ENHANCED RESOLUTION OF EVAPOTRANSPIRATION BY SHARPENING THE LANDSAT THERMAL BAND

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ABSTRACT
Evapotranspiration (ET) is the major consumptive use of irrigation water, and thus, spatial and temporal quantification of ET is important to agricultural water management. In water rights management and precision irrigation, information on ET is desirable on a field or subfield scale. Therefore, fine resolution satellite imagery such as Landsat and ET products derived from the satellite imagery are highly desirable. However, for a majority of satellites, spatial resolution of the longwave (thermal) band(s) is coarser than the coincident shortwave bands, which creates a compatibility and correspondence issue for the data used for energy balance (EB) and increases the net pixel resolution and reduces fidelity of ET calculations.

Typically, surface temperature ($T_s$) and vegetation indices (VI) are closely correlated, especially under conditions of high availability of soil water, due to the effects of evaporative cooling by vegetation, especially some days after wetting events, when the exposed soil surface is dry and warm relative to vegetation. This physical relationship can be exploited to sharpen $T_s$ using VI if the assumption of cooled surface by vegetation holds. This paper describes a technique developed for application with the METRIC and SEBAL EB procedures that uses the concept of hot and cold thermal conditions associated with dry and wet surface conditions during calibration as a means to distribute $T_s$ at a subpixel scale using subpixel VI. The result is an image of $T_s$ that has the same spatial resolution of the short wave images. Therefore, the resolution of ET images created during the METRIC or SEBAL processes can have equally high resolution. Applications made in Idaho and New Mexico using sharpened thermal imagery are described.

INTRODUCTION

Evapotranspiration (ET) is the major consumptive use of irrigation water, and thus, spatial and temporal quantification of ET is important to agricultural water management, especially in areas experiencing scarcity in the total fresh water resource. In water rights management and precision irrigation, information on ET is desirable on a field or subfield scale. Therefore, fine resolution satellite imagery and ET products derived from the satellite imagery are highly desirable.

Satellite-based remote sensing using surface energy balance (EB) is considered to be the most feasible way to estimate the spatial distribution of ET over large areas (Bastiaanssen et al., 1998, 2005). Most satellite-based EB models use information from the shortwave and longwave regions of the spectrum to estimate the EB components. However, for a majority of satellites, spatial resolution of the longwave (thermal) band(s) is coarser than the coincident shortwave bands, which creates a compatibility and correspondence issue for the data used for EB and increases the net pixel resolution and reduces fidelity of ET calculations.
ET is generally estimated in EB processes as a residual of the energy balance as:

\[ LE = R_n - G - H \]  

where LE is the latent energy consumed by ET, \( R_n \) is net radiation flux density at the surface, G is heat flux density into the ground and H is sensible heat flux density into the air. Component H is a strong function of surface temperature, \( T_s \), and therefore, the resolution of \( T_s \) carries strongly into the resolution of LE and ET.

Lemeshewsky (1998, 2002) and Lemeshewsky and Schwengerdt (2001) summarized a procedure to sharpen the Landsat 7 thermal band using an artificial neural network method, which is based on an assumed correlation between image edge contrast patterns in the thermal band and bands 7, 5, and 2 of Landsat 7. However, specific algorithms were not made available. Kustas et al (2003) formulated a methodology that uses a statistical relationship between the normalized difference vegetation index (NDVI) and \( T_s \) to sharpen remotely sensed surface temperature imagery to the higher resolution of the NDVI, that is based on the red and near-infrared bands. The methodology was tested using high resolution remote sensing data (aircraft), GOES (Kustas et al 2003) and Landsat 5 data (Kustas et al. 2004a,b). Typically, \( T_s \) and vegetation indices (VI) are closely correlated, due to the effects of evaporative cooling by vegetation, especially some days after wetting events, when the availability of soil water is high and the exposed soil surface is dry and warm relative to vegetation. This physical relationship can be exploited to sharpen \( T_s \) using VI. In this paper an application procedure similar to that of Kustas is applied, except where the “hot” and “cold” calibration pixels of METRIC (Allen et al. 2007) are used to associate \( T_s \) with NDVI for consistency with the METRIC EB process.

**NEED FOR A SHARPENING PROCEDURE**

In remote sensing EB applications, shortwave information is often used for surface and vegetation condition assessment, commonly in the form of band combination indices such as NDVI. Longwave (infrared) radiation information is commonly used to retrieve surface temperature and associated EB components of surface longwave radiation, emissivity, and sensible heat flux. Sharpening of thermal data to resolutions of shortwave can increase fidelity of the EB and subsequent ET and H flux density calculations.

Figure 1 illustrates the loss of fidelity in \( T_s \), compared to vegetation indices, when the thermal band has lower spatial resolution than the short wave spectral bands. While an NDVI map derived from the 30 m resolution bands 3 and 4 of Landsat 5 TM allows identification of features such as individual fields, cities and roads, a \( T_s \) image derived from the 120 m resolution of the Landsat 5 thermal band tends to mix surface features with a loss of detail. This mixing of surface characteristics translates into error and loss of resolution in the estimates of energy balance fluxes including ET.

Figure 2 shows how shortwave and longwave (thermal) information are typically assembled in EB processes at different spatial resolutions, and how the final product is commonly assumed to have the resolution of the short wave inputs. In the example process shown (Allen et al., 2007), estimates of ET at 30 m resolution were produced by the METRIC EB process using a Landsat 5 image, where the long wave band of 120 m resolution was used for calculation of some of the components of the EB. Figure 3 shows how the coarse resolution thermal data degrades the resolution of the final ET estimation, producing a net resolution somewhere between 30 and 120 m resolution.

The use of NDVI or some other vegetation index for sharpening \( T_s \) is effective because of the close correspondence between evaporative cooling of vegetated surfaces and the amount of vegetation (Kustas et al. 2003). Applications of satellite-based energy balance have demonstrated the close correspondence between surface temperature and vegetation amount, where full leaf cover under high levels of soil moisture tends to function similar to a wet bulb psychrometer (Allen et al. 2007, Bastiaansen, 1998a,b) and approach a near equilibrium surface temperature that is a function of energy availability and vapor pressure deficit of the air. On the other extreme, dry, bare soil surfaces tend to approach a nearly constant temperature that is in near equilibrium with available energy, surface albedo and general, effective radiative and thermal temperatures of the atmosphere.
Figure 1. Left: NDVI image from southern Idaho derived from Landsat 5 TM at 30 m spatial resolution. Right: $T_s$ values corresponding to the NDVI image, where warmer areas are brighter. The right image is clearly less sharp due to the 120 m resolution of the thermal infrared band. Both images were orthocorrected to 30 m using nearest neighbor resampling.

Figure 2. Typical combination of remote sensing data having different spatial resolution (Landsat 5) during energy balance computations (SR = sampled resolution).
Exceptions to the relationships between $T_s$ and NDVI exist for moist, bare soil that experiences evaporative cooling and for open water. In these situations, the sharpening of $T_s$ using NDVI or any other vegetation index may incur substantial error. In these situations, indices such as the Tassle Cap (Huang et al., 2002) and other methods that use mid-infrared information (for example bands 5 and 7 of Landsat) may be able to identify bare soils that are moist (van Deveter et al., 1997; Thoma et al., 2004) so that modifications in any $T_s – \text{NDVI}$ relationships can be applied. The association of a vegetation index such as NDVI with surface temperature is somewhat congruent with some energy balance calibration processes, such as that used within the METRIC (Mapping evapotranspiration at High Resolution with Internal Calibration) (Allen et al., 2007) and SEBAL (Surface Energy Balance Algorithms for Land) (Bastiaanssen, 1995, 1998a, 2005).

The NDVI has the advantage over e.g. soil adjusted vegetation index (SAVI) and some other indices because NDVI tends to ‘saturate’ at about the same amount of ground-cover by vegetation as the evapotranspiration rate. This is due to the tendency of NDVI to reach maximum levels at about 80% ground cover (by vegetation) or at leaf area indices of about 3.0 (Ritchie, 1972, Wright, 1982) and for ET to reach maximum levels at these same levels. In comparison, the SAVI index tends to extend past 90 to 95% ground cover. Because the impact of evaporative cooling on $T_s$ is largely proportional to the latent heat flux, and because ET is generally found to be linearly proportional to NDVI, the relationship between $T_s$ and NDVI is considered to be more linear and monotonic than that for SAVI.

**METHODOLOGY**

The basic sharpening philosophy and procedure followed here is based on the application of an established $T_s$ vs NDVI relationship to produce a first estimate of $T_s$ at every short wave pixel (referred to as pixel$_{sw}$), assuming a linear relationship and correspondence between NDVI and $T_s$. Later, to preserve original $T_s$ information, this first estimate of $T_s$ is adjusted so that $T_s$ averaged over all pixel$_{sw}$ lying within an original thermal pixel (referred to as pixel$_{th}$) matches the original average $T_s$ of that thermal pixel. In some cases the redistribution of the bias between the original pixel$_{th}$ and the resampled pixel$_{th}$ is an iterative process. Our process sharpens $T_s$ rather than total thermal radiance, where radiance is proportional to the product of surface emissivity and $T_s^4$ for several reasons. One, a relation between NDVI and $T_s$ can sometimes be better defined than for radiance. Two, the use of $T_s$ allows one to use a lapse corrected $T_s$ when defining NDVI vs. $T_s$ relationships for use in areas having variable terrain and elevation. Three, the uncertainty in the overall sharpening and final product is much larger than differences caused by targeting the conservation of the original $T_s$ of a thermal pixel rather than conservation of the original radiation of the pixel. Future research will explore the sensitivity and impacts of sharpening temperature over radiance. Details of the sharpening procedure, which requires image by image determination and iteration of a $T_s$ vs. NDVI relationship for each image, are discussed in another paper.

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**Figure 3.** (a) NDVI map derived from Landsat 5 TM at 30 m spatial resolution for path 40, row 30 (07/23/1989), with higher values bright, lower values dark. (b) Corresponding thermal band (band 6). (c) Daily ET map derived by energy balance via METRIC. The impact of band 6 resolution on final ET estimates is pronounced.
relationship and iterative bias correction within each thermal pixel to preserve the original $T_s$ value, is described in detail in Allen et al. (2008).

To perform the sharpening analysis, it is necessary to ‘identify’ the locations and outlines of original thermal pixels (having dimensions of 120 m for Landsat 5 and 60 m for Landsat 7). Therefore, during orthocorrection of the satellite images, it is necessary that nearest neighbor (NN) resampling be employed when resampling the thermal pixels to a 30 m equivalent. The resampled 30 m thermal image is overlain on the shortwave image layers (bands) during the sharpening process to determine which shortwave pixels are contained in the original thermal pixel. Because the ‘shape’ of a thermal pixel is often contorted from the original square shape (4 x 4 for LS5 and 2 x 2 for LS7) during orthocorrection, it is necessary to use a clumping program in an image processor or GIS system that can identify contiguous 30 m resampled thermal pixels that have a common value (digital number) and were therefore part of an initial 120 (or 60 m) thermal pixel. In ERDAS, the Clump tool can be used and in ArcGIS, the Region Group tool can be used. Future work will be to determine whether images that have been resampled using cubic convolution during georectification and terrain correction can be sharpened to a similar extent as with NN.

Sharpening Thermal Images Containing Open Water

Surface temperature for water cannot be sharpened using NDVI using the $T_s$ vs. NDVI process, because NDVI takes on negative values for water. We propose two procedures for sharpening thermal pixels containing water. A simple procedure is based on an apparent NDVI. Using a $T_s$ vs NDVI relationship for the image, we find the value of NDVI that reproduces the average temperature associated with major water bodies in an image. This “apparent” NDVI is used during sharpening for all pixels identified as being water. This method is generally sufficient to produce satisfactory sharpening of pixel$_{sw}$ near shorelines of water bodies larger than about 1 km$^2$. In the case of streams that are narrower than the dimension of pixel$_{sw}$ and where the pixel$_{sw}$ is comprised of a mixture of land and water, the sharpened temperature can become higher than actual for the water, but in these cases the sharpening process is complicated and perhaps impossible, because NDVI values are contaminated from different surface types. A second procedure that is somewhat more complicated uses a surface temperature that is assigned to water. This procedure works well on medium to larger water bodies and somewhat better than the simple approach for small or narrow water bodies such as streams.

APPLICATIONS

Figure 4 shows two subimage areas illustrating results of applying the sharpening procedure to Landsat 5 imagery (path 40, row 30 of southern Idaho). The image had previously been orthocorrected, with the 120 m thermal pixels resampled to 30 m using nearest neighbor resampling. Visually, the effect of the sharpening procedure improved resolution of $T_s$ between surfaces having different NDVI characteristics. The original average $T_s$ of each thermal pixel was preserved in the sharpened image for all pixel$_{th}$. Definition of field shapes was much improved, even for field sizes smaller than the 120 m thermal pixel size. Roads and residential areas in Fig. 4 are significantly better defined. The $T_s$ along the diagonal highway in Fig. 4 (top) is relatively uniform along the highway, which indicates relatively unbiased sharpening. The original 120 m pixels, often no longer square following resampling using NN and orthocorrection. Figure 5 shows the thermal pixels identified in a subarea using the Region Group tool of ArcGIS. Adjacent pixel$_{th}$ having the same DN were grouped together. However, this did not generally cause problems in sharpening $T_s$ since these pixel$_{th}$ normally have similar NDVI.

Figures 6 and 7 show sharpened $T_s$ in central Spain and in New Mexico. In the New Mexico image, the $T_s$ for narrow riparian systems along the Rio Grande became much more concise following the sharpening to 30 m.

Testing the Accuracy of the Sharpening Procedure

As a partial test of the accuracy of the sharpening procedure, Landsat 7 images were employed to provide a first estimation of possible error associated with sharpening of the more coarse Landsat 5 images. Landsat 7 derived NDVI at 30 m resolution was first degraded to a 60 m resolution by combining pixels within each 60 m pixel$_{th}$ to match the resolution of the native thermal band (band 6) and original surface temperature $T_s$. The 60 m NDVI and $T_s$ were then used as the “true” values for comparison. Then, 60 m $T_s$ was degraded to 120 m by combining four 60 m pixels to obtain $T_s$ at 120 m resolution. Finally, the sharpening procedure was applied to estimate $T_s$ at 60 m resolution using the synthetic $T_s$ having 120 m resolution and synthetic NDVI having 60 m resolution.
Figure 4. Original $T_s$ (left) and sharpened $T_s$ (right) for an irrigated area in S. Idaho on 07/23/1989 (top) and for an irrigated area containing a small town on 08/22/2000 (bottom) for Landsat 5 images, path 40, row 30.

Figure 5. False color composite of a subimage area in southern Idaho showing “reconstructed” thermal pixels of Landsat 5 using a statistical clumping procedure. The irregular boundaries were caused by NN resampling to 30 m during orthocorrection and ‘large’ pixel areas are comprised of individual thermal pixels having the same digital number (DN) in the original image.

Figure 8 shows a comparison of $T_s$ at 60 m resolution estimated by applying the sharpening procedure to the synthetic 120 m resolution $T_s$ vs. “true” observed $T_s$ at 60 m Landsat 7 resolution. This was a difficult sharpening exercise because each thermal pixel (120 m) was composed of only four 60 m pixels, thus the degrees of freedom...
for allocating $T_s$ bias within pixel$_{th}$ was small. Some error was caused by nonlinearity between an averaged NDVI over the 4-30 m pixels.

![Image](image.png)

**Figure 6.** Original $T_s$ (upper left), sharpened $T_s$ (upper right), $ET_r F$ (i.e., $K_c = ET/ET_r$) before sharpening (lower left) and $ET_r F$ after sharpening (lower right) for an area west of Albacete, Spain during 2002 (Landsat 5 image).

The root mean square error (RMSE) statistic was used to assess the level of agreement between estimated and “true” $T_s$. According to Kustas and Norman (2000), a value of RMSE/$\sigma \sim 1$, where $\sigma$ is the standard deviation of the $T_s$ observations, indicates poor agreement between predictions and observations, whereas RMSE/$\sigma < 0.5$ suggests that the approach is capable of estimating values in satisfactory agreement with observations. In our case, a value of
1.2 K was obtained for RMSE when comparing the sharpened 60 m $T_s$ to the original 60 m $T_s$ of Landsat 7; the value of $R^2$ was 0.988 and the value for $\text{RMSE}/\sigma$ was 0.16. All of these statistics indicate that the procedure performed well. These values are similar to ones obtained by Kustas and Norman (2000) but the $R^2$ value is significantly better.

**Evaluating the Effect of Thermal Pixel Sharpening on Modeled ET from METRIC**

The performance of the sharpening procedure in terms of improved estimation of ET was tested using ET measurements obtained from precision weighing lysimeters near Kimberly, Idaho. The analysis is described in detail in Allen et al. (2008). The lysimeter ET data were collected by Dr. J.L.Wright at the USDA Agricultural Research Service facility during the 1970’s and 1980’s. Figure 9 compares lysimeter-measured ET for sugar beets on image dates that were sharpened for $T_s$ with ET estimated using METRIC before and after sharpening. ET from METRIC was sampled from the small 2.5 ha field of sugar beets surrounding the lysimeter, and was slightly improved on one date and slightly worsened on two other dates, with no change on other dates from the sharpening.

**Figure 8.** Comparison between sharpened and “True” surface temperature for a June 4, 2000 Landsat 7 image for path 40, row 30 where NDVI was coarsened to 60 m and $T_s$ was coarsened to 120 m prior to sharpening.

**Figure 9.** Lysimeter-measured ET from sugar beets on Landsat 5 image dates during 1989 and ET estimated using METRIC before and after sharpening of $T_s$ from the surrounding field.
SUMMARY AND CONCLUSIONS

The ‘sharpening’ of surface temperature from the native 120 m of Landsat 5 to a 30 m equivalent that corresponds to resolution of short-wave bands improves the resolution that can be derived for ET estimated from surface energy balance. The NDVI based approach appears to have merit. Improvement is ongoing.

REFERENCES


