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RESEARCH PAPER

Enhanced sharpening procedures on edge difference and water stress index basis over heterogeneous landscape of sub-humid region

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Abstract Land Surface Temperature (LST) is a key parameter in the energy balance model. However, the spatial resolution of the retrieved LST from sensors with high temporal resolution is not accurate enough to be used in local-scale studies. To explore the LST–Normalised Difference Vegetation Index relationship potential and obtain thermal images with high spatial resolution, six enhanced image sharpening techniques were assessed: the disaggregation procedure for radiometric surface temperatures (T_sHARP), the Dry Edge Quadratic Function, the Difference of Edges (T_s^*DL) and three models supported by the relationship of surface temperature and water stress of vegetation (Normalised Difference Water Index, Normalised Difference Infrared Index and Soil wetness index). Energy Balance Station data and *in situ* measurements were used to validate the enhanced LST images over a mixed agricultural landscape in the sub-humid Pampean Region of Argentina (PRA), during 2006–2010. Landsat Thematic Mapper (TM) and Moderate Resolution Imaging Spectroradiometer (EOS-MODIS) thermal datasets were assessed for different spatial resolutions (e.g., 960, 720 and 240 m) and the performances were compared with global and local T_sHARP procedures. Results suggest that the T_s^*DL technique is the most adequate for simulating LST to high spatial resolution over the heterogeneous landscape of a sub-humid region, showing an average root mean square error of less than 1 K.

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1. Introduction

Land Surface Temperature (LST) products with moderate and high spatial and temporal resolutions are needed for many applications in environmental monitoring and emergency early warning response. Improvements in the spatial resolution of LST images could extend their potential significantly (Yang et al., 2011). Thus, efforts have been made to obtain a correct

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estimation of Land Surface Temperature (LST) by downscaling resolution over the PRA. However, owing to the relatively lower thermal radiation that is emitted by land surfaces in such areas, most satellite sensors are incapable of providing as much fine-scale information in the TIR wavelengths compared with the visible/near infrared (VNIR) and short wave infrared (SWIR). Currently, various types of sensors operate on-board satellite platforms with bands in the VIS–SWIR (0.4–7.3 µm) and TIR (8.0–14.0 µm) spectral ranges attuned to different spatial resolutions. Sensors such as EOS-MODIS provide TIR bands with coarse spatial resolutions ($\geqslant 1$ km) and VNIR bands with moderate spatial resolution (250 m) with a fine temporal resolution ($\leqslant 1$ day). Sensors with moderate spatial resolution thermal data (> 250 m) such as the Advanced Spaceborne Thermal Emission Reflection Radiometer (ASTER), Enhanced Thematic Mapper Plus (ETM+) and Landsat Data Continuity Mission (LDCM) are available with a coarse temporal resolution (16 days or request).

The concept of sharpening refers to disaggregating an image with coarse spatial resolution to a downscaling of the spatial resolution, by combining two or more image sets from the same or different sensors, preserving the radiometric content of the image. The sharpening procedure must ensure an accurate spatial description of the LST variability and preserve the coherence in the radiometry of the original TIR band (Rodriguez-Galiano et al., 2012). Different sharpening methods for enhancing the spatial resolution of LST have been developed, such as fractal interpolation (Kim and Barrows, 2002), empirical relationships (Kustas et al., 2003; Agam et al., 2007a; Jeganathan et al., 2011), analytical and physical models (Merlin et al., 2008), linear or spectral mixture models (Liu and Pu, 2008; Zurita-Milla et al., 2009), sequential disaggregation (Merlin et al., 2009) and geostatistical downscaling cokriging (Rodriguez-Galiano et al., 2012).

The Disaggregation procedure for Radiometric Surface Temperature technique (*DisTrad*) was proposed by Kustas et al. (2003), using the empirical relationship between LST and the Normalised Difference Vegetation Index (NDVI) (Rouse et al., 1974). Agam et al. (2007a,b) redefined the *DisTrad* procedure under the assumption that the LST variability is controlled by the fraction vegetation cover (f_c) and called it T_sHARP. The *DisTrad* technique disaggregates a coarse spatial resolution LST image to fine spatial resolution. It is defined by the negative slope variation generated in a least squares regression model fitted to the relation between the LST and NDVI, where both are from a coarse spatial resolution image (denoted by the subscript LR) (Kustas et al., 2003; Jeganathan et al., 2011; Yang et al., 2011). The sharpening methodology is as follows:

$$LST^{*}(NDVI_{LR}) = f(NDVI_{LR}) \quad (1)$$

The slope and intercept parameters of the least squares regression model are applied to the coarse spatial resolution NDVI image to simulate a coarse spatial resolution thermal image (the star symbol indicates a predicted LST value). The residual error (Δt_{LR}) is due to forces driving surface temperature other than the amount of vegetation cover (e.g., soil moisture) (Kustas et al., 2003; Agam et al., 2007a) (see Fig. 1). The residual error can be assessed at the coarse scale as follows:

$$\Delta t_{LR} = LST_{LR} - LST^{*}_{LR} \quad (2)$$

Therefore, the sharpened sub-pixel temperatures within each coarse pixel are computed by Eq. (3), using the estimated coefficients derived from the coarse spatial resolution data on the NDVI to the high spatial resolution (denoted by the subscript HR) (Agam et al., 2007a).

$$LST^{*}_{HR} = LST^{*}(NDVI_{HR}) + \Delta t_{LR} \quad (3)$$

Here, Δt_{LR} is the coarse spatial resolution residual added to the fine spatial resolution predicted temperature to increase the accuracy of the simulated image, considering the proportion of water in the plant-soil system. This procedure requires that a range of surface temperature and vegetation indices be present within the image scene, in order to develop a significant regression relationship. Therefore, *DisTrad* does not perform well over scenes in which there is little variability in surface temperature (e.g., night-time and early morning). Furthermore, the water body and cloud pixels were not considered when fitting the regression model because these tend to be outliers in the NDVI-LST relationship (Agam et al., 2007a).

The inverse linear relationship established widely between vegetation cover and LST is used for enhanced sharpening procedures. This relationship is controlled by various factors including the thermal properties of the surface, soil and vegetation water content, evapotranspiration and net radiation (Sandholt et al., 2002; Holzman et al., 2014). Also, it is influenced strongly by annual seasonality. Sun and Kufatos (2007) observed that the relationship is negative in warm seasons and positive in the winter. Hence, the current study assumes a negative relationship due to the warm climatic conditions over the PRA.

Many studies on sharpening have focused on the statistical regression methods taking into account the NDVI-LST relationship (Kustas et al., 2004; Li et al., 2008; Merlin et al., 2009; Yang et al., 2011). However, there are few background studies on the above sharpening techniques based on the use of the integrated dry and wet edge. Chen et al. (2010) used the dry and wet edge to develop a model called Soil Wetness Index Stepwise Fitting (SWISF) based on the Soil Wetness Index (SWI).

The aim of this paper is to research the application and evaluate the results of six different enhanced sharpening thermal models based on the NDVI-LST relationship and to determine the most accurate technique with ground-based radiative temperature (T_{rad}) measurements over the heterogeneous landscape of the Pampean Region of Argentina.

2. Methodology

2.1. Enhanced sharpening basis functions

Mixed vegetation cover is a typical feature of the land cover of the PRA. This heterogeneous area is covered with a mixture of crops, bare soil, water and small-scale impervious components (see Section 3). To obtain high-temporal resolution temperatures of individual agricultural fields to support drought monitoring and energy balance studies, six different sharpening methodologies based on the T_sHARP technique were employed with the aim of improving sub-pixel LST estimations. The first model uses the fitted dry edge extracted from the 2nd-degree polynomial regression between the LST and NDVI relationship, which is called the Dry Edge Quadratic