A MODIFIED VEGETATION INDEX BASED ALGORITHM FOR THERMAL IMAGERY SHARPENING

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1. INTRODUCTION

Land surface temperature (LST) at both high spatial and temporal resolution is required for routine monitoring of surface energy fluxes. However, spatial and temporal resolution are always contradicted with each other in current thermal infrared imagery.

Significant inverse relationship between LST and vegetation indices has been observed by many related studies[1,2]. Based on this, Kustas et al. developed a procedure referred to as DisTrad for disaggregating LST to the NDVI-pixel resolution [3]. This procedure was utilized later by Anderson et al.[4] and refined by Agam et al. through involving alternative sharpening basis functions[5], which was renamed as TsHARP algorithm. Their methodology involves a single least-squares regression relationship between LST and vegetation indices in a specific scene.

In this paper, a modified algorithm named as soil wetness index stepwise fitting (SWISF) algorithm is proposed for thermal imagery sharpening. Multiple least-squares regression relationships between LST and vegetation indices were acquired for bins of pixels with different soil wetness index (SWI) values.. The comparison of the performance of SWISF and DisTrad is implemented over middle reaches of Heihe river basin in western China, based on ASTER products.

2. METHODOLOGY

2.1. DisTrad (TsHARP) algorithm

Major steps of this technique are described briefly as follows (see also in [5]):

The first step is to aggregate NDVI to the coarser LST resolution, then performs a least-squares regression between LST and functions of NDVI at coarser resolution ($NDVI_{low}$):

$$\hat{T}_s(NDVI_{low}) = f(NDVI_{low}) \tag{1}$$

This regression relationship is then applied to finer resolution NDVI ($NDVI_{high}$). The divergence of the retrieved temperatures from the observed temperatures, which is caused by some non-vegetation factors, such as soil moisture variations, can be assessed at the coarse scale:

$$\Delta\hat{T}_{s\_low} = T_{s\_low} - \hat{T}_s(NDVI_{low}) \tag{2}$$

The final step is to add back this coarse scale residual field into the retrieved higher resolution LST:

$$\hat{T}_{s\_high} = \hat{T}_s(NDVI_{high}) + \Delta\hat{T}_{s\_low} \tag{3}$$

Where the first term of the right-hand side is evaluated by the regression function f from Eq.(1), and the second term is constant over the coarse pixel area.

2.2. SWISF algorithm

The theoretical basis of this algorithm is the triangular space relationship (Fig.1) between LST and vegetation indices which has been investigated by many authors. Sandholt et al. created an index referred to as temperature-vegetation dryness index (TVDI) from the triangular space[6] , which is contrary to the soil wetness index (SWI) built up by Mallick et al. [7] .

The sharpening methodology is as follows: The first step is also to aggregate NDVI to the coarser resolution. Then the maximum and minimum NDVI values are extracted from the coarser map. All the NDVI values are stratified into certain segments (e.g. 30 sects) using these two extrema. In the coarser LST-NDVI space, extreme values of LST corresponding to each NDVI bin are extracted. Then a least-squares regression is performed between the maximum temperatures ($T_{s\max}$) and their corresponding NDVIs in order to form the dry edge:

$$\hat{T}_{s\max} = f(NDVI_{T_{s\max}}) \tag{4}$$

The wet edge of the space could be the mean or the least of the minimum temperatures ($T_{s\min}$).

The next step is to calculate SWI for each pixel using wet and dry edge:

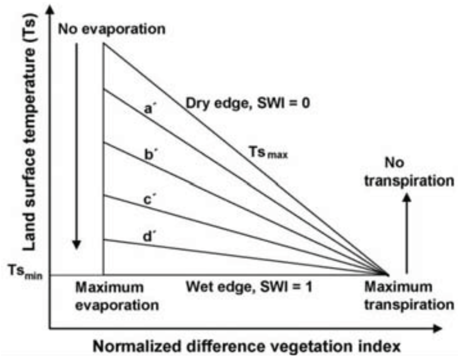
$$SWI(i) = \frac{T_{s\max}(i) - T_s(i)}{T_{s\max}(i) - T_{s\min}} \tag{5}$$

Where the SWI value of pixel i is limited in 0～1. Zero stands for extremely dry pixels, and one, on the other hand, represents extremely wet pixels.

Continue to segment SWI into several parts and perform least-squares regression between LST and NDVI in each SWI bin. Finally, finer resolution LST is retrieved using the original finer resolution NDVI as input of those regression relationships.

3. DATA

ASTER data and its related products were collected during the Watershed Allied Telemetry Experimental Research (WATER) field campaign which was conducted in the middle reaches of Heihe river basin in Gansu province of China, where the agricultural production is dominated by corn and wheat.



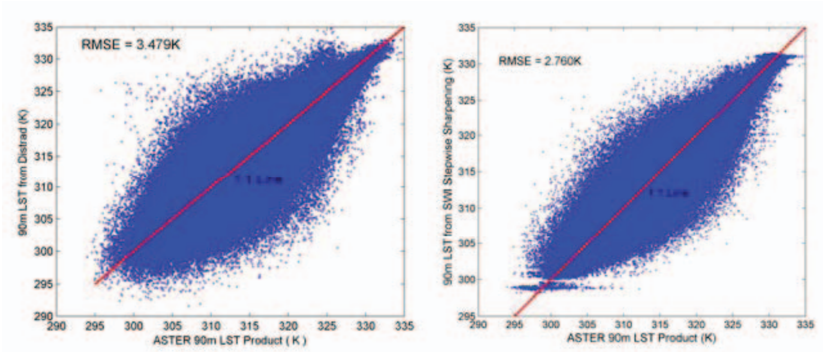
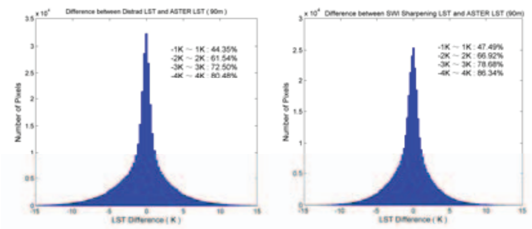


Fig.1 Conceptual diagram of LST-NDVI triangle for determining SWI[7] .

Fig.2 Relationships between reference temperature and sharpened temperature from Distrad (left) and SWISF (right)



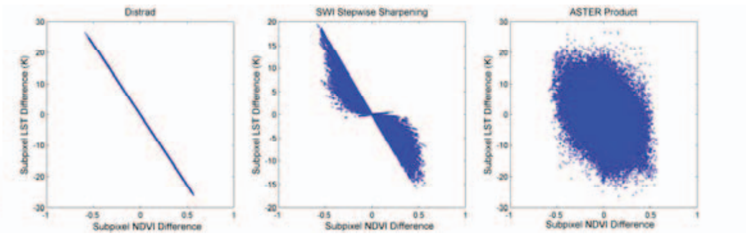


Fig.3 Histograms of absolute error map from Distrad (left) and SWISF (right)

Fig.4 Relationships between subpixel LST and NDVI difference from Distrad(left), SWISF(middle) and ASTER product (right)

For this study, two ASTER products were involved, which are surface reflectivity (ASTER_07) and thermal radiance (ASTER_09T). For comparison of the two algorithms mentioned above, the 15m resolution surface reflectivity products on June 4, 2008 were aggregated linearly to 90m and 360m respectively for calculating corresponding NDVI, which was followed by the aggregation of the 90m resolution surface radiance and sky irradiance products to 360m. Then 90m and 360m LST were retrieved using ASTER TES algorithm.

4. RESULTS AND DISCUSSION

4.1. Land surface temperature

The root mean square error (RMSE) statistic was used to assess the level of agreement between the reference and sharpened temperature. From Fig.2, we can see that RMSE of SWISF algorithm (2.76K) is less than that of DisTrad algorithm (3.479K), and the relationship between ASTER LST product and sharpened temperature from DisTrad is also much more scattered than that from SWISF algorithm. We can also find the relatively dissatisfied sharpening results of SWISF algorithm in Fig. 2 (right part), these poor results all come from cold pixels because of the fact that the relationship between LST and NDVI is much less significant in cold wet regions. The histograms (Fig.3) of the difference between sharpened and reference temperature also show that the SWISF algorithm slightly outperform the DisTrad. The number of pixels with absolute error less than 2K from SWISF algorithm is 5.4% more than that from DisTrad.

4.2. Relationship between subpixel LST and NDVI difference

In addition, relationship between subpixel LST difference and its corresponding NDVI difference was discussed. Under different soil moisture conditions, two sets of subpixels with the same NDVI difference should have distinct LST difference (Fig.1). DisTrad algorithm utilizes only one regression relationship between LST and NDVI in a scene, which would not be able to consider this fact. However, SWISF algorithm could consider this part in a certain way through multiple least-squares regression relationships (Fig.4).

5. CONCLUSION

The need for high-spatial/high-temporal resolution thermal data has led to a further modification of the sharpening procedure (DisTrad) first developed by Kustas et al. A new algorithm with the same theoretical basis has been proposed and utilized in Heihe river basin of China during the crop growing season, using ASTER products. Sharpening simulated thermal maps (360m) to ASTER thermal resolution (90m) using both DisTrad and SWISF shows that the latter algorithm slightly outperform the former one. As to the relationship between subpixel LST difference and its corresponding NDVI difference, DisTrad does not have the ability to consider the fact that the same NDVI difference may have distinct LST difference under different soil moisture conditions, while SWISF algorithm could consider this fact to some extent through multiple regression between LST and NDVI in a single scene.

Although SWISF algorithm has been proved more accurate than Distrad in this study, both thermal image sharpening techniques are still unable to consider the subpixel soil moisture variation. Without information about the subpixel variability in moisture, the sharpening techniques have limited capability. Water related indices such as LSWI (Land surface water index), NDWI (Normalized difference water Index), and SASI (Shortwave angle slope index) have been proposed in many studies. Future work may involve these indices in the sharpening strategies to breakthrough the bottleneck problem.

6. REFERENCES

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