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A two-step framework for reconstructing remotely sensed land surface temperatures contaminated by cloud

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ABSTRACT

Land surface temperature (LST) is one of the most important parameters in land surface processes. Although satellite-derived LST can provide valuable information, the value is often limited by cloud contamination. In this paper, a two-step satellite-derived LST reconstruction framework is proposed. First, a multi-temporal reconstruction algorithm is introduced to recover invalid LST values using multiple LST images with reference to corresponding remotely sensed vegetation index. Then, all cloud-contaminated areas are temporally filled with hypothetical clear-sky LST values. Second, a surface energy balance equation-based procedure is used to correct for the filled values. With shortwave irradiation data, the clear-sky LST is corrected to the real LST under cloudy conditions. A series of experiments have been performed to demonstrate the effectiveness of the developed approach. Quantitative evaluation results indicate that the proposed method can recover LST in different surface types with mean average errors in 3–6 K. The experiments also indicate that the time interval between the multi-temporal LST images has a greater impact on the results than the size of the contaminated area.

1. Introduction

Land surface temperature (LST) is of primary importance in understanding global environment change, urban climatology, and land-atmosphere energy exchange (Kustas and Anderson, 2009; Weng, 2009; Weng and Fu, 2014; Estoque and Murayama, 2017; Zhang and Li, 2018). LST observations are therefore widely used in a variety of fields, including hydrology, meteorology, climate change, vegetation ecology, environmental monitoring, and military reconnaissance (Anderson et al., 2008; Arnfield, 2003; Hansen et al., 2010; Shen et al., 2016). Given the complexity of surface temperatures over land, ground stations cannot provide spatially consistent and temporally continuous measurements over large areas. Satellite remote sensing offers the only possibility for observing LST over the entire globe with acceptable temporal resolution and completely spatial coverage (Li et al., 2013). Satellite-based LST is often retrieved using thermal infrared (TIR) data with the generalized split-window algorithm (Jimenez-Munoz and Sobrino, 2003; Qin et al., 2001; Wan and Dozier, 1996). However, like all the other TIR data-based retrieval methods, the generalized split-window algorithm can only work well when the data are acquired under clear-sky conditions. When solar radiation is obstructed by cloud and/or impacted by other atmospheric disturbances, the retrieval of LST will be greatly affected. As a result, in LST images, only clear-sky pixels have useable information, whereas cloud-covered regions are filled with invalid values (Rajasekar and Weng, 2009). As completely cloud-free weather is rare, especially in rainy seasons or in humid regions, most LST images are contaminated by cloud. Cloud contamination, therefore, greatly limits the subsequent applications of satellite-derived LST in related fields (Yoo et al., 2018).

It has been found that reconstruction techniques can effectively recover missing information and improve the usability of the deteriorated LST. A number of methods have been developed, which can be generally divided into three types according to the sources of reference information: (1) spatial information, (2) multi-temporal observations, and (3) other complementary data, for

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example, from ground meteorological stations. The basic spatial information-based methods are spatial interpolation approaches, including inverse distance weighting, spline function and geostatistical interpolation methods. Some studies have attempted to take more factors into account using some multi-variable interpolation methods, such as cokriging (Cai et al., 2009; Ke et al., 2011; Neteler, 2010). As only limited spatial information is referred, the reconstructed regions are often blurred resulting in unsatisfied accuracy. A spectral angle distance weighting reconstruction method has been explored (Shuai et al., 2014). The property of the land surface is quantitatively considered in this study by calculating the spectral angle of original multispectral images. The temporal information-based methods have also been well developed. Reconstruction methods based on time domain analysis have also been developed (Xu and Shen, 2013). The temporal filtering methods, like harmonic analysis, often work well for regions with frequent and dense cloud cover. However, extreme LST values may not be well reconstructed due to the smoothing effect of low-pass filtering. Zeng et al. (2015) filled invalid LST values using a multi-temporal classification and a robust temporal regression. Compared with the temporal filtering approach, the method can fill invalid LST values accurately with much less reference data.

It should be noted that the aforementioned methods can only provide hypothetical clear-sky LST values, but not the real LST under cloudy conditions. In general, during daytime the cloud-covered LST is lower than the cloud-free LST because the land surface receiving solar radiation is hidden by cloud. For the third type of reconstruction methods, other land surface information is incorporated to estimate the real LST. Jin (2000) proposed a neighboring-pixel (NP) approach to reconstruct the LST of cloudy pixels based on the surface energy balance. In this approach, the LST of cloudy pixels is interpolated from the neighboring clear pixels surrounding the cloudy pixels. In addition, surface wind and air temperature are also incorporated. Based on Jin's approach, a temporal NP method was developed to estimate cloudy LST pixels from geostationary satellites (Lu et al., 2011). Then, a spatially and temporally NP method was also proposed to reconstruct cloud-contaminated pixels in daily MODIS LST products (Yu et al., 2014). Since the surface energy balance is considered, the NP-based method can reconstruct the real LST for cloudy pixels. However, for these methods, ground-based measurements are often needed to calculate regional parameters, which makes them difficult to implement for ungauged or poorly gauged regions.

With the development of the above methods, the usability of satellite-derived LST has been greatly improved. However, these methods all have their advantages and limitations under different circumstances. In general, the temporal information-based methods are more effective, but the real LST cannot be obtained. The surface energy balance-based methods are more accurate, but the parameters are difficult to obtain. The overall objective of this study is therefore to develop a new flexible and effective method for cloud-contaminated LST reconstruction. The advantage of the newly developed approach is that it can generate more accurate LST for cloudy pixels, without depending largely on ground-based ancillary data. This approach makes satellite-based LST observations more applicable to large areas, and should be valuable in meteorological and hydrological studies and applications. In the following sections, we first describe the algorithm, and then demonstrate its performance based on both simulated and actual experiments.

2. Method

As shown in the flowchart of Fig. 1, first, a multi-temporal reconstruction process is employed to obtain the ideal clear-sky LST for the cloud-contaminated region in combination with the

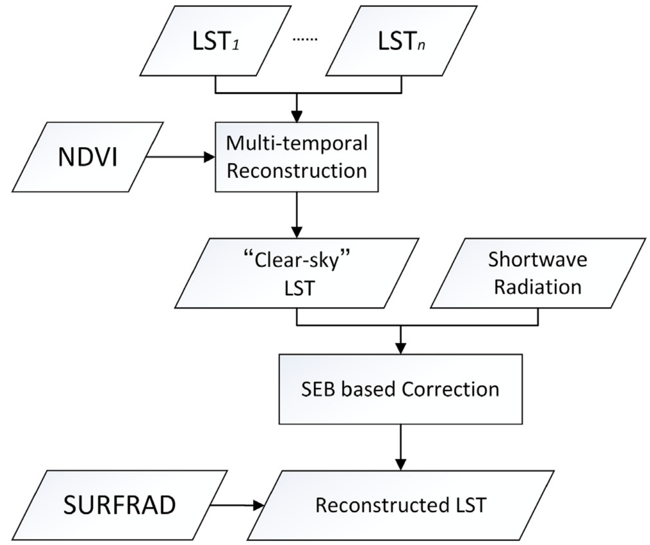

Fig. 1. Flowchart of the proposed two-step framework for LST reconstruction.

Normalized Difference Vegetation Index (NDVI). Second, a surface energy balance (SEB) equation-based method is used to correct the clear-sky LST to the real LST with surface shortwave radiation information. And the results are verified using SURFace RADiation (SURFRAD) ground measurements.

2.1. Multi-temporal reconstruction

In the first step, a multi-temporal reconstruction method was introduced to obtain the clear-sky land surface temperature. It has been shown that two LST maps acquired during a short period change linearly for the same type of feature (Zeng et al., 2015). Therefore, the contaminated LST can be reconstructed by the LST acquired at another time:

$$T_{s0} = a \cdot T_{s0}{}' + b \tag{1}$$

where $T_{s0}$is the LST to be recovered, $T_{s0}{}'$is the reference LST acquired at a near time for T_{s0}, and a and b are regression coefficients. Since pixels with the similar land surface property have similar trends in LST change, the regression coefficients a and b can be calculated by the similar common pixels (common pixels are referred to as the pixels with valid values in both LST images) of the contaminated LST image and the reference LST image. The procedures are shown in Fig. 2.

It has also been found that LST has a strong relationship with the vegetation index (VI) (Amiri et al., 2009, Dousset and Gourmelon, 2003; Jin and Dickinson, 2010; Schultz and Halpert, 1995). A hypothesis is therefore proposed here: during a period, the change of LST is related to vegetation index values. To test this hypothesis, an example is shown in Fig. 3. Two MODIS LST images acquired on January 1, 2010, and January 5, 2010 are shown in Fig. 3(a). The difference map between the two LST images is shown in Fig. 3(b). The corresponding NDVI map for the same area is shown in Fig. 3(c). Fig. 3(d) shows the scatterplot of the temperature difference against NDVI. The distribution of the black dots indicates a strong relationship between the temperature difference and NDVI, showing a correlation coefficient (R) of 0.666.

Therefore, the VI could also be involved in the calculation of the regression coefficients in Eq. (1). Since VI values often remain constant in a short term, multi-day composite VI can be used for convenience. In this paper, an adaptive determination procedure for the similar pixel selection was employed (Zeng et al., 2013). In