 270 m resolution for window size 3x3, 5x5 and 7x7 are 0.01 K, 0.01 K and 0.02 K (after adding the residual). It is found that in all the resolutions, RMSE of predicted temperature using the 5x5 pixel block is less in comparison with 3x3 and 7x7 pixel block, because in 3x3 window the uncertainty of the relationship is more as the number of sample is low and in the 7x7 window size possibility of heterogeneous effect in the regression is high. Hence, the optimum window size could be 5x5.

<table>
<thead>
<tr>
<th>Mask</th>
<th>Resolution</th>
<th>RMSE without residual</th>
<th>RMSE with residual</th>
<th>Mean Error without residual</th>
<th>Mean Error with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>3x3 Block</td>
<td>810 m</td>
<td>0.95</td>
<td>0.98</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>630 m</td>
<td>1.11</td>
<td>1.13</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>270 m</td>
<td>1.38</td>
<td>1.39</td>
<td>0.01</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>180m</td>
<td>2.41</td>
<td>2.40</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>90 m</td>
<td>3.38</td>
<td>3.38</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>5x5 Block</td>
<td>810 m</td>
<td>1.09</td>
<td>0.73</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>630 m</td>
<td>1.24</td>
<td>0.88</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>270 m</td>
<td>1.48</td>
<td>1.15</td>
<td>0.01</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>180m</td>
<td>2.40</td>
<td>2.25</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>90 m</td>
<td>3.39</td>
<td>3.24</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>7x7 Block</td>
<td>810 m</td>
<td>1.15</td>
<td>0.74</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>630 m</td>
<td>1.30</td>
<td>0.89</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>270 m</td>
<td>1.53</td>
<td>1.17</td>
<td>0.01</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>180m</td>
<td>2.48</td>
<td>2.28</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>90 m</td>
<td>3.41</td>
<td>3.25</td>
<td>0.03</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Table 5-13: RMSE & mean error table of spatial contextual regression model with different non-overlapping block.
Figure 5-38 (a) RMSE & (b) mean error plot spatial contextual regression model 3x3 non-overlapping block

Figure 5-39: (a) RMSE & (b) mean error plot spatial contextual regression model 5x5 non-overlapping block

Figure 5-40: (a) RMSE & (b) mean error plot spatial contextual regression model 7x7 non-overlapping block
In this approach the difference in RMSE without and with adding the residual is much less in comparison with other approaches, because of prediction of temperature considering the local window (contextual) based relationship. In the 3x3 window size the RMSE of predicted temperature without and with adding the residual is almost same. But RMSE difference is increasing with increasing window size. Hence, it can be conclude that the addition of residual error to the predicted LST has very less effect on RMSE of predicted LST.

Predicted LST and error at 270 m resolution is shown (Figure 5.41) in the small subset of the study area (agriculture patch).

![Figure 5-41: Location of the agricultural patch, FCC and observed temperature at 270 m resolution](image)

Figure 5-42 shows the predicted LST and error at 270 m resolution using 3x3, 5x5 and 7x7 masks. It is found that the temperature is less in the vegetated pixels in comparison with fallow land, as well as the error in predicted LST is very less in the vegetated pixels compare to other landuse. It is also found that the range of the error in LST, predicted using 5x5 pixels block is less in compare to other mask size.

![Figure 5-42: Predicted LST and error at 270 m resolution derived using the non-overlapping window based regression](image)
Table 5.14 shows that the RMSE and mean error of predicted LST at different resolution derived using overlapping (focal 3x3, 5x5 and 7x7) window based regression. It is found that after 270 m resolution the RMSE of the predicted LST is highly increasing.

<table>
<thead>
<tr>
<th>Mask</th>
<th>Resolution</th>
<th>RMSE</th>
<th>Mean Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>without residual</td>
<td>with residual</td>
</tr>
<tr>
<td>810 m</td>
<td>0.87</td>
<td>0.71</td>
<td>0.01</td>
</tr>
<tr>
<td>630 m</td>
<td>1.05</td>
<td>0.87</td>
<td>0.00</td>
</tr>
<tr>
<td>3x3 Focal</td>
<td>450 m</td>
<td>1.32</td>
<td>1.15</td>
</tr>
<tr>
<td>270 m</td>
<td>1.84</td>
<td>1.70</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>180 m</td>
<td>2.37</td>
<td>2.27</td>
</tr>
<tr>
<td></td>
<td>90 m</td>
<td>3.35</td>
<td>3.27</td>
</tr>
<tr>
<td>5x5 Focal</td>
<td>450 m</td>
<td>1.40</td>
<td>1.14</td>
</tr>
<tr>
<td></td>
<td>270 m</td>
<td>1.89</td>
<td>1.70</td>
</tr>
<tr>
<td></td>
<td>180 m</td>
<td>2.40</td>
<td>2.25</td>
</tr>
<tr>
<td></td>
<td>90 m</td>
<td>3.35</td>
<td>3.24</td>
</tr>
<tr>
<td>7x7 Focal</td>
<td>450 m</td>
<td>1.60</td>
<td>1.31</td>
</tr>
<tr>
<td></td>
<td>270 m</td>
<td>2.05</td>
<td>1.82</td>
</tr>
<tr>
<td></td>
<td>180 m</td>
<td>2.49</td>
<td>2.31</td>
</tr>
<tr>
<td></td>
<td>90 m</td>
<td>3.45</td>
<td>3.31</td>
</tr>
</tbody>
</table>

Table 5-14: RMSE & mean error table of spatial contextual regression model with different overlapping block.

![Figure 5-43](image.png)

Figure 5-43: (a) RMSE & (b) mean error plot spatial contextual regression model 3x3 overlapping block
At the 270 m resolution RMSE of predicted LST is 1.70 K derived using both 3x3 and 5x5 pixel based spatial regression model. The RMSE of LST derived using 7x7 overlapping mask is rather high (1.82 K) in compare to other mask size. The mean error curve shows that the temperature is over predicted in this approach (LST derived using 3x3, and 5x5 mask). Only in the predicted LST of 810 m to 450 m resolution, derived using 7x7 overlapping mask having under prediction. The difference in RMSE of predicted LST without and with adding the residual is very low in this approach. The mean error of curve also shows that up to 270 m resolution the over prediction of temperature is 0.01 K and after that the mean error is increasing.

Figure 5.46 shows the predicted LST and error at 270 m resolution derived using different overlapping mask. The location of the area is mentioned in the Figure 5.31.
5.5.9.1. Comparison of window type and size over agricultural area:

The suitable window size and type for spatial contextual regression is identified by applying the sharpening model in a homogeneous agricultural area. The Figure 5.43 (a) shows that non-overlapping 5x5 window, which produced least RMSE (1.39 K) in comparison with other overlapping and non-overlapping window based regression. The Figure 5.43 (b) shows that the over prediction of temperature is 0.001 K which is the least in compare to other window size based regression procedure. Hence it can be conclude that non-overlapping 5x5 pixel block based regression is the most suitable for sharpening of LST using spatial contextual regression.

Figure 5-46: Predicted LST and error at 270 m resolution derived using the overlapping window based regression.
Figure 5-47: Comparison of window size & type for spatial contextual regression over agricultural Landscape

Figure 5.48 shows the predicted observed and predicted LST derived 5x5 non-overlapping mask at 810 m, 270 m and 90 m resolution in the above mentioned agricultural area. It is found that the
disaggregation of pixels maintained the spatial pattern of the temperature. The relationship was established with respect to observed and predicted LST of this particular area (Figure: 5.49), which
shows that at the 810 m resolution the observed and predicted LST has very strong relationship (R-square is 0.9325). But towards the high resolution the relationship between observed and predicted LST is become weaker, because heterogeneous effect at finer resolution. R-square value at the 270 m and 90 m resolution is 0.7227 and 0.3831 respectively. Hence, it can be conclude that sharpening of temperature should be done up to 270 m resolution.

Figure 5-49: Relationship between observed and predicted LST at 810, 270 and 90 m resolution.

5.6. Comparison of different sharpening approach:

Figure 5-50: RMSE of 9 different approaches with respect to resolution
In order to compare the 9 different sharpening approaches, RMSE, Mean error and skewness are plotted with respect to different target resolution (Figure : 5.50, 5.51, 5.52). The RMSE plot indicates that upto 450 m resolution adjusted NDVI based sharpening approach produces the lowest RMSE and 450 m to 90 m resolution spatial contextual regression (window based regression) approach produces lowest RMSE. Mean error is also lowest in the spatial contextual regression approach and the distribution of error is much systematic (skewness is very low in compare to others approaches). Hence, out of this 9 sharpening procedure, 3 approaches: approach 9, 8 and 3 were found to be
providing good results. Spatial contextual regression approach (Approach-9) was giving the best results out of all, followed by Adjusted NDVI based linear model (Approach-8) and linear relationship with \(cv\) (Approach-3). The only disadvantage of adjusted NDVI approach is selection of appropriate pixels between fine and coarse resolution.

5.7. **Applicability of selected sharpening approaches with respect to various NDVI value ranges:**

In order to understand the selected sharpening approaches (9, 8 and 3) in detail, the resultant prediction error from these approaches were analyzed with respect to various NDVI value ranges (Figure: 5.53, 5.54 and 5.55). In this process the NDVI was classified into 7 classes with 0.1 interval. Within the each NDVI range-class RMSE and ME was calculated, which shows that the distribution of error is not constant over the NDVI space. RMSE of the predicted temperature is high upto 0.4 NDVI range and after that RMSE reduces. The Mean error is positive over NDVI range upto 0.4 which represent the over prediction and after 0.4 range the mean error is negative which indicate under prediction of temperature from true value.

![Figure 5-53: Distribution of prediction error in different NDVI range in linear relationship with cv approach.](image)

![Figure 5-54: Distribution of prediction error in different NDVI range adjusted NDVI based approach.](image)
5.8. Analysis of residual error:

In the sharpening model it is needed to add the residual of coarse resolution regression model to finer resolution predicted temperature. Previous study also followed the same procedure (Kustas et al. 2003; Agam et al. 2007). Since there is a greater variability in NDVI & LST values at finer spatial resolution, it is logical to assume that the mean of the fine-resolution pixels (LST) should give equivalent LST values at coarse resolution pixel. Hence, it is important to examine the extent to which it meets this assumption, which was not tested in the previous studies. In order to do this the following procedure was carried out:

![Schematic representation of residual error analysis](image)

**Figure 5-55:** Distribution of prediction error in different NDVI range (spatial contextual regression approach).

**Figure 5-56:** Schematic representation of residual error analysis.
Figure 5-57: (a) Difference image between predicted temperature (90m aggregated to 990) without adding residual and reference LST (990m). (b) Difference image between aggregated predicted 990m temperature added residual and ref LST 990m.

(a) ![Figure 5-57a](image1.png)  
(b) ![Figure 5-57b](image2.png)

Min = -15.86  Max = 5.73
Mean = -0.16  standard deviation = 1.96

Min = -0.78  Max = 0.59
Mean = -0.0  standard deviation = 0.05

Figure 5-58: (a) Histogram of difference image between aggregated predicted 990m temperature without added residual and ref LST 990m. (b) Histogram difference image between aggregated predicted 990m temperature added residual and ref LST 990m.

(a) ![Histogram 5-58a](image3.png)  
(b) ![Histogram 5-58b](image4.png)
Figure 5.57(a) shows that the constraint (mean of the fine-resolution pixels should equal the equivalent coarse resolution pixel) is not met and there is spatial pattern. In the agricultural area the difference is less in comparison with fallow and other areas. It is also visible that after adding the residual [Figure: 5.57(b)], the difference between aggregated 990 m LST and reference LST 990m is very less. Hence, this procedure also validates the applicability of sharpening model for disaggregating coarser resolution thermal data.

5.9. Representation of prediction error spatially:

In order to represent the spatial pattern of prediction error, error map of 270 m resolution was classified in 4 categories; upto 2 K, 2 K to 4 K, 4 K to 6 K and > 6 K. Prediction error of three sharpening approaches which was found to be best among 9 approach (linear relation with \(cv\), Adjusted NDVI with \(cv\) and spatial contextual regression) were tested.

![Classification of error map at 270 m resolution](image)

Figure 5-59: Classification of error map at 270 m resolution (a)linear relation with \(cv\), (b)Adjusted NDVI with \(cv\) and (c) spatial contextual regression).

The yellow colored area in the classified error map shows the error less than 2K. The maximum area covered by yellow color belongs to agricultural land (see the FCC Figure: 3.2).

<table>
<thead>
<tr>
<th>Error in (K)</th>
<th>Linear relation cv % of area</th>
<th>Adjusted NDVI % of area</th>
<th>Spatial contextual regression % of area</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 to 2</td>
<td>74.03</td>
<td>72.73</td>
<td>75.69</td>
</tr>
<tr>
<td>2 to 4</td>
<td>21.58</td>
<td>23.58</td>
<td>20.04</td>
</tr>
<tr>
<td>4 to 6</td>
<td>3.73</td>
<td>3.24</td>
<td>3.47</td>
</tr>
<tr>
<td>&gt;6</td>
<td>0.66</td>
<td>0.45</td>
<td>0.80</td>
</tr>
</tbody>
</table>

Table 5-15: Percentage of area under each error class.
From the Table 5.15 it is visible that more than 72% area on predicted LST is having less than 2 K error for all three approaches. Among the three approaches spatial contextual regression produces less error in predicted LST. Because more than 75% area of the predicted LST is having less than 2 K error, 20% area is having less than 4 K error and only 4% area having error more than 4 K.

5.10. Sharpening MODIS data:

After applying the 9 different algorithms on aggregated ASTER (990 m) resolution, it was found that 3 approaches are most suitable for sharpening; spatial contextual regression, adjusted NDVI based approach and linear relationship with cv. Hence, these three algorithms are applied on MODIS data. After applying the disaggregation procedure on ASTER data it was found that upto 270 m resolution disaggregation is feasible and beyond this resolution the RMSE of predicted LST is increasing. Because of this reason disaggregation procedure is applied 250 m MODIS NDI data sets.

At first established the relationship at MODIS 1000 m resolution (NDVI vs. LST) and calculated the residual error at 1000 m resolution. The model established at 1000 m resolution was applied on MODIS 250 m resolution NDVI and added back the residual of 1000 m model. The predicted LST at 250 m is validated with ASTER aggregated 250 m LST.

5.10.1. Linear relationship with cv:

In this process the linear model (with cv) was applied for establishing the relationship between NDVI and LST at 1000 m resolution. The relation is shown in the Figure: 5.60.

![Figure 5-60: NDVI & LST relationship with cv based on MODIS data](image)

The linear model equation created at 1000 m resolution is given below:
\[ \hat{LST}_{1000m} = 325.8 + (-38.413 \times NDVI_{1000m}) \]  

(Equation 4.5)

This equation was applied on MODIS 250 m NDVI and predicted temperature. RMSE and ME of predicted temperature is shown below:

<table>
<thead>
<tr>
<th></th>
<th>RMSE without residual</th>
<th>RMSE with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>ME</td>
<td>RMSE</td>
</tr>
<tr>
<td>3.3944</td>
<td>-2.08</td>
<td>3.084</td>
</tr>
</tbody>
</table>

Table 5-16: RMSE & mean error table of MODIS 250 m predicted temperature (approach 3).

Table: 5.16 shows that the predicted LST is 3.39 K without adding the residual and 3.08 K after adding the residual. In this process the under prediction of temperature is 2.01 K (after adding the residual).

5.10.2. Adjusted NDVI with cv:

Adjusted NDVI based sharpening also applied on MODIS data. Relationship was established between 250 m resolution NDVI and 1000 m resolution NDVI (Figure: 5.61).

![Relation between NDVI 250 m and NDVI 1000 m](image)

\[ R^2 = 0.605 \]

Figure 5-61: Relationship for adjusted derivation of NDVI.

The equation was generated to adjust the NDVI 250 m resolution with NDVI 1000 m is following:

\[ NDVI_{adj} = 0.0471 + 0.8839 \times NDVI_{FR} \]

After computing the adjusted NDVI, sharpening model was applied (Equation 4.5) and residual of 1000 m was added back to the predicted temperature.
RMSE and ME of predicted temperature is shown below:

<table>
<thead>
<tr>
<th></th>
<th>RMSE without residual</th>
<th>RMSE with residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>ME</td>
<td>RMSE</td>
</tr>
<tr>
<td>3.469</td>
<td>-2.04</td>
<td>2.924</td>
</tr>
</tbody>
</table>

Table 5-17: RMSE & mean error table of MODIS 250 m predicted temperature (approach 8).

In this process the RMSE of the predicted LST is 3.46 K without adding the residual and 2.92 K after adding the residual. Temperature is under estimated. The mean error is less in predicted LST without adding the residual.

![Predicted thermal image from MODIS 250 m NDVI](image)

Figure 5-62: Predicted thermal image from MODIS data based on 250 m MODIS NDVI.

The Figure: 5.62 shows the predicted LST at 250 m resolution from MODIS datasets. It found that in the agricultural area (blue colour in the image) temperature is low compare to fallow and other land use (red and yellow colour in the image).

5.10.3. Spatial contextual regression:

In this approach prediction of temperature at 250 m resolution was done using the linear regression model established at 1000 m resolution in 3x3 and 5x5 non-overlapping pixels mask (Block).

<table>
<thead>
<tr>
<th>Mask size</th>
<th>RMSE without residual (K)</th>
<th>ME</th>
<th>RMSE with residual (K)</th>
<th>ME</th>
</tr>
</thead>
<tbody>
<tr>
<td>3x3 mask</td>
<td>2.75</td>
<td>-2.14</td>
<td>1.98</td>
<td>-0.05</td>
</tr>
<tr>
<td>5x5 mask</td>
<td>2.66</td>
<td>-2.15</td>
<td>3.06</td>
<td>2.11</td>
</tr>
</tbody>
</table>

Table 5-18: RMSE & mean error table of MODIS 250 m predicted temperature (approach 9).
The RMSE plot (Figure 5.63) shows that 3x3 spatial block produce lowest RMSE (1.98 K) and mean error (-0.05 K) after adding the residual. It is found that for disaggregation of MODIS data the 3x3 spatial mask based regression is much suitable in comparison with 5x5 mask.

Figure 5-64: FCC and observed LST at 250 m resolution (ASTER)

Figure 5-65: Predicted LST and error in agricultural area using approach 3, 8, and 9.
Figure 5.64 shows the FCC and observed LST of the agricultural area. From the Figure: 5.65 it is visible that in the agricultural area prediction error is much less in compare to fallow and others areas. The prediction error map shows that in the fallow landuse (red colour in the predicted LST) temperature is under estimated by the spatial contextual regression model. It is also found that approach 9 produce least RMSE in (1.35 K) in compare to approach 3 and approach 8. Hence, it can be conclude that among the above mentioned three approaches approach 9 (spatial contextual regression with 3x3 mask) is most suitable for disaggregation of MODIS up to 250 m resolution.
6. Conclusion and Recommendation:

The main objective of this research is enhancing the spatial resolution of thermal image from coarse spatial resolution to finer spatial resolution. The study was undertaken over a heterogeneous landscape of Haryana, India. In order to analyse the disaggregation procedure, the current study examined the relationship between the Normalized Difference Vegetation index and Land surface temperature.

It was found that the LST is linearly correlated with NDVI. The linear correlation is much better in the agricultural area in comparison with other landuse.

The current study tested the relationship between LST and fractional vegetation cover over heterogeneous landscape and observed that LST is nonlinearly correlated with $f_c$. Hence, the study conclude that in the heterogeneous landscape $f_c$ may not be suitable for disaggregation of thermal data.

Sharpening procedures were tested to predict the temperature at finer resolution using MODIS (1000 m) and ASTER dataset (90 m resolution). At first, in order to understand and validate the disaggregation process, the ASTER datasets (NDVI & LST) were aggregated to various coarser resolutions; 180 m, 270 m, 450 m, 630 m, 810 m & 990 m, and then relationship was established between them at respective resolutions. These relationship, coefficients were analysed for their consistency. Nine different sharpening procedures, as mentioned below, were tested:

- Whole image based linear model without considering coefficient of variation ($cv$).
- Whole image based polynomial model without considering $cv$.
- Whole image based linear model considering $cv$.
- Whole image based polynomial model considering $cv$.
- Landcover classification based linear model considering $cv$.
- NDVI threshold based linear model considering $cv$.
- NDVI threshold based polynomial model considering $cv$.
- Adjusted NDVI based linear model considering $cv$.
- Spatial contextual regression.

Out of this 9 sharpening procedure, 3 approaches were found to be providing good results. Spatial contextual regression approach (Approach-9) was giving the best results out of all, followed by Adjusted NDVI based linear model (Approach-8) and linear relationship with $cv$ (Approach-3).
It was found that 990 m resolution aggregated ASTER thermal data could be disaggregated to 270 m with the RMSE of 1.70 K and beyond this resolution the RMSE of the predicted temperature increases rapidly. Hence, it can be said that disaggregation from 990 m was possible up to 270 m only.

In order to validate this algorithm three recommended disaggregation procedure (Approach-9, Approach-8 & Approach-3) were tested on MODIS data to predict the temperature at 250 m resolution. It was found that MODIS 1000 m thermal data can be disaggregate to 250 m resolution with the RMSE of 1.98 K (using the approach 9). Hence, it can be conclude that disaggregation of thermal data is possible up to 250 m resolution.

It was found that the error in predicted image is less in agricultural area in comparison with fallow and others area. It was also found that RMSE of the predicted temperature is high if the NDVI value is less than 0.4, and RMSE was low in the higher NDVI range (i.e., beyond 0.4).

**Recommendations:**
During the study it was found that mean error may not be considered as an indicator in understanding the error variation in the models output. The further study may analyse variability of mean error with different spatial landcover distribution and at different resolution.

“Add residual back” to finer resolution predicted LST was evaluated and it was found that adding the residual back violate constrain, that the mean of the fine-resolution pixels should equal the equivalent coarse resolution pixel. This needs further investigation.

Temperature can vary over quite short time scales. It can be happen that if a particular day the temperature is high, the very next day temperature can be low. The average temperature and, therefore, LST could be quite different. But the vegetation index does not change within a very short period. If we develop the relationship between NDVI and LST of previous day and apply the sharpening model no next day to predict the temperature, the temperature will be over predicted (in this situation). In this case the slope of the relationship could be same but the intercept will need to be adjust for actual prediction of LST. In order to overcome this problem, mean temperature could be subtract from the thermal image and regression model could be established with NDVI, then apply this model to predict the LST and add the mean temperature back. But this needs further investigation of NDVI and LST relationship over a long period in a crop growing region. It is also important to see variation of this relationship with respect to type of crop reference.
References:


Appendix

Appendix 1

R script for generating the regression model:
Data import:

Data = read.table("data.txt", header=T)
fix (data)

Linear model
lm.x.y <- lm((y) ~ (x), data = data)
summary(lm.x.y)
plot(lm.x.y)
par(mfrow = c(2, 2))
plot(lm.ndvi.lst.02)

scatter plot of xy
plot(x,y)

Fitting the line
abline(lm.ndvi.lst.02)

Polynomial model
polynomial <- lm((y) ~ (x) + I(x^2), data=data)

Confidence interval plot:

upper limit
summary(lm.x.y)$coef[1]+qt(0.975,325)*summary(lm.x.y)$coef[2]

Estimate
summary(lm.x.y)$coef[1]

lower limit
summary(lm.x.y)$coef[1]-qt(0.975,325)*summary(lm.x.y)$coef[2]

ANOVA analysis for models comparison:
anova(lm.x.y,polynomial)
Appendix 2

NDVI & LST relationship establishment

Following steps was carried for NDVI LST relationship establishment.

Step-1: NDVI and LST image of same resolution was converted into ESRI grid format.

Step-2: Input NDVI and LST in Arc/Info Workstation

Step-3: Generate the samples using the following command

Sample_NDVI_LST = sample (NDVI, LST)

Step-4: Open the file into .tst format and import it into MS access

Step-5: Screen out the missing pixels value using select command.

Step-6: Import the sample data into R statistical software for relationship establishment.

Appendix 3

Spatial contextual regression algorithm is customize in ArcGIS Modeler.

The installation procedure of this model is shown in the window.