Disaggregation of LST over India: Comparative analysis of different vegetation indices

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Disaggregation of LST over India: Comparative analysis of different vegetation indices

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Abstract
The non-availability of high spatial resolution thermal data from satellites on a consistent basis led to the development of different models for sharpening coarse spatial resolution thermal data. Thermal sharpening models that are based on the relationship between Land Surface Temperature (LST) and a Vegetation Index (VI) like NDVI or Fraction Vegetation Cover (FVC) have gained much attention due to their simplicity, physical basis and operational capability. However, there are hardly any studies in the literature examining comprehensively various vegetation indices apart from NDVI and FVC, which may be better suited for thermal sharpening over agricultural and natural landscapes. The aim of this study is to compare the relative performance of five different vegetation indices, NDVI, FVC, Normalised Difference Water Index (NDWI), Soil Adjusted Vegetation Index (SAVI) and Modified Soil Adjusted Vegetation Index (MSAVI) for thermal sharpening using the DisTrad thermal sharpening model over agricultural and natural landscapes in India. LST from MODerate Imaging Spectroradiometer (MODIS) sensor was disaggregated from 960 m to 120 m and compared with the observed Landsat-7 LST at 120 m. In addition to this, MODIS LST was disaggregated from 960 m to 480 m and compared with ground measurements at five sites in India. It was found that NDVI and FVC performed better only under wet conditions whereas under drier conditions, NDWI performed superior to other indices and produced accurate results. SAVI and MSAVI always produced poorer results than NDVI/FVC and NDWI for wet and dry cases respectively.

Keywords
Land Surface Temperature, Vegetation index, DisTrad, Landsat-7 ETM+, MODIS

1. Introduction
Land Surface Temperature (LST) observed by thermal sensors on board remote sensing satellites is a vital input for various hydro-meteorological and agricultural applications. Satellites with thermal sensors provide LST data at different spatial and temporal resolutions. There exists a trade-off between the spatial and the temporal resolution of thermal sensors such that the satellite systems have either a higher spatial resolution with a lower temporal resolution or a lower spatial resolution with a higher temporal resolution (Agam et al., 2007a). However, in most of the sensors, the data from the visible and infrared (VIR) bands are available at a finer spatial resolution than the thermal band. This finer resolution VIR data can be combined with the coarser resolution thermal data for disaggregating the latter.

Earlier developed models utilized the relationship between LST and a vegetation index (VI) like NDVI or Fraction Vegetation Cover (FVC) for thermal sharpening. A simple regression (linear or polynomial) between LST and NDVI or FVC (DisTrad model) has been used and tested for thermal sharpening over agricultural or natural landscapes (Kustas et al., 2003, Agam et al., 2007a, 2007b, Jeganathan et al., 2011) and urban settings (Essa et al., 2012). The major assumption in the DisTrad model is the observed regression relationship between LST and NDVI/FVC is independent of the spatial scale. Though the DisTrad model was found to work with reasonable accuracy, it has been reported that the
model was not able to reproduce the LST patterns in recently irrigated fields and had a pronounced boxy effect (Agam et al., 2007b, Gao et al., 2012). Bindhu et al. (2013) developed a non-linear DisTrad model in which the dry edge of the LST-NDVI scatter is modelled using a polynomial function and the residuals generated at coarse spatial resolution are modelled using an Artificial Neural Network (ANN) model. Though more sophisticated and accurate thermal sharpening models (e.g. Gao et al., 2012) have been developed the LST-VI based models can still be looked upon for its simplicity yet reasonable accuracy, physical basis and operational capability. The aim of this paper is to compare the relative performance of five different vegetation indices NDVI, FVC, Normalized Difference Water Index (NDWI), Soil Adjusted Vegetation Index (SAVI) and Modified Soil Adjusted Vegetation Index (MSAVI) for thermal sharpening using the DisTrad model over agricultural and natural landscapes. This objective was due to the fact that to the best knowledge of the authors, there are no studies reporting, if alternate vegetation indices apart from either NDVI or FVC are better suited for thermal sharpening over agricultural and natural landscapes.

2. Study Area and Datasets

2.1 Study Area
Two spatial grids in India (Grids 1 and 2 in Figure 1) each of size 96 km by 96 km were chosen in the states of Punjab (North of India, Grid 1) and Karnataka (South of India, Grid 2) for the study. Characteristics of the two selected spatial grids are given in Table 1. The selected grids comprise of both rainfed and irrigated agricultural lands and the grid in Karnataka contains natural vegetation as well. Apart from this, data from five micrometeorological tower sites (popularly called Agro-Met Stations abbreviated as AMS) were used in the study (Sites 1-5 in Figure 1). Table 2 gives some information about the five AMS sites.

2.2 In-Situ data
The ground data for validation of satellite derived LST was obtained from the network of micrometeorological towers (known as Agro-Met stations and abbreviated as AMS) developed by the Space Applications Center of the Indian Space Research Organisation. For this study, data from five AMS sites were used. More information on the AMS instrumentation can be had from Eswar et al. (2013). The incoming and outgoing longwave radiation measured by the four component net-radiometer mounted on the AMS was used for estimating in-situ LST.

2.3 Satellite Data
Three clear sky datasets over each spatial grid from the Landsat-7 satellite were downloaded from the United States Geological Survey earth explorer portal (http://earthexplorer.usgs.gov/). For Grid 1, images were obtained on 26-Jan-2001, 11-Feb-2001 and 27-Feb-2001. Similarly, For Grid 2, images were obtained on 14-Jan-2001, 03-Mar-2001 and 03-Dec-2002. The period of image acquisition coincided with the cropping period in Grid 1 and dry period in Grid 2. Apart from Landsat data, daily LST (MOD11A1) and daily surface reflectance (MOD09GA) products of the MODIS sensor aboard the Terra satellite were also downloaded for the same dates as of Landsat-7 data acquisition over the two spatial grids.
In addition to acquiring satellite data over two spatial grids, LST and surface reflectance data from the MODIS sensor aboard the Terra and Aqua satellites were downloaded over the five AMS sites for performing the ground based validation of the disaggregated LST. 162 MODIS datasets were downloaded and used over all the five AMS sites together.

3. Methodology

3.1 Model description

3.1.1 DisTrad Thermal Sharpening model

The DisTrad thermal sharpening model is based on a scale invariant relationship between LST and a vegetation index (VI). Kustas et al. (2003) used NDVI and Agam et al. (2007a and 2007b) used FVC in the DisTrad model. The generalized steps of the DisTrad model are given here. First, a linear least square fit was performed between LST and the selected VI at a coarse spatial resolution and the slope and intercept of the least square fit were estimated.

\[ LST_{coarse} = a + b(VI_{coarse}) \]  \hspace{1cm} (1)

Where, \( VI_{coarse} \) is the selected VI at coarse spatial resolution and \( LST_{coarse} \) is estimated using the least square fit at the coarse spatial resolution. The parameters \( a \) and \( b \) are respectively the intercept and slope of the least square fit. The residual (\( \Delta T \)) between the observed LST at coarse resolution (\( LST_{obs} \)) and that estimated (\( LST_{coarse} \)) from Equation (1) is given as,

\[ \Delta T = LST_{obs} - LST_{coarse} \]  \hspace{1cm} (2)

The residual \( \Delta T \) was distributed equally among all the fine resolution pixels within a single coarse resolution pixel. The regression parameters estimated from Equation (1) was applied with fine resolution VI (\( VI_{fine} \)) to obtain (\( LST_{fine} \)) as given by

\[ LST_{fine} = a + b(VI_{fine}) \]  \hspace{1cm} (3)

LST at fine resolution (\( LST_{fine} \)) was then estimated as given below,

\[ LST_{fine} = LST_{fine} + \Delta T \]  \hspace{1cm} (4)

For performing the least square fit of Equation (1), 25 percent of VI pixels of coarse resolution with minimum coefficient of variation (CV) from the image were selected (Kustas et al., 2003, Agam et al., 2007a). The CV of each of the coarse VI pixel was obtained using the fine resolution VI pixels associated with it. For fitting the Equation (1), only positive values of NDVI, FVC, SAVI and MSAVI were considered, whereas for NDWI the entire range of values were used since dry land surfaces may have negative NDWI.

3.1.2 Temperature Vegetation Dryness Index

Temperature Vegetation Dryness Index (TVDI) (Sandholt et al., 2002) is based on the triangular relationship between LST and NDVI. While, TVDI was used in earlier studies to infer soil moisture status (Sandholt et al., 2002), in this study TVDI was used as an indicator of dryness of the satellite scenes. For a given satellite scene the observed LST and NDVI formed a triangular relationship as shown in Figure 2. Segment \( \overline{AB} \) is known as
the ‘dry edge’ along which evapotranspiration (ET) will be occurring at a minimal rate. TVDI will take a value of one, along the dry edge $AB$. On the other hand, segment $BC$ is called the wet edge along which the ET is assumed to take place at the potential rate and the TVDI will be zero along the wet edge. For any pixel $i$ in the satellite scene, TVDI was estimated as

$$TVDI = \frac{LST_i - LST_{\text{min}}}{LST_{\text{max}} - LST_{\text{min}}}$$

(5)

Here $LST_i$ is the LST of the pixel $i$, $LST_{\text{max}}$ is the maximum temperature corresponding to the NDVI value of that pixel, and $LST_{\text{min}}$ is temperature corresponding to the wet edge of the scene. In this study, dry edge was determined by the linear regression between LST and NDVI using the algorithm given in Tang et al. (2010) and the wet edge was determined as the minimum temperature at the maximum NDVI (Jiang and Islam, 1999). For this study, TVDI was estimated from the MODIS data at 960 m spatial resolution. Scenes with mean TVDI greater than 0.6 were classified as dry and those scenes with mean TVDI less than or equal to 0.6 were classified as wet.

### 3.2 Data Processing

#### 3.2.1 Landsat data processing

The area pertaining to the spatial grids were extracted from the Landsat images. The digital numbers (DN) of the extracted pixels were converted into at-sensor radiance using the equations and calibration coefficients given in Landsat-7 science data users handbook (LSDUH) [http://landsathandbook.gsfc.nasa.gov/](http://landsathandbook.gsfc.nasa.gov/). The radiances of all bands except the panchromatic band were averaged to 120 m and 960 m. This was done to simulate the averaging effects of the coarse resolution sensors as closely as possible (Kustas et al., 2003). The low gain image of the thermal band was used for the study. The at-sensor radiances of the VIR bands were converted into the corresponding surface reflectances by correcting for the atmospheric and the sun angle effects as suggested by Chavez (1996). The five different vegetation indices used in the study were estimated from the surface reflectances using equations given in Table 3.

The at-sensor radiance of the thermal band was corrected for the atmospheric effects using the online atmospheric correction parameter calculator [http://atmcorr.gsfc.nasa.gov/](http://atmcorr.gsfc.nasa.gov/) developed by Barsi et al., (2003). Land surface emissivity required for the estimation of LST was estimated from the NDVI data following Valor and Caselles (1996). Finally the corrected thermal radiances were converted to LST following Srivastava et al. (2009).

#### 3.2.2 MODIS-Landsat inter-sensor calibration

For the MODIS-Landsat disaggregation exercise, the LST and surface reflectance data pertaining to the two spatial grids were extracted at 960 m spatial resolution from the MODIS tiles. The five different vegetation indices were computed using the surface reflectance data, with the equations given in Table 3. The LST retrieved from the three images of MODIS and three images of Landsat for each spatial grid were pooled together and a linear regression relation was developed (i.e. one relation per spatial grid) between MODIS LST and Landsat LST at 960 m resolution. This relation was used to convert the MODIS LST into its Landsat equivalent LST at 960 m (Bindhu et al., 2013). Similarly all
the five vegetation indices estimated from MODIS were converted to their Landsat equivalent by developing regression relations. An example of such relations between MODIS and Landsat for the images acquired over grid 2 is given in Figure 3 and the regression coefficients for all the variables at the two spatial grids are listed in Table 4. The sensor corrected MODIS LST and vegetation indices at 960 m were used in the DisTrad model along with the vegetation indices from Landsat at 120 m to get disaggregated LST at 120 m. Disaggregated LST at 120 m was compared with the Landsat LST observed at 120 m.

3.2.3 Disaggregation using MODIS data only

The MODIS LST at 960 m spatial resolution obtained over the five AMS sites was disaggregated to 480 m using the vegetation indices obtained from MODIS surface reflectance data. A small area or approximately 90 Km x 90 Km containing the AMS location was extracted from the original MODIS tiles and vegetation indices were computed from the surface reflectance data. Since NDWI cannot be estimated at finer than 480 m spatial resolution from MODIS, disaggregation was not carried out finer than 480 m. The disaggregated LST was compared with the LST estimated from AMS data.

3.2.4 In-Situ data processing

LST from ground measurements were obtained from the upwelling ($L_u$) and downwelling ($L_d$) long wave radiation recorded at AMS at the time closest to MODIS overpass using the following equation (Wang and Liang, 2008)

$$LST = \left[ \frac{L_u - (1 - \epsilon)L_d}{\sigma \epsilon} \right]^{\frac{1}{4}}$$

(6)

Where, $\epsilon$ is the surface broad band emissivity and $\sigma$ is the Stefan-Boltzmann constant ($5.67 \times 10^{-8}$ W m$^{-2}$ K$^{-4}$). The surface broad band emissivity was estimated following Valor and Caselles (1996) using NDVI of the pixel (at 960 m resolution) containing the AMS tower. Since MODIS LST is compared with the AMS data, the emissivity available with MODIS LST product was not used in Equation 6.

4. Results and Discussions

4.1 MODIS LST disaggregated to Landsat scale

The results of disaggregation of the sensor corrected MODIS LST from 960 m to 120 m with five different vegetation indices are tabulated in Table 5. The three images analysed in grid 1 were classified as wet (mean TVDI of the scene less than or equal to 0.6) and the three images in grid 2 were classified as dry (mean TVDI of the scene greater than 0.6) cases. It was observed that for the dry cases, LST disaggregated with NDWI had the lowest Root Mean Square Error (RMSE) when compared with LST disaggregated with other indices. For the wet cases NDVI and FVC based disaggregation yielded better results than other indices based disaggregation. SAVI and MSAVI produced inferior results for both wet and dry cases and hence are not considered for further analyses.
4.2 Comparison of disaggregated LST with ground data

The MODIS LST disaggregated from 960 m to 480 m was compared with the LST estimated from the AMS measurements. Here also the results were separated into dry and wet cases based on the mean TVDI of the scene. The number of images classified as dry was 8, 10, 18, 0 and 24 for sites 1, 2, 3, 4 and 5 respectively. Similarly, the number of wet cases was 33, 13, 27 and 16 for sites 1-5 respectively.

For the dry cases, the RMSE of the 960 m MODIS LST product was 2.77 K for all the five sites put together. For the Disaggregated product, the RMSE was 3.26 K, 3.21 K and 2.46 K for NDVI, FVC and NDWI based sharpening respectively. Similarly, for the wet cases, the RMSE was 2.48 K, 2.36 K, 2.36 K and 2.52 K respectively for the 960 m product and disaggregated products based on NDVI, FVC and NDWI respectively. The error values for individual sites are listed in Table 6. Scatter plots between the satellite derived LST and the LST estimated from AMS tower are presented in Figure 4.

It was observed that, NDWI based disaggregation yielded better results for the dry cases and NDVI based disaggregation yielded improved results. Further it was observed, that for the dry cases, LST disaggregated using NDWI had a marginally lower RMSE and bias than the original LST at 960 m. Similarly, for the wet cases, LST disaggregated using NDVI had a marginally lower RMSE and bias than the LST observed at 960 m. However, choosing a wrong index (i.e. NDVI for dry cases and NDWI for wet cases) produced errors higher than the 960 m original LST product. Out of the 60 dry cases analysed for all the five sites together, only in 5 cases (8.33%), NDVI performed better than NDWI. Whereas out of the 102 wet cases in total, NDWI performed marginally superior to NDVI in 32 cases (31.37%). This suggested that choosing a suitable index especially during drier conditions is necessary for obtaining an improved disaggregated LST product.

Apart from these analyses, a synthetic study have been carried out (results not shown here) at twelve spatial grids across the globe, using datasets only from Landsat-7 satellite (Landsat-7 LST data aggregated to 960 m and disaggregated back to 480 m, 240 m and 120 m spatial resolutions) to confirm the performance of different vegetation indices for thermal sharpening. The results of the synthetic study also confirmed the results obtained in the present study.

The relatively better performance of NDWI for the dry cases suggested that the vegetation moisture content may be the primary factor controlling the transpiration of vegetation and hence regulating LST during water stress conditions. Only during water abundant conditions, vegetation vigour (as indicated by NDVI) regulates LST. Moreover, the relatively poor performance of SAVI and MSAVI indicated that removal of soil effect from chosen VI will lead to increased errors in sharpening.

5. Conclusions

Five different vegetation indices NDVI, FVC, NDWI, SAVI and MSAVI were compared for their use in thermal sharpening using the simple DisTrad model over agricultural and natural landscapes. LST from MODIS sensor was disaggregated from 960 m to 120 m and compared with the observed Landsat-7 LST at 120 m. Moreover, MODIS LST was disaggregated from 960 m to 480 m and compared with ground measurements at five sites in India. The performance of different vegetation indices varied with the dryness of the study area. SAVI and MSAVI produced inconsistent results for both wet and dry cases and hence cannot be relied upon for operational purposes. For LST disaggregation, it
was found that NDWI performed superior for dry cases while NDVI performed better for wet cases. These observations were consistent among the various sites and multi-temporal images analysed in this study. Even though, the conclusions were based on a particular VI based thermal sharpening model (DisTrad), the results may be applicable among other VI based models for example Bindhu et al. (2013). In this study, the analyses were focused using MODIS scale images. However, similar studies of LST sharpening from geostationary scales would be required for ascertaining the suitable vegetation index to be used in the sharpening models.

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<table>
<thead>
<tr>
<th>Grid</th>
<th>Location</th>
<th>Geographical extent</th>
<th>Agro Climatic Zone</th>
<th>Major Crops</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grid 1</td>
<td>Punjab</td>
<td>29.95° N – 30.82° N 74.97° E – 75.97° E</td>
<td>Trans-Gangetic Plain region</td>
<td>Rice, wheat and sugarcane</td>
</tr>
<tr>
<td>Grid 2</td>
<td>Karnataka</td>
<td>11.44° N – 12.31° N 76.25° E – 77.14° E</td>
<td>Southern plateau and hill region</td>
<td>Rice, Sugarcane, pulses, vegetables</td>
</tr>
</tbody>
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Table 2 Details about the five AMS sites

<table>
<thead>
<tr>
<th>Site number (AMS ID)</th>
<th>Site name</th>
<th>Geographical coordinates</th>
<th>Climate &amp; soil</th>
<th>Major Crops/Vegetation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1 (AMS 09)</td>
<td>Forest Research Institute, Dehradun</td>
<td>30.33°N, 78.00°E</td>
<td>Sub-humid/Red</td>
<td>Young Pine Forest</td>
</tr>
<tr>
<td>Site 2 (AMS 13)</td>
<td>Bharatpur, Rajasthan</td>
<td>27.20°N, 77.45°E</td>
<td>Semi-arid/Alluvial</td>
<td>Green manure, weed, Mustard (irrigated)</td>
</tr>
<tr>
<td>Site 3 (AMS 14)</td>
<td>Chakdah, West Bengal</td>
<td>23.06°N, 88.54°E</td>
<td>Sub-humid/Alluvial</td>
<td>Rice</td>
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<tr>
<td>Site 4 (AMS 08)</td>
<td>Powarkheda, Madhya Pradesh</td>
<td>22.70°N, 77.75°E</td>
<td>Sub-humid/black</td>
<td>Soybean, Wheat (irrigated)</td>
</tr>
<tr>
<td>Site 5 (AMS 24)</td>
<td>Maddur, Karnataka</td>
<td>11.78°N, 76.61°E</td>
<td>Semi-arid/red-black</td>
<td>Mixed Crops (Sugarcane, Vegetables, Turmeric, Maize)</td>
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</table>
### Table 3: Equations for estimating the different vegetation indices used in the study

<table>
<thead>
<tr>
<th>VI</th>
<th>From Landsat(^a)</th>
<th>From MODIS(^b)</th>
</tr>
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<tbody>
<tr>
<td>NDVI</td>
<td>((\rho_4 - \rho_3) / (\rho_4 + \rho_3))</td>
<td>((\rho_2 - \rho_1) / (\rho_2 + \rho_1))</td>
</tr>
<tr>
<td>FVC</td>
<td>1 - (1 - NDVI)^0.625</td>
<td>1 - (1 - NDVI)^0.625</td>
</tr>
<tr>
<td>NDWI</td>
<td>((\rho_4 - \rho_5) / (\rho_4 + \rho_5))</td>
<td>((\rho_2 - \rho_{5b}) / (\rho_2 + \rho_{5b})) (^b)</td>
</tr>
<tr>
<td>SAVI</td>
<td>([((\rho_4 - \rho_5) / (\rho_4 + \rho_5 + 0.5)) * (1 + 0.5)])</td>
<td>([((\rho_2 - \rho_1) / (\rho_2 + \rho_1 + 0.5)) * (1 + 0.5)])</td>
</tr>
<tr>
<td>MSAVI</td>
<td>((2\rho_4) + 1 - \sqrt{(2\rho_4 + 1)^2 - 8(\rho_4 - \rho_3)})</td>
<td>((2\rho_2) + 1 - \sqrt{(2\rho_2 + 1)^2 - 8(\rho_2 - \rho_1)}) (^2)</td>
</tr>
</tbody>
</table>

\(^a\)\(\rho_{\text{band}}\) refers to the surface reflectance value in the corresponding band present in the respective satellite.

\(^b\)Band 5 was used for data from the Aqua satellite and band 6 was used for the data from Terra satellite.

### Table 4: Regression parameters for converting MODIS data into its Landsat equivalent

<table>
<thead>
<tr>
<th>Variable</th>
<th>Spatial Grid 1</th>
<th></th>
<th></th>
<th>Spatial Grid 2</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Slope(^c)</td>
<td>Intercept(^c)</td>
<td>(R^2)</td>
<td>Slope(^c)</td>
<td>Intercept(^c)</td>
<td>(R^2)</td>
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<tr>
<td>LST</td>
<td>1.073</td>
<td>-22.671</td>
<td>0.87</td>
<td>1.044</td>
<td>-14.098</td>
<td>0.91</td>
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<tr>
<td>NDVI</td>
<td>1.275</td>
<td>-0.250</td>
<td>0.75</td>
<td>0.984</td>
<td>-0.097</td>
<td>0.91</td>
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<tr>
<td>NDWI</td>
<td>1.351</td>
<td>0.173</td>
<td>0.68</td>
<td>0.970</td>
<td>0.031</td>
<td>0.91</td>
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<tr>
<td>SAVI</td>
<td>0.976</td>
<td>-0.111</td>
<td>0.77</td>
<td>0.899</td>
<td>0.002</td>
<td>0.88</td>
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<td>MSAVI</td>
<td>0.840</td>
<td>-0.074</td>
<td>0.77</td>
<td>0.867</td>
<td>0.005</td>
<td>0.88</td>
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\(^c\)\(X_{\text{Landsat}} = (\text{Slope} * X_{\text{MODIS}}) + \text{Intercept}\), Where \(X\) is the variable to be sensor corrected.
Table 5 Results of comparison between disaggregated LST and Landsat LST

<table>
<thead>
<tr>
<th>Grid</th>
<th>Date</th>
<th>Mean TVDI</th>
<th>Root Mean Square Error$^d$ (K)</th>
<th>NDVI</th>
<th>FVC</th>
<th>NDWI</th>
<th>SAVI</th>
<th>MSAVI</th>
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<tr>
<td>Grid 1</td>
<td>26-Jan-2001</td>
<td>0.30</td>
<td>0.95</td>
<td>1.40</td>
<td>1.59</td>
<td>1.74</td>
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<tr>
<td></td>
<td>11-Feb-2001</td>
<td>0.34</td>
<td>1.12</td>
<td>1.26</td>
<td>1.97</td>
<td>2.37</td>
<td>2.91</td>
<td></td>
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<tr>
<td></td>
<td>27-Feb-2001</td>
<td>0.37</td>
<td>1.45</td>
<td>1.47</td>
<td>2.20</td>
<td>2.42</td>
<td>3.00</td>
<td></td>
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<tr>
<td>Grid 2</td>
<td>14-Jan-2001</td>
<td>0.76</td>
<td>2.74</td>
<td>2.82</td>
<td>2.08</td>
<td>2.84</td>
<td>3.13</td>
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<td>2.29</td>
<td>2.95</td>
<td>3.03</td>
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$^d$RMSE = \[ n^{-1} \sum_{i=1}^{n} (LST_{\text{disaggregated}} - LST_{\text{reference}})^2 \]^{1/2}

Where, \( n \) is the number of pixels in an image

Table 6 Error estimates of satellite derived LST at the five AMS sites

<table>
<thead>
<tr>
<th>Dry/wet</th>
<th>Site</th>
<th>RMSE (K)$^e$</th>
<th>Bias (K)$^f$</th>
</tr>
</thead>
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<tr>
<td></td>
<td></td>
<td>LST 960 m</td>
<td>LST Disaggregated 480 m</td>
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<td></td>
<td></td>
<td>NDVI</td>
<td>FVC</td>
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</table>

$^e$RMSE = \[ n^{-1} \sum_{i=1}^{n} (LST_{\text{Satellite}} - LST_{\text{Tower}})^2 \]^{1/2}

$^f$Bias = \[ n^{-1} \sum_{i=1}^{n} (LST_{\text{Satellite}} - LST_{\text{Tower}}) \]

Where \( n \) is the number of datasets for each site
Figure Captions

Figure 1 The two spatial grids and the five AMS sites used in the study

Figure 2 Schematic representation of the LST-NDVI triangular space for the estimation of TVDI

Figure 3 Scatter plots showing the linear relationship between MODIS and Landsat derived geophysical variables a) NDWI b) LST c) NDVI d) SAVI and e) MSAVI

Figure 4 Scatter plots between satellite derived LST and the LST estimated from AMS data a) Original LST at 960 m b) LST Disaggregated to 480 m using NDVI c) LST Disaggregated to 480 m using FVC and d) LST Disaggregated to 480 m using NDWI.
Figure 1 The two spatial grids and the five AMS sites used in the study
253x329mm (300 x 300 DPI)
Figure 2 Schematic representation of the LST-NDVI triangular space for the estimation of TVDI

\[ TVDI_i = \frac{LST_i - LST_i^{\text{min}}}{LST_i^{\text{max}} - LST_i^{\text{min}}} \]

\[ LST_i^{\text{max}} = a + b \cdot (NDVI_i) \]

\[ LST_i^{\text{min}} = LST_i^{\text{min}} \]

NDVI = 0

TVDI = 0

TVDI = 1

A

B

C

LST

NDVI

LST_{\text{min}}
Figure 3 Scatter plots showing the linear relationship between MODIS and Landsat derived geophysical variables a) NDWI b) LST c) NDVI d) SAVI and e) MSAVI.

219x279mm (300 x 300 DPI)
Figure 4 Scatter plots between satellite derived LST and the LST estimated from AMS data a) Original LST at 960 m b) LST Disaggregated to 480 m using NDVI c) LST Disaggregated to 480 m using FVC and d) LST Disaggregated to 480 m using NDWI.