Estimation of subpixel land surface temperature using an endmember index technique based on ASTER and MODIS products over a heterogeneous area

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2011-07-27
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1 Introduction

- When referring to land observation from space, the land surface temperature (LST) is a physical parameter very important to a wide variety of scientific studies (Sobrino et al., 1991; Wan & Li, 1997; Qin et al., 2001).
- A common use of thermal infrared (TIR) data is to derive surface energy budgets (Kustas et al., 2003; Liang, 2004) from high-resolution thermal data, providing assessments of evapotranspiration (ET) down to scales of individual agricultural fields. However, surface heterogeneity induces uncertainty in estimating subpixel temperature.
1 Introduction

As a result, LST products retrieved from satellite TIR data are often composed of a mixture of different temperature components (Lakshmi & Zehrfuhs, 2002; Liu et al., 2006). Therefore, there is a need for enhancing the spatial resolution of the current LST products.

In recent years, many studies have focused on the estimation of subpixel LST and developed a number of corresponding approaches at either thermal digital number (DN) level, or thermal radiance level or LST level:

- **Statistical regression methods** (e.g., Sandholt et al., 2002; Kustas et al., 2003; Agam et al., 2007; Yang et al., 2010)
- **Modulation methods** (e.g., Liu and Moore, 1998; Nichol, 2009; Stathopoulou & Cartalisa, 2009)
- **Hybrid methods** (e.g., Pu et al., 2006; Liu & Pu, 2008)
1 Introduction

◆ Statistical regression methods

Development of the relationship between a vegetation index/variable (e.g., the Normalized Difference Vegetation Index, NDVI; vegetation fraction, ) and radiometric surface temperature by a polynomial or power function.

◆ Modulation methods

Concentrate more on how to distribute the thermal radiance of a thermal pixel block and to balance it among those visible pixels in such a big block; many scaling factors, such as effective emissivity, or combining emissivity and LST altogether.

◆ Hybrid methods

Hybrid algorithms combine statistical regression and modulation methods, while straightforwardly connecting subpixel information with thermal block pixel radiance on the basis of the scale invariance of radiance.
In this research, we propose a new hybrid disaggregation method, which is using the endmember index based technique (DisEMI) to estimate 90 m resolution subpixel temperature (Ts90) from 990 m resolution MODIS LST product (Ts990) and 30 m resolution ASTER reflectance data (VNIR30).
Changping District, located in the northeast of Beijing City, China, was chosen as the study area. The representative land use/land cover (LULC) types in the study area typically consist of the vegetation, bare soil, impervious (including villages and towns), and water.
2 Study area and data sets

Data sets:

ASTER - ASTER surface reflectance (AST_07) and surface kinetic temperature (AST_08) products, observed on 19 May 2001, were collected from the Earth Observing System Data Gateway (EDG).

MODIS - MOD02_QKM, MOD02_HKM, MOD02_1KM, MOD03_L1A, MOD07_L2, MOD11B1, and MOD11_L2 data acquired also on 19 May 2001, were collected from the Land Processes Distributed Active Archive Center (LP DAAC) of U.S. Geological Survey (USGS). They are geolocation, atmospheric profile, reflectance and LST products, respectively.
3 Methodology

A workflow of estimating subpixel temperature based on the endmember indices.
3.1 Selection of remote sensing indices

As the heart of the DisEMI technique, to discover which index is best for the prediction of LST from available nine ASTER bands, the normalized difference spectral indices (NDSI) was employed, examined and compared based on their linear relationships with “pure pixels” temperature at the 90 m resolution for each land cover type:

\[
LST \sim NDSI_{(x,y)} = \frac{r_x - r_y}{r_x + r_y}
\]

Vegetation: \(SAVI = \frac{(ASTER_3 - ASTER_2)}{(ASTER_3 + ASTER_2 + L)}(1 + L)\)

Bare soil: \(NMDI = \frac{ASTER_3 - (ASTER_4 - ASTER_5)}{ASTER_3 + (ASTER_4 - ASTER_5)}\)

Impervious: \(NDBI = \frac{ASTER_4 - ASTER_2}{ASTER_4 + ASTER_2}\)

Water surface: \(NDWI = \frac{ASTER_1 - ASTER_3}{ASTER_1 + ASTER_3}\)

The contour maps of coefficients of determination (R²) between NDSI and LST at 90 m resolution. The symbol “+” represents the maximal R².
3.2 Classification of land cover types

With a supervised classification algorithm—support vector machines (SVM) and the remote sensing indices calculated from the ASTER data (SAVI, NMDI, NDBI, and NDWI), the land cover in the experimental area was classified into four types, namely, vegetation, bare soil, impervious surface and water surface.
3.3 Statistics of area ratio and EMI

In this study, the area proportion of each of the four land cover types within 990 m and 90 m resolution pixels were calculated to obtain AR990 and AR90.

Maximum, minimum, mean and variance of the remote sensing indices in the individual pixels at 990 m and 90 m resolutions were used as change indicators of remote sensing indices within the individual pixels.
3.4 GA-SOFM-ANN training and output

A network with the selected SOFM of three hidden layers was designed. Each vector computing unit in the network corresponded to a group of input parameters (4 for area ratios and 16 for statistical parameters of the endmember indices of the four land cover types) and an output value of temperature.

The SOFM network's biggest drawbacks are the slowness of convergence and the lack of effective evaluation mechanisms to terminate the iteration. However, GA (genetic algorithms) is able to solve these problems and possesses the characteristics of adaptation, global optimization. To take the advantages of both GA and SOFM, we combined the two algorithms and used GA to optimize the parameters' value in the process of rough and fine regulation.
4 Results and analysis

(1) The analysis of area ratios

(a) AR₉₀₀ of vegetation
(b) AR₉₀₀ of vegetation
(c) AR₉₀₀ of bare soil
(d) AR₉₀₀ of bare soil
(e) AR₉₀₀ of impervious
(f) AR₉₀₀ of impervious
(g) AR₉₀₀ of water
(h) AR₉₀₀ of water
4 Results and analysis

(1) The analysis of area ratios

- AR90 and AR990 are generally similar in spatial distribution. However, since the spatial resolution of AR990 is lower 11 times than that of AR90, the AR90, compared to AR990, can show more detailed information of area ratio change of the four land cover types than AR90.

- The progression of AR990 of the four land cover types was relatively large, resulting in a relatively continuous change process of area ratios. Meanwhile, the occurrence probability of pure pixel was greatly reduced. Conversely, AR90 show the opposite results.

<table>
<thead>
<tr>
<th>Area ratio</th>
<th>Vegetation (%)</th>
<th>Bare soil (%)</th>
<th>Impervious (%)</th>
<th>Water (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODIS 990, n=448 pixels at 990 m resolution</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥0.25</td>
<td>86.61</td>
<td>55.13</td>
<td>22.10</td>
<td>3.35</td>
</tr>
<tr>
<td>≥0.50</td>
<td>47.77</td>
<td>20.09</td>
<td>5.13</td>
<td>0.22</td>
</tr>
<tr>
<td>≥0.75</td>
<td>10.71</td>
<td>2.01</td>
<td>0.89</td>
<td>0.00</td>
</tr>
<tr>
<td>≥0.90</td>
<td>1.34</td>
<td>0.22</td>
<td>0.22</td>
<td>0.00</td>
</tr>
<tr>
<td>ASTER 90, n=54208 pixels at 90 m resolution</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥0.25</td>
<td>61.16</td>
<td>40.39</td>
<td>23.75</td>
<td>3.67</td>
</tr>
<tr>
<td>≥0.50</td>
<td>48.19</td>
<td>29.11</td>
<td>14.10</td>
<td>2.27</td>
</tr>
<tr>
<td>≥0.75</td>
<td>35.93</td>
<td>20.29</td>
<td>7.38</td>
<td>1.48</td>
</tr>
<tr>
<td>≥0.95</td>
<td>24.91</td>
<td>12.88</td>
<td>2.45</td>
<td>0.83</td>
</tr>
</tbody>
</table>
4 Results and analysis

(2) The analysis of endmember remote sensing indices

The histogram distributions at the two resolutions for SAVI~ were very similar, but for the other three remote sensing index means, their histogram distributions at the 990 m resolution were more continuous.

Histograms of the four remote sensing index means at the 990 m and 90 m resolutions.
4 Results and analysis

(2) The analysis of endmember remote sensing indices

The errors of temperature estimated by a linear regression model between temperature and individual parameters of area ratios and remote sensing indices at the 990m (left) and 90 m (right) resolution.

- 990 m resolution: RMSE and MAE were about 2 K and 1.5 K, respectively.
- 90 m resolution: RMSE and MAE were about 5 K and 3 K, respectively.

The result indicated that at the 90 m resolution, the spatial variability of surface temperature was very obvious, and considerable error might be expected if single independent variables and single statistical regression models were adopted for subpixel temperature estimation.
4 Results and analysis

(3) Profile analysis of LST images

![LST profiles for L1(a) and L2(b) locations](image)

Along the L1 and L2 transects, the LST profiles (curves) have a generally varying tendency. They have consistent “peaks” and “low points” along transects.

The slight difference of LST between them might be caused by subpixel registration error and calibration difference of the two sensor systems.

However, as expected, LST variability reduced with resolution decreasing.
4 Results and analysis

Evaluating the accuracy of downscaled temperature

- An estimation error for the 73.82% of total pixels over the study area was within ± 3K.
- The overall estimated accuracy of the subpixel temperature at the 90 m resolution was relatively high ($R^2 = 0.709$, $MAE = 2.217$ K and $RMSE = 2.702$ K).

<table>
<thead>
<tr>
<th>Area ratio</th>
<th>Vegetation</th>
<th></th>
<th>Bare soil</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE(K)</td>
<td>RMSE (K)</td>
<td>$R^2$</td>
</tr>
<tr>
<td>0&lt;AR≤0.25</td>
<td>2.257</td>
<td>2.728</td>
<td>0.636</td>
</tr>
<tr>
<td>0.25&lt;AR≤0.5</td>
<td>2.265</td>
<td>2.734</td>
<td>0.621</td>
</tr>
<tr>
<td>0.5&lt;AR≤0.75</td>
<td>2.261</td>
<td>2.722</td>
<td>0.615</td>
</tr>
<tr>
<td>0.75&lt;AR≤1.0</td>
<td>2.244</td>
<td>2.693</td>
<td>0.625</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Area ratio</th>
<th>Impervious</th>
<th></th>
<th>Water</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE(K)</td>
<td>RMSE(K)</td>
<td>$R^2$</td>
</tr>
<tr>
<td>0&lt;AR≤0.25</td>
<td>2.093</td>
<td>2.573</td>
<td>0.506</td>
</tr>
<tr>
<td>0.25&lt;AR≤0.5</td>
<td>1.993</td>
<td>2.408</td>
<td>0.435</td>
</tr>
<tr>
<td>0.5&lt;AR≤0.75</td>
<td>1.878</td>
<td>2.222</td>
<td>0.338</td>
</tr>
<tr>
<td>0.75&lt;AR≤1.0</td>
<td>1.748</td>
<td>2.030</td>
<td>0.290</td>
</tr>
</tbody>
</table>
4 Results and analysis

(5) DisEMI V.S. TsHARP technique

In order to assess advantages of our method, it is necessary to compare this new method with one or more present or widely used methods. Given it is a widely used regressive method, The TsHARP technique (Agam et al., 2007), a follow up improvement to the disaggregation procedure for radiometric surface temperature (DisTrad, Kustas et al., 2003), was selected to compare with our method.

The accuracy of estimating 90 m resolution temperature produced by using the TsHARP method in this study was lower than that by using our DisEMI method.
5 Discussion and conclusions

- The great difference between the spatial resolutions of MODIS LST and ASTER VNIR / SWIR data used in this study led to certain errors in geometrical registration, which directly influenced the accuracy of subpixel temperature estimation.
- MODIS and ASTER have some differences in the thermal infrared wavelength range, waveband response and temperature inversion algorithm, so there exist some problems in verifying subpixel temperature by ASTER LST product.
- If estimating temperature in a large area, the DisEMI method must be optimized to improve the computational efficiency based on prior knowledge.
- The increase of spatial resolution will increase the proportion of pure pixels, which may make a wider variation range of area ratios. The higher resolution also reduces the variation progression of area ratios and leads to an approximately uniform distribution. Various remote sensing indices related to pixel temperatures should be fully used to ensure a high accuracy of subpixel temperature estimation.
- ASTER LST product was used to verify the estimated subpixel temperatures, and the final estimated temperature distribution was basically consistent with that of ASTER LST product \( R^2 = 0.709, \text{ MAE} = 2.217 \text{ K and RMSE} = 2.702 \text{ K} \).
- Future work should emphasize on sensitivity analysis of other remote sensing indices to subpixel LST retrieval and absolute validation with ground measurements.
For more details, please refer to ScienceDirect website: http://www.sciencedirect.com/science/article/pii/S0034425711000174

Thanks for your attention!