Assessing Drought Conditions in Cloudy Regions Using Reconstructed Land Surface Temperature

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ABSTRACT

Temperature vegetation dryness index (TVDI) in a triangular or trapezoidal feature space can be calculated from the land surface temperature (LST) and normalized difference vegetation index (NDVI), and has been widely applied to regional drought monitoring. However, thermal infrared sensors cannot penetrate clouds to detect surface information of sub-cloud pixels. In cloudy areas, LST data include a large number of cloudy pixels, seriously degrading the spatial and temporal continuity of drought monitoring. In this paper, the Remotely Sensed Daily Land Surface Temperature Reconstruction model (RSDAST) is combined with the LST reconstructed (RLST) by the RSDAST and applied to drought monitoring in a cloudy area. The drought monitoring capability of the reconstructed temperature vegetation drought index (RTVDI) under cloudy conditions is evaluated by comparing the correlation between land surface observations for soil moisture and the TVDI before and after surface temperature reconstruction. Results show that the effective duration and area of the RTVDI in the study area were larger than those of the original TVDI (OTVDI) in 2011. In addition, RLST/NDVI scatter plots cover a wide range of values, with the fitted dry–wet boundaries more representative of real soil moisture conditions. Under continuously cloudy conditions, the OTVDI inverted from the original LST (OLST) loses its drought monitoring capability, whereas RTVDI can completely and accurately reconstruct surface moisture conditions across the entire study area. The correlation between TVDI and soil moisture is stronger for RTVDI ($R = -0.45$) than that for OTVDI ($R = -0.33$). In terms of the spatial and temporal distributions, the $R$ value for correlation between RTVDI and soil moisture was higher than that for OTVDI. Hence, in continuously cloudy areas, RTVDI not only expands drought monitoring capability in time and space, but also improves the accuracy of surface soil moisture monitoring and enhances the applicability and reliability of thermal infrared data under extreme conditions.

Key words: land surface temperature reconstruction, Remotely Sensed Daily Land Surface Temperature Reconstruction model (RSDAST), temperature vegetation dryness index (TVDI), soil moisture, drought

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1. Introduction

Drought is a complex and multi-attribute natural phenomenon characterized by high frequency, long duration, and widespread influence; thus, it has a serious impact on the national economy, especially agricultural production. Statistics show that economic losses caused by global meteorological disasters account for 85% of the losses caused by all natural disasters. The losses from drought account for more than half of the losses caused by meteorological disasters (Yi, 2010; Wang, 2017; Zhang et al., 2017). Insufficient understanding of drought development and the lack of timely preparation and effective responses are possible reasons for the great losses caused by drought events (Yan et al., 2018). In comparison with other natural disasters, droughts develop slowly across a
wide area. This means that droughts can difficultly be detected before serious damage has occurred (Wood et al., 2015). Therefore, drought indicators must be continually monitored as a part of prevention and risk reduction (Sun et al., 2012, 2013; Hao et al., 2014; Sheffield et al., 2014; Ahmadalipour et al., 2016; Yan et al., 2018).

Remote sensing technology, which is macroscopic, fast, and economic, can compensate for the spatial-scale deficiencies of site monitoring and can realize regional or global drought monitoring (Rhee et al., 2010; Zhu et al., 2017). Soil water deficiencies restrict vegetation growth, and several vegetation indices can be used to indirectly describe regional soil water content (Tian, 2006; Anderson et al., 2013). However, the sensitivity of vegetation index to short-term soil moisture changes is low; therefore, vegetation index alone cannot accurately describe changes in drought conditions at short-time scales (Fensholt and Sandholt, 2003). Soil moisture evaporation increases in warmer climates, and regional droughts are more likely to occur when precipitation is uneven (Tian, 2006; Anderson et al., 2013). Studies have shown a strongly negative correlation between surface temperature and vegetation index (Price et al., 1990; Lambin and Ehrlich, 1995). Sandholt (2002) proposed a simplified land surface dryness index, called the temperature vegetation dryness index (TVDI), which is based on an empirical parameterization of the land surface temperature (LST) and normalized difference vegetation index (NDVI) space. The spatial pattern of the TVDI was shown to be closely related to the soil surface moisture simulated with the MIKE SHE model. Garcia et al. (2014), Zhang et al. (2017), Amani et al. (2017), Liu et al. (2017), Liu and Yue (2018), and Zhang et al. (2019) have successfully applied the LST–NDVI triangle method for monitoring surface soil moisture in a variety of climatic environments at regional or global scales. Sun et al. (2012) proposed an advanced TVDI to monitor soil moisture status using an improved surface temperature and a vegetation index space formed by the theoretical dry edge, as determined by the surface energy balance principle, and the wet edge based on water surface temperature.

The LST reconstruction of sub-cloud pixels is crucial to soil moisture evaluation (Zhang et al., 2015; Kou et al., 2016). The surface information in cloud-covered areas cannot be captured by thermal infrared sensors, resulting in a large number of vacancies in thermal infrared remote sensing data in cloudy areas (Ke et al., 2013; Shuai et al., 2014; Fu et al., 2019). TVDI is estimated on the basis of the triangle feature space formed by the vegetation index and surface temperature scatter, and its result depends solely on image data (Sun et al., 2017). If the land cover of a region varies from bare soil to dense vegetation and the soil moisture condition varies from drought to humid, then the spread of points in a scatter plot of LST versus NDVI is trapezoidal or triangular (Tian, 2006). If numerous cloudy pixels exist in the study area, then forming the triangular feature space will be difficult for LST/NDVI. In this case, the soil moisture condition of the regional surface cannot be comprehensively and continuously monitored. Numerous studies have focused on the LST reconstruction of sub-cloud pixels and have proposed many algorithms and models. Xu and Yan (2013) reconstructed the surface temperature of the cloudy pixels in MODIS data using filtering analysis (Harmonic Analysis of Time Series, HANTS). Fu et al. (2019) effectively estimated the surface temperature of sub-cloud pixels by combining the coupled weather research and forecast model and a random forest regression algorithm. Sun et al. (2017) analyzed in detail the relationship between clear sky and cloudy pixels across varying spatial distances and surface environments, and reconstructed the surface state of cloudy pixels to the greatest extent possible by applying different weight distributions. Neteler (2010) and Metz et al. (2014) used elevation, solar angle, precipitation, and temperature as additional variables in the spline interpolation method to reconstruct LST values. Zhou et al. (2012) used spatial interpolation (gradient plus inverse distance squared, SIDS) to estimate LST under cloud cover based on cloudless ETM+ imagery, but assuming the existence of cloud cover. Duan et al. (2015) proposed a method to generate an all-weather LST product by merging MODIS and AMSR-E data. Zhou et al. (2017) explored the suitability of the data interpolating empirical orthogonal functions (DINEOF) method in MODIS LST reconstruction around Ali on the Tibetan Plateau. The reconstruction of sub-cloud pixels can increase the quantity of valid pixels and fill in missing pixel LSTs in some surface types, such that the LST/NDVI feature space with complex surfaces can closely represent the real surface moisture conditions. Consequently, drought monitoring by using TVDI in cloudy areas with complex surface types becomes more accurate.

In this study, a reconstructed temperature vegetation dryness index (RTVDI), which is calculated by using the reconstructed LST and vegetation index, is proposed by combining the Remotely Sensed Daily Land Surface Temperature Reconstruction model (RSDAST) established by Sun et al. (2017) and the TVDI (Sandholt et al., 2002). This new model was applied to monitor spring
and summer droughts in Chongqing, China, in 2011. The accuracy of RTVDI was evaluated by comparison with soil moisture observations. The value and significance of the RSDAST algorithm for drought monitoring in cloudy areas were evaluated by comparing the correlations among OTVDI, RTVDI, and soil moisture.

2. Study area and data

2.1 Study area

Chongqing, as the study area, is located in the upper reaches of the Yangtze River, Southwest China, over 28°10′–32°13′N, 105°11′–110°11′E (Fig. 1a). The region spans 470 km east–west and approximately 450 km north–south, covering an area of 82,000 km². Chongqing is situated on the Yangtze River with Hunan and Hubei to the east, Sichuan to the west, Shanxi to the north, and Guizhou to the south. Its terrain is composed mainly of hills and low mountains characterised by valleys and ridges, with an average altitude of 400 m. Due to the influences of topography, atmospheric circulation, equatorial eastern Pacific SST, snow cover on the Qinghai–Tibetan Plateau, and other external factors, Chongqing is prone to extreme high temperatures in summer (Li, 2003; Bao et al., 2007; Peng et al., 2007; Zou and Gao, 2007). Periods of continuous high temperatures cause regional drought (summer drought).

Figure 1b shows the proportion of cloudy pixels in the MODIS data for Chongqing in 2011. The proportion influenced by clouds in high-altitude areas is relatively low, but still exceeds 65%; the proportion in low-altitude areas is 93%. Long-term cloud cover across a large area causes a spatial and temporal discontinuity in thermal infrared data, which greatly limits the application of thermal infrared remote sensing data in the Chongqing area.

2.2 MODIS data

MODIS is an important sensor on the Terra and Aqua satellites, providing full-spectrum coverage in 36 discrete spectral bands ranging from 0.4 μm (visible) to 14.4 μm (thermal infrared). The data used in this paper are the daily MODIS LST product (MOD11A1 collection 6), with 1-km spatial resolution and 1-day temporal resolution, from 1 January to 31 December 2011. The tiles of the study are h27v05 and h27v06. The vegetation index product MOD13A2 is a synthetic dataset with 16-day resolution. There is no daily vegetation index product corresponding to surface temperature. The MODIS MCD43A4 Version 6 Nadir Bidirectional Reflectance Distribution Function (BRDF)-Adjusted Reflectance (NBAR) dataset is produced daily by using 16 days of Terra and Aqua MODIS data at 500-m resolution. The daily vegetation index in the study was calculated by using the above data. The spatial resolutions of MCD43A4 and MOD11A1 were matched by resampling.

2.3 Soil moisture data

Soil moisture observations during 2011 were obtained from 12 evenly-distributed sites in Chongqing (Fig. 1). A DZN2-type automatic soil moisture sensor was used to measure soil moisture content automatically at depths of 10, 20, 30, 40, and 50 cm. The main types of soil around the site are loam and sandy loam. Table 1 shows detailed
The combination of LST and NDVI yields information complementarity and provides potential for monitoring regional soil moisture (Tian, 2006). A large number of field experiments have shown a close negative correlation between LST and NDVI (Fig. 2), and the LST/NDVI fitting line can be used to represent the soil moisture content in a region. If the LST/NDVI fitting line is close to the horizontal line, then the soil moisture content in the region is high. On the contrary, for steep slopes of the fitting line, the soil moisture content is low. In a region where the surface cover varies from bare soil to closed vegetation canopy and the soil moisture ranges from arid to semi-arid to humid, scatter plots of LST versus NDVI are trapezoidal or triangular (Price, 1990; Lambin and Ehrlich, 1995).

Theoretical model and field experimental results demonstrate the LST/NDVI feature space. On this basis, Sandholt et al. (2002) proposed the concept of TVDI, calculated as follows:

\[
\text{TVDI} = \frac{\text{LST} - \text{LST}_\text{min}}{\text{LST}_\text{max} - \text{LST}_\text{min}},
\]

where LST refers to the surface temperature. LST\textsubscript{min} refers to the minimum surface temperature corresponding to a given NDVI value, and the fitting line of all minimum values \(\text{LST}_\text{min} = a_1 + b_1 \times \text{NDVI}\) is the wet edge (TVDI = 0). LST\textsubscript{max} refers to the maximum surface temperature corresponding to a given NDVI value, and the fitting line of all maximum values \(\text{LST}_\text{max} = a_2 + b_2 \times \text{NDVI}\) is regarded as the dry edge (TVDI = 1). The variables \(a_1\), \(a_2\), \(b_1\), and \(b_2\) are the dry–wet edge fitting coefficients. When the LST is close to the dry edge, the TVDI value is large, and the soil moisture is low. On the contrary, when the LST is close to the wet edge, the TVDI value is small, and the soil moisture is high. The application of TVDI can compensate for the deficiency of soil moisture monitoring approaches that only consider NDVI or LST. This effectively reduces the effect of vegetation coverage on drought monitoring, thereby improving the accuracy and practicability of remote sensing drought monitoring. TVDI has been widely used in regional soil moisture monitoring.

### 3.2 Principles of the RSDAST algorithm

The relationship between geographic units in a geographic space is related to the distance between them. When two pixels are close, their surface characteristics are similar. When the distance between pixels is sufficiently close, their solar radiation, temperature, and precipitation can be regarded as similar in the same weather conditions. Thus, the temperature difference between a certain pixel and its adjacent pixel can be assumed to remain stable in a time series. This assumption was validated by Sun et al. (2017), wherein

\[
\text{LST}(x_0, y_0, t_0) - \text{LST}(x_r, y_r, t_0) = \text{LST}(x_0, y_0, t_p) - \text{LST}(x_r, y_r, t_p),
\]

where

| Site | Latitude | Longitude | Elevation (m) | Soil type | Land cover |
|------|----------|-----------|--------------|-----------|------------|
| 57333 | 31°56′40″N | 108°38′47″E | 798.2 | Sandy loam | Cropland |
| 57409 | 30°04′42″N | 105°46′18″E | 200 | Sandy loam | Grass |
| 57425 | 30°17′36″N | 107°18′40″E | 412 | Loam | Vegetables |
| 57432 | 30°45′43″N | 108°23′39″E | 186.7 | Sandy loam | Pepper |
| 57437 | 30°23′24″N | 108°07′19″E | 349.3 | Loam | Citrus |
| 57502 | 29°42′59″N | 105°42′00″E | 384.9 | Clay loam | Grain |
| 57506 | 29°21′40″N | 106°16′45″E | 353.0 | Clay loam | Corn |
| 57511 | 29°50′31″N | 106°26′36″E | 240.8 | Sandy loam | Corn |
| 57512 | 29°57′56″N | 106°16′45″E | 212.9 | Clay | Citrus |
| 57513 | 29°54′00″N | 106°43′00″E | 548.0 | Clay loam | Corn |
| 57517 | 29°53′50″N | 106°42′31″E | 235 | Sandy loam | Wheat |
| 57633 | 28°49′07″N | 108°46′17″E | 799 | Loam | Grass |

Fig. 2. LST/NDVI feature space map (Sandholt et al., 2002).
On the basis of Eq. (2), Sun et al. (2017) proposed a model to reconstruct the land surface temperature of a cloudy pixel (RSDAST) by using pixel values for clear sky areas surrounding cloudy pixels at adjacent observation times. Equation (3) shows the implementation of this process.

\[
LST(x_0; y_0; t_0) = \sum_{p=t_0+D}^{p=t_0+D+N} W_i \cdot \left[ LST(x_0, y_0, t_p) - LST(x_i, y_i, t_p) + LST(x_i, y_i, t_0) \right].
\] (3)

In Eq. (3), \(LST(x_0, y_0, t_0)\) is the LST value of the cloudy pixel that is to be reconstructed. The variable \(t_0\) refers to the time of image reconstruction, \(i\) refers to the pixels under clear sky in a movable window, \(D\) refers to the adjacent time scale, and \(N\) refers to the total number of pixels under clear sky in a movable window. Sun et al. (2017) included valid pixels at the adjacent observation time \(t_p\) in the reconstruction algorithm while also considering the distance factor, to increase the number of valid pixels. \(LST(x_0, y_0, t_p)\) is the LST corresponding to the cloudy pixel at \(t_p\), \(LST(x_i, y_i, t_p)\) is the LST under clear sky in a movable window at \(t_p\), and \(LST(x_i, y_i, t_0)\) is the valid LST in a movable window at \(t_0\). \(W_i\) is the weight coefficient representing the contribution of LST \((x_i, y_i)\) to the reconstructed \(LST(x_0, y_0, t_0)\), and its value is related to distance factor \((D_i)\) and similarity factor \((S_i)\). The formula for \(W_i\) is as follows:

\[
W_i = \frac{1 / (D_i \cdot S_i)}{\sum_{i=1}^{N} \left[ 1 / (D_i \cdot S_i) \right]}.
\] (4)

\(D_i\) refers to the distance factor. On the basis of the first law of geography, the correlation between pixels is inevitably related to the distance between them. When the distance is close, the correlation between pixels is strong (Tobler W. 1970; Li et al. 2007). In other words, during surface temperature reconstruction, the distance between pixels with a uniform surface texture is close, their surface temperature values are close, and their contribution to the reconstruction of \(LST(x_0, y_0, t_0)\) is high. Therefore, the distance factor between \((x_0, y_0)\) and \((x_i, y_i)\) is defined as

\[
D_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}.
\] (5)

However, a close distance between pixels does not reflect a small difference in their surface temperature. The correlation is also affected by the surface environment. Sun et al. (2017) introduced a similarity factor \((S_i)\) to characterize the similarity of the surface environments of adjacent pixels. Theoretically, if no significant difference exists in the surface environment over a short period of time, then the difference in surface temperature between pixels \((\Delta LST)\) does not significantly change with time. Therefore, the difference in surface temperature between adjacent pixels \((\Delta LST)\) can be used to characterize the similarity of the surface environment. If \(\Delta LST\) is small, the surface environment of the two pixels is similar. That is, in the absence of \(LST(x_0, y_0, t_0)\), the LST difference of pixel pair \((LDPP)\) at \(t_p\) can be used to define the similarity of the \((x_i, y_i)\) and \((x_0, y_0)\) surface pixels. If \(LDPP\) is small, then the surface cover of two pixels is similar. The similarity factor \((S_i)\) can be calculated as

\[
S_i = \left[ LST(x_0, y_0, t_p) - LST(x_i, y_i, t_p) \right] + 1.
\] (6)

Equation (4) shows that if \(S_i\) is small, the contribution of the adjacent valid LST to the reconstructed LST \((x_0, y_0, t_0)\) is high. The purpose of adding 1 is to avoid the case \(S_i = 0\) when the surface temperatures of two adjacent pixels are the same.

### 3.3 Validation method

#### 3.3.1 Validation of the RSDAST surface temperature reconstruction algorithm

On the basis of the RSDAST method, the LST value of a pixel under clear sky that is adjacent in time and space is adopted to reconstruct a cloudy pixel LST. The reconstructed LST is under clear-sky conditions, and is not the real LST of the sub-cloud pixel. Therefore, validating the reconstructed LST using the site-measured LST is inappropriate. In this study, the removal–reconstruction–comparison method was adopted. That is, pixels under clear sky in the original data were screened out to simulate cloud-contaminated pixels. After the removal of simulated cloud-contaminated pixels, the RSDAST method was adopted to fill and reconstruct the missing pixels. Finally, the original pixel values were used as validation data to compare and analyze the reconstructed pixel values. The accuracy of surface temperature reconstruction under clear sky was characterized by \(R\), Bias, and RMSE as follows.

\[
R = \frac{\sum_{i=1}^{N} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{N} (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^{N} (Y_i - \bar{Y})^2}},
\] (7)

\[
\text{Bias} = \frac{\sum_{i=1}^{N} (Y_i - X_i)}{N},
\] (8)

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (Y_i - X_i)^2}{N}},
\] (9)

where \(X_i\) refers to the original LST (OLST), and \(Y_i\) refers to the reconstructed LST (RLST); \(\bar{X}\) and \(\bar{Y}\) are the sample means of \(X_i\) and \(Y_i\), respectively; and \(N\) is the...
sample size.

In Sun et al. (2017), the window size and time span were set as $9 \times 9$ and 8 days. However, some regions are continuously covered by cloud for more than 10 days, resulting in no valid pixel pair in the LST reconstruction procedure. Therefore, to determine the optimal combination of window size and time span, simulation window sizes ranged from $5 \times 5$ to $19 \times 19$, and the adjacent time span ranged from 4 to 30 days. The clear-sky LST of cloudy pixels in the simulation area was reconstructed according to the different window sizes and time span combinations. Then, the reconstruction accuracy of LST using these different combinations was compared to find the optimal combination of window size and adjacent time scale in the RSDAST model.

3.3.2 Applicability of the RSDAST algorithm for drought monitoring in cloudy areas

The daily value of RTVDI in the study area was obtained by combining the RLST and NDVI inversion. To verify the practicability and reliability of the RTVDI for drought monitoring in cloudy areas, the following points were considered. (1) The actual contribution of the RSDAST algorithm to drought monitoring in cloudy areas was verified by comparing the fitting of dry–wet edges before and after reconstruction. The fitting results of dry–wet edges determine the calculated TVDI to a certain extent. In a large area covered by clouds, an excessive number of cloudy pixels will complicate the fitting of the dry–wet edges in the region and the assessment of the difference between the fitted dry–wet edges and actual surface conditions. (2) RTVDI was validated by ground-based soil moisture measurements and was then used to evaluate the capability of the RSDAST algorithm for drought monitoring over long time scales in cloudy areas.

4. Results

4.1 RSDAST validation and determination of the best combination

Figure 3a shows the verification of the RSDAST algorithm accuracy for different window sizes and time scales in the simulation area (the red box in Figs. 1a, b) in DOY 107. The $R$ value between OLST and RLST ranges from 0.956 to 0.988, the bias ranges from $-0.31$ to $0.16$ K, and the RMSE is from 0.31 to 0.64 K. The high $R$ value and low RMSE and bias indicate that RSDAST can accurately reconstruct the surface temperature of sub-cloud pixels. Under the condition that the window

![Fig. 3. Variations of $R$ (orange line; right-hand axis), RMSE/Bias (blue/grey line; right-hand axis) between reconstructed LST and original LST with different combinations of (a) window sizes ($5\sim19$) and time scales ($N4\simN30$), and (b) window sizes ($11$, $13$, and $15$) and time scales ($N17\simN19$). The abbreviations: $W$ and $N$ denote the window size and nearby dates, respectively.](image-url)
size remains unchanged, as N increases from 4 to 30 days the results show that two regions of high R (N17–N19, N28–N29, with R values of approximately 0.988) and one region of low R (N4–N12, with R values ranging from 0.955 to 0.968). The relatively low accuracy of LST reconstructions in N4–N12 is related to the number of missing adjacent time pixels in the simulated LST data. To verify the potential of the RSDAST model for LST reconstruction under long-term cloudy conditions, within 12 consecutive days of DOY107, only DOY106 was less affected by cloud. Therefore, in N4–N12, the effective pixels adopted by the LST reconstruction were mainly from DOY106, leading to a very low accuracy of the reconstructed LST at this time scale, and an unchanged R value. When the time scale was larger than 12 days, the incorporation of a large number of clear sky pixels caused a steep upwards trend in the R value. In N15–N29, the bias is close to 0 K, and in N17–N23, the RMSE value is less than 0.4 K. Although R is relatively large in N28–N29, the corresponding RMSE value is also relatively large. Conversely, for the time scale N17–N19, R is relatively large while the bias and RMSE are relatively small. Overall, this study neglects the small difference in R value, thus concluding that the RSDAST algorithm achieves its highest accuracy when the time scale is N17–N19.

For different windows, the trends in R, RMSE, and bias with time are similar, indicating that the window size has little influence on the LST reconstruction. With increasing window size, the mean value of R increases for a range of time scales, whereas RMSE decreases. When the window size is 11–15, the R value increases, whereas the RMSE and bias both decrease. Hence, the RSDAST algorithm achieves its best reconstruction when the window size is 11–15. By combining the optimum window size and time scale (Fig. 3b), this study compares changes in the accuracy indices (R and RMSE) in three windows (11, 13, and 15), respectively, at different time scales. The LST obtained using the adjacent 18-day clear-sky data combined with the reconstruction of clear-sky pixels in the 11 × 11 window around the sub-cloud pixels achieved the highest accuracy.

4.2 Analysis of the LST/NDVI feature space

In a scatter plot of vegetation index and land surface temperature, with conditions varying from dry to wet and bare soil to closed vegetation, points typically plot in a region that is trapezoidal or triangular. However, the occurrence of clouds renders it impossible to obtain valid data covering the entire range from dry to wet. Consequently, scatter plots often show concave, convex, or irregular shapes which may yield false wet-edges or dry-edges. To assess the fitting of dry–wet edges before and after LST reconstruction, 213 groups of valid dry–wet edges were fitted using the original LST, and 335 groups of valid dry–wet edges were fitted using the reconstructed LST.

Figures 4 and 5 show OLST, RLST, NDVI, and their LST/NDVI feature space maps for DOY120 and DOY121. The DOY120 OLST contains a large number of vacancies in cloud-covered areas, but these cloudy pixels in the RLST data were reconstructed by the RSDAST model. Reconstructed pixels can also be seen in the respective LST/NDVI scatterplot. There are clearly more effective pixels in the RLST/NDVI scatterplots than in the OLST/NDVI scatterplots; here, the extra points are the reconstructed LSTs for cloud-covered pixels. Owing to the excessive number of missing pixels in the DOY121 OLST, the OLST/NDVI feature space does not have the triangular or trapezoidal characteristics; however, the triangular form was regained following reconstruction by the RSDAST model. As shown in Figs. 4 and 5, there are obvious differences between the LST/NDVI dry–wet edge equations before and after LST reconstruction. In DOY120, the OLST/NDVI dry edge equation is \( y = -23.78x + 325.04 \), and the wet edge equation is \( y = 10.55x + 280.75 \). However, the RLST/NDVI dry–wet edge equations are \( y = -24.62x + 325.52 \), \( y = 6.57x + 282.69 \), respectively. This difference arises because of the many vacancies in the original data for DOY120 in the southeast of the research area. The dry–wet edge based on OLST/NDVI fitting only represents the soil moisture status in the Northwest. After reconstruction, the effective LST pixels are distributed across the whole study area. The dry–wet edge fitted by RLST/NDVI represents the soil moisture status of the whole study area. On DOY121, the OLST/NDVI scatterplots present irregular forms with false dry–wet edges. However, the dry–wet edge equations based on RLST/NDVI are well fitted.

The dry–wet edges directly determine the TVDI. Figures 6 and 7 show how the TVDI cannot be accurately calculated when there are large gaps. On DOY120, the OTVDI based on OLST/NDVI inversion was unable to capture the soil moisture status in the southwestern part of the study area, and by DOY121 was unable to capture soil moisture status in any of the study area, because of excessive vacancies. Applying the RTVDI obviously enlarged the effective range of soil moisture monitoring in the study area, especially on DOY121 when RTVDI was able to capture the soil moisture status of the whole study area. In addition, there are some differences between
OTVDI and RTVDI extracted at the same site, which are caused by the different dry–wet edge equations. The $R$ value for the correlation between DOY120 RTVDI and soil moisture is greater than that for OTVDI ($-0.2$ to $-0.28$). On DOY121, the extracted OTVDI is invalid at all sites because of excessive OTVDI vacancies, so the accuracy of the OTVDI inversion cannot be verified. The $R$ value for the correlation between RTVDI and soil
moisture is $-0.47$; this stronger correlation reflects that RLST/NDVI represents the surface conditions of the whole study area. Since TVDI is valid under all conditions from dry to wet and from bare soil to closed vegetation, the RTVDI based on the RLST/NDVI inversion is better suited to real surface soil moisture conditions.

4.3 Validation and analysis of drought monitoring based on TVDI

To eliminate errors caused by spatial location and uneven site distribution, the domain analysis method was adopted, in which monitoring at the study site was based on the mean TVDI in a $3 \times 3$ window. Figure 8 shows a scatterplot of TVDI values extracted from all sites versus 10-cm soil moisture in 2011. Each point represents the TVDI for one day at a given site. The plots shows greater scatter in RTVDI than that in OTVDI, and a significantly negative correlation between TVDI and soil moisture. The correlation of site observation data with RTVDI is stronger than that with OTVDI ($R_{RTVDI} = -0.42$, $R_{OTVDI} = -0.37$). Therefore, the RSDAST algorithm can not only reconstruct cloudy pixels, but can also improve the accuracy of RTVDI inversion of surface soil moisture across the entire area.

Figure 9 shows temporal changes in $R$ values between TVDI (OTVDI, RTVDI) and soil moisture in Chongqing during 2011; $R_{RTVDI}$ is between $-0.1$ and $-0.95$ and $R_{OTVDI}$ is between $-0.1$ and $-0.78$. Most of the extracted OTVDI values are invalid due to the large number of missing OTVDI pixels on many dates. Consequently, the correlation between OTVDI and soil moisture on that day cannot be evaluated. The cloudy pixels are reconstructed with the RSDAST algorithm, thereby increasing the number of valid values in the extracted RTVDI. This analysis demonstrates that the accuracy of remote sensing inversion results can be verified using surface observation data. Figure 9 also shows that $R_{RTVDI} > R_{OTVDI}$ for days in which $R_{OTVDI}$ can be calculated.

In Fig. 10, the correlation between TVDI (OTVDI, RTVDI) and soil moisture at 12 sites in Chongqing dur-
ing 2011 yields higher $R$ values for RTVDI than for OTVDI. In particular, at sites 57432, 57502, 57511, 57513, and 57633 the $R$ values much higher for RTVDI than for OTVDI, while there was no correlation between OTVDI and soil moisture at sites 57511 ($R = -0.45$) and 57633 ($R = -0.33$). The improved correlation between RTVDI and soil moisture has two explanations. First is the greater number of clear-sky pixel pairs in RTVDI. The scatter plot between TVDI (OTVDI, RTVDI) and soil moisture at sites 57511 and 57633 (Fig. 11) shows that RTVDI has more valid pixels than OTVDI. At site 57633, the soil moisture corresponding to OTVDI is mainly concentrated in the range 10%–50%, whereas the soil moisture corresponding to RTVDI is in the range 10%–80%. Owing to the cloudy pixels, OTVDI extracted at site 57633 was invalid on the dates with soil moisture in the range 50%–80%. Therefore, OTVDI cannot accurately reflect the surface soil moisture content in this period at Site 57633. Secondly, RTVDI based on RLST/NDVI is more representative of true soil moisture conditions. Differences in the number of clear-sky pixels between OLST and RLST result in different dry–wet edges fitted by LST/NDVI. The number of clear-sky pixels in OLST is small, and the dry–wet edges based on OLST/NDVI fitting only represent the soil moisture status in a limited region. The clear-sky pixels in RLST are distributed across the whole study area, so the dry–wet edges fitted by RLST/NDVI represent the soil moisture status in the whole region.

4.4 Spatial and temporal characteristics of drought in Chongqing in 2011

The spatial and temporal characteristics of drought in Chongqing in 2011 are analyzed in detail on the basis of agrometeorological data from the Chongqing Meteorological Bureau, ecological and agrometeorological data from the China Weather Network, and the soil moisture data described above. Spring drought and summer high-temperature drought both occurred in Chongqing in 2011. Sustained spring drought prevents the sowing of maize, rice, and other major cash crops in the spring tillage season. The observed daily soil moisture timeseries
Fig. 8. Scatter plots of (a) original TVDI (OTVDI) and (b) reconstructed TVDI (RTVDI) versus soil moisture (SM; %) at 12 sites in 2011. Correlation coefficients between TVDI and SM ($R_{\text{OTVDI}}$ and $R_{\text{RTVDI}}$) are indicated in the lower left corner of (a) and (b).

Fig. 9. Temporal variation of correlation coefficients ($R$) of OTVDI (denoted by blue crosses) and RTVDI (denoted by orange bars) with soil moisture in 2011.

Fig. 10. Validation of correlation coefficients ($R$) of OTVDI (denoted by orange bars) and RTVDI (denoted by blue bars) with soil moisture at 12 observation sites in Chongqing during 2011.

(Fig. 12) shows that sites 57333, 57425, and 57506 were seriously affected by spring drought. Because of the relatively large distances between stations, the periods affected by spring drought were different at each station (as shown by the red line in Fig. 12): these periods were DOY104–DOY130, DOY117–DOY140, and DOY115–
DOY140 at sites 57333, 57425, and 57506, respectively. Soil moisture content during the spring drought ranged from 0% to 40%, especially during DOY118–DOY125, with moisture contents less than 20% considered as extreme drought. However, due to persistently cloudy weather, the original LST data during DOY118–DOY125 contain a large number of cloud-contaminated pixels, causing the OTVDI to lose its ability to assess drought in this period (Fig. 13). This can be compared with the RTVDI map, in which the RSDAST model was applied to reconstruct cloud-contaminated pixels, with the RLST data then used to show changes in surface soil moisture across the study area. Respective correlation coefficients $R$ between RTVDI and soil moisture were $-0.58$, $-0.61$, $-0.26$, $-0.47$, $-0.16$, $-0.11$, $-0.32$, and $-0.22$ on DOY118–DOY125. The spatial distribution of RTVDI during DOY118–DOY125 revealed that drought mainly occurred in the western and northwestern areas of Chongqing, consistent with the ground-based monitoring results.

Extreme high temperature weather events occur frequently in summer in Chongqing. There are typically four periods of persistently sunny, hot weather: late June to early July, mid–late July to late July, 7 to 22 August, and mid–late August to late August (He et al., 2012). Sustained high temperatures lead to excessive water loss from the surface soil, and Chongqing is seriously affected by summer drought (mainly during DOY220–DOY250 at site 57502; see Fig. 12d).

5. Discussion

The combination of the RSDAST model and TVDI enables the use of optical remote sensing for daily drought monitoring in cloudy areas. TVDI is a simplified land surface dryness index based on an empirical parameterization of the relationship between surface temperature and vegetation index, which is widely used in various land surface drought monitoring applications. The TVDI inversion results only depend on LST/NDVI feature space image data, but TVDI often loses its ability to characterize the surface soil moisture state under cloudy conditions excessive pixels are missing. RSDAST is a flexible and efficient surface temperature reconstruction model, able to reconstruct missing LST pixels by establishing relationships between missing pixels and their adjacent clear sky pixels based on their spatial distance and surface environments. After combining the RSDAST model and TVDI index, the reconstructed LST data were applied to the TVDI, thereby improving the scope, temporal resolution and accuracy of drought monitoring in cloudy areas. However, the fol-
lowing factors need to be considered when joining the two models.

5.1 Cloud effects

The MODIS cloud mask is a science data product. The main purpose is to determine the confidence in which the satellite’s view of the land and ocean surface is unobstructed by clouds. If the pixel is covered by clouds, the LST data will be invalid (http://modis-atmos.gsfc.nasa.gov/). However, cloud-edge effects, such as cloud shadows, can also have a significant impact on LST products: they will reduce the quality of the clear sky composite products and may introduce systematic deviations into the long-term records (Khlopenkov and Trishchenko, 2007). Although only good quality pixels are selected for reconstruction, the algorithm may still fail to detect some cloud shadow pixels (Luo et al., 2008).

5.2 Number of cloudy pixels and cloud cover duration

The number of clear sky pixels in the moving window of the RSDAST model has a great influence on the LST reconstruction of cloudy pixels. When the cloud cover area is large or has a long duration, the number of samples of clear sky pixels in the moving window will be reduced; thus, the accuracy of the reconstructed LST will be reduced. When the cloud coverage is too large or the duration is too long, the RSDAST model based on a specific form size and time scale will not be able to reconstruct the cloudy pixel LST. It can be seen from Fig. 9 that the LST reconstruction of cloud-contaminated pixels based on the RSDAST algorithm is poor because of the continuous cloudy weather during DOY250–DOY300. Although the LST reconstruction of cloudy pixels in this region can be filled by increasing the window size or the adjacent time scale, Fig. 3 shows that increasing either the window size or time scale will reduce the accuracy of LST reconstruction.

5.3 Potential improvements

Pixels with cloud shadow are not specifically labelled in MOD11A1, but are clearly marked in the quality control dataset MOD11_L2. In this paper, MOD11A1 can be replaced by MOD11_L2 data to reduce the impact of cloud shadows on LST reconstruction.

If only the clear sky pixels in the original data are used as reconstruction samples, then when the cloud-covered area is larger than the reconstruction window, or the
cloud cover duration is longer than the reconstruction time scale, the number of successfully reconstructed cloudy pixels will be severely limited. To maximize the number of reconstructed cloudy pixels, it is planned to include the reconstructed “clear sky pixels” as effective samples in the reconstruction of the next adjacent cloudy pixels. This method can greatly increase the number of effective samples in the moving window, thereby improving the reconstruction of vacant values.

This paper analyzes a historic drought event in Chongqing in 2011, on the basis of an LST obtained before and after the reconstruction of cloudy pixels. Further validation is needed to assess whether this algorithm is suitable for real-time drought monitoring, if only the previous valid pixels are used in the LST reconstruction.

6. Conclusions

A new drought monitoring model (RTVDI) that can be applied to continuously cloudy areas has been developed by combining the RSDAST and TVDI algorithms. To evaluate the RTVDI in the practical application of...
drought monitoring under cloudy conditions, the regional moisture inversion capabilities of OTVDI and RTVDI are compared. The comparison shows that the number of valid dry–wet edges fitted by the RTVDI model (335 groups) in Chongqing in 2011 is considerably more than that fitted by OTVDI (213 groups). In addition, the scatter plot for the RTVDI model covers a wide range, such that fitted dry–wet edges closely represent the real soil moisture characteristics across the entire study area. Under continuously cloudy conditions (DOY118–DOY125), OTVDI loses its ability to monitor regional drought, whereas RTVDI can completely reconstruct surface water conditions in the entire study area. Respective $R$ values between RTVDI and soil moisture were $-0.58$, $-0.61$, $-0.26$, $-0.47$, $-0.16$, $-0.32$, and $-0.22$ during DOY118–DOY125. Across the entire study area, the accuracy of drought monitoring using the RTVDI model ($R = -0.45$) is higher than that using OTVDI ($R = -0.33$). In the time series, the number of periods when RTVDI achieves accurate results is considerably greater than that for OTVDI, and $R_{RTVDI}$ is larger than $R_{OTVDI}$ in the OTVDI observation period. In terms of spatial extent, $R_{RTVDI}$ is larger than $R_{OTVDI}$ at all sites. Overall, in continuously cloudy areas, the RTVDI model can not only extend the time and space range of drought monitoring, but can also improve the accuracy of surface soil moisture monitoring.

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