An Improved Up-scaling Algorithm Combined TSA and PSF

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Abstract. Taking the Guanzhong Plain of Shanxi Province as the research area, the combine method of trend surface analysis method (TSA) and point spread function (PSF) (TSA+PSF) were used to up-scale the vegetation temperature condition index (VTCI) retrieved from Landsat 8 images (Landsat-VTCI) from a finer resolution to a coarser resolution. The up-scaled results were compared with VTCI images retrieved from Aqua MODIS (MODIS-VTCI) to provide technical support for the comprehensive application of drought monitoring results on two spatial scales. Meanwhile, a range of indicators, such as the semivariogram function (SVF), the structural similarity (SSIM), the correlation coefficients (r), root mean square errors (RMSE) were used to systematically compared the up-scaled methods. The results show that TSA+PSF performed better than TSA in terms of SSIM, the correlation and RMSE, the up-scaling model TSA+PSF has the higher accuracy, and it is more effective and robust than TSA. The model that uses PSF to analyze trend surface constructed by TSA is an improvement for up-scaling Landsat-VTCI images from a finer resolutions to a coarser resolutions.

1. Introduction

Drought is one of the most severe natural disasters that can severely threaten crop production, also causing enormous economic losses [1]. Traditional meteorology-based and hydrology-based drought monitoring methods are lack of regional representation due to fewer meteorological stations. Remote-sensing techniques are extensively used in monitoring drought temporal and spatial evolution for the advantage of large scale coverage and real-time processing. Different drought-related index have been used to monitor drought, such as the normalized difference vegetation index (NDVI), land surface temperature (LST) and a combination of them [2-3]. Because of droughts are slow, complex, cumulative events, trait and characteristics of droughts are not easily to discern. VTCI was developed to detect characterize the onset, duration and intensity of droughts based on the assumption that the shape of scatter plots for the LST and NDVI is triangular [4]. The VTCI has been extensively used to study droughts in the Gujarat State, India [5] and southern Great Plains, USA [6].

The development and perfection of technology of remote sensing has made it widely used in studying land surface processes [7]. However, the comparability of spectral radiances and surface parameters when interpreted at different resolutions is weak because of differences in sensors, changes in the surface heterogeneity, and the nonlinearity of algorithms for retrieving land surface parameters. And in practical investigations, Scale factors play important roles. So it is key considerations for integrating different spatiotemporal data to study the scale effect and to develop suitable transforming methods. In the 1990s,
Meentemeyer and Goodchild have proposed the concept of scale of science [8-9]. Friedl et al. have developed a model to simulate imagery produced by instruments such as the Landsat Thematic Mapper and the Advanced Very High Resolution Radiometer to examine the effect of subpixel variance in leaf area index (LAI) on relationships among LAI, FPAR, and NDVI [10]. Braswell et al. have retrieved land cover distributions in two different parts of the Brazilian Amazon region by estimating relationships which derived using a Bayesian-regularized artificial neural network (ANN) between land cover fractions derived from 30 m resolution ETM+ and reflectance data from 1 km resolution MODIS and MISR [11]. Wang et al. have used the contextual approach based on mixed pixels and support vector machine (SVM) algorithm to make the scaling model of NPP retrieved from the fine resolution (TM) to the coarse resolution (MODIS), and accomplished the correction of scale effect to NPP retrieved from coarse resolution data of MODIS [12].

The main purpose of this study is to develop and improve the up-scaling method by combining PSF with TSA for up-scaling Landsat-VTCI images from a finer spatial resolution to a coarser. And the performance and superiority in efficiency and flexibility of PSF+TSA in up-scaling Landsat-VTCI images were validated and evaluated by comparing to the original method of TSA.

2. Overview of Study Area and Data Processing

2.1. Study Area

The research area in this study is the Guanzhong Plain which located in Shaanxi Province in Northwest China. The area covers approximately $5.55 \times 10^4$ km$^2$ (Fig. 1). Because of its low relief and special soil types, this area is the most important farming area in Shaanxi Province for its fertile soil. The main crop of the region is winter wheat in spring and early summer. This area is sensitive to climatic changes because it is located in a warm temperate semi-humid monsoon climate zone. The average annual rainfall of study area is 500-750 mm with a high variability, which approximately 60% is distributed from June to September, and approximately 10% is distributed from November to February of the next year.

![Fig.1 Map of the study area in the Guanzhong Plain](image)

2.2. Data Source Types and Data Processing

2.2.1. Data Source Types

Based on the cloud cover over the study area is less than 5% (CC ≤ 5%), multi-temporal Aqua MODIS and Landsat 8 (L8) data during March to June from 2013 to 2018 were selected. And the daily surface reflectance products (MYD09GA) and the daily LST products (MYD11A1) were also selected to obtain the daily reflectance and LST products at the spatial resolution of 926.62×926.62 and the temporal resolution of 1 to 2 days.
2.2.2. Landsat Data Processing
The radiometric calibration and atmospheric correction which collectively known as the relative radiometric correction were performed to reduce distortion based on the latest calibration coefficients of the OLI/TIRS spectral bands and the FLAASH module of ENVI. These data were then geo-referenced to the Universal Transverse Mercator (UTM) projection.

NDVI is calculated based on the reflectance in the near-infrared and red band of Landsat data. BT is retrieved from the brightness temperature at band 10 in L8.

\[
\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}}} \quad (1)
\]

where \(\rho_{\text{NIR}}\) and \(\rho_{\text{red}}\) are the reflectance of bands 5 and 4 in L8, respectively.

\[
BT = K_2 \ln \left(1 + \frac{K_1}{L_{10}}\right) \quad (2)
\]

where \(L_{10}\) is the radiance from the thermal infrared band 10 in L8; \(K_1\) and \(K_2\) are obtained from the header file of TIRS band 10, with \(K_1=774.89 \text{ mwm}^{-2} \text{ sr}^{-1} \mu\text{m}^{-1}\) and \(K_2=1321.08 \text{ K}\).

2.2.3. MODIS Data Processing
The daily NDVIs were calculated based on the daily reflectance products of MODIS for corresponding period of L8. And the 10-day maximum MODIS-NDVI and MODIS-LST products for each year at 10-day intervals were obtained by the method of the maximum value compositing (MVC) based on the daily NDVI and daily LST products [13].

2.2.4. Determining the VTCI
The calculation method of VTCI was defined in Sun [4]:

\[
\text{VTCI} = \frac{\text{LST}_{\text{max}}(\text{NDVI}_i) - \text{LST}(\text{NDVI}_i)}{\text{LST}_{\text{max}}(\text{NDVI}_i) - \text{LST}_{\text{min}}(\text{NDVI}_i)} \quad (3)
\]

\[
\text{LST}_{\text{max}}(\text{NDVI}_i) = a + b\text{NDVI}_i \quad (4)
\]

\[
\text{LST}_{\text{min}}(\text{NDVI}_i) = a' + b'\text{NDVI}_i \quad (5)
\]

where \(\text{NDVI}_i\) is the NDVI value in the \(i\) period; \(\text{LST}_{\text{max}}(\text{NDVI}_i)\) and \(\text{LST}_{\text{min}}(\text{NDVI}_i)\) are the maximum and minimum LST values of the pixels that have the same \(\text{NDVI}_i\) value within a study region, respectively; \(\text{LST}(\text{NDVI}_i)\) denotes the LST value of one pixel whose NDVI value is \(\text{NDVI}_i\); and \(a, b, a'\) and \(b'\) are undetermined coefficients that are estimated from the scatter plots of the LST and NDVI by using different composite NDVI and LST products.

2.2.5. Coordinate Transformation
MODIS-VTCI image and L8 image are involved in this study, with different types of projection. Therefore, it is a frequent task to perform coordinate transformation. First, the MODIS-VTCI image with the plane coordinates was converted to the geographic coordinates by using the Lambert reverse calculation algorithm. Then, the geographic coordinates was converted to a plane coordinate in the UTM projection.

2.3. Up-scaling Method
In this study, we applied TSA combined with PSF to up-scale Landsat-VTCI images from a finer spatial resolution of 30×30m to a coarser of 930×930m.

TSA is a multiple statistic method that can approximate and represent the best-fit estimates of the actual spatial distribution and regional variations of drought by constructing surfaces, which is usually decomposed into the residual surfaces and the trend surfaces [14]. From the earlier work [15], we choose the quadratic polynomials trend surface to produce the trend surface.

\[
\text{VTCI}_i(x_i, y_i) = \text{VTCI}_{\text{T}}(x_i, y_i) + \varepsilon_i(x_i, y_i) \quad (6)
\]
where $VTCI_t(x_i, y_i)$ is the VTCI values which retrieved from L8, and $VTCI_t(x_i, y_i)$ and $e_i(x_i, y_i)$ are the trend and residual VTCI values of variable $VTCI_t$ at location $(x_i, y_i)$, respectively, $i$ is the number of selected data, and $c_0$ to $c_5$ are the polynomial coefficients.

The coefficients from $c_0$ to $c_5$ were estimated by using the least-squares method and the common elimination method, and then substituted into the fitting model to obtain the quadratic polynomials TSA equations. The trend surfaces of each local window could be obtained with these equations.

Up-scaling drought information is actually the aggregation of drought information, which is visually represented as the gradual smoothing and blurring of detailed information of texture and edge in same spatial region. PSF is an indicator to describe transfer, exchange and connection between the object space and the image space in optical system. PSF of each part of information acquisition and transmission degenerates the image, and causes image blur, while image blur can be regarded as a convolution process of a two-dimensional PSF and the original image [16]. Therefore, the smoothing characteristics of PSF can be used to realize the weighting of the VTCI at different positions of local 31×31 window by weighting function, i.e., to calculate the distance-weighted using weighting function through simulating a weighted window, and then perform re-sampling according to the distance-weighted to up-scaling Landsat-VTCIs of the local window.

The general form of PSF is as following [16]:

$$PSF(x_i, y_i) = \frac{1}{2\pi ab} \exp\left[-0.5 \left(\frac{x_i^2}{a^2} + \frac{y_i^2}{b^2}\right)\right]$$

(9)

where $a$ and $b$ are the optical widths of the two directions perpendicular to each other.

In reality, the optical system usually consists of different components, including lenses, detectors, amplifiers, etc., so PSF of the optical system can be considered as the combination of the PSF of the various components. Therefore, PSF can be obtained by the Gaussian function as following [16]:

$$PSF(x_i, y_i) = k \cdot \exp\left(-\frac{x_i^2 + y_i^2}{2\sigma^2}\right)$$

(10)

where $\sigma$ is the radius of PSF, $2\sigma$ is the spatial revolution of MODIS-VTCI image, i.e. 926.62m, $k$ is the gain of sensor systems. Since the gain of the system has been considered in data preprocessing process, so $k=1$.

First, the corresponding periods of Landsat-VTCI images and MODIS-VTCI images were selected, and to register plane coordinates of Landsat-VTCI as the above. Then we chose a center pixel from a geo-referenced Landsat-VTCI and extended 15 pixels above, below, left and right to obtain a local window with 31×31 pixels. TSA was used to produce the trend surface of local window, then PSF was used to up-scale Landsat-VTCIs by analyzing spatial data of the trend surface. This was used extract drought information over each block of 31×31 pixels of Landsat-VTCI image to aggregate into one pixel, which was thought as the point with the same geodetic coordinate information. With aggregation process, Landsat-VTCIs were up-scaled from a finer spatial resolution of 30×30m to a coarser of 930×930m.

2.4. Evaluating the Up-scaling Methods

There exists the phenomenon of information loss and variation in up-scaling original Landsat-VTCIs to a smaller number of VTCI units over the same spatial extent to some extent using different up-scaling
methods[17]. SVF, SSIM, r and RMSE between up-scaled Landsat-VTCI images and MODIS-VTCI images were calculated to quantitatively compare different methods.

A semivariogram function (SVF) is a comprehensive index to measure the spatial dependence and heterogeneity [18].

\[ \gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (VTCI_i - VTCI_{i+h})^2 \]  

(11)

where \( N(h) \) is the number of VTCI pairs, and \( VTCI_i \) and \( VTCI_{i+h} \) are the VTCI values at two pixels \( VTCI(x,y) \) and \( VTCI_{i+h}(x,y) \), respectively, which are separated by a lag \( h \).

The image structure contains the main information of the image, and SSIM can provide structural information from the perspective of image composition based on comparisons of three variables: luminance, contrast and structure [19].

\[ S(L,M) = l(L,M)^{\alpha} c(L,M)^{\beta} s(L,M)^{\gamma} \]  

(12)

\[ S(L,M) = \left( \frac{2\mu_x\mu_y + C_1}{\delta_x^2 + \delta_y^2 + C_1} \right) \]  

(13)

where \( L \) and \( M \) are up-scaled image and MODIS-VTCI image, respectively, \( l(L,M) \), \( c(L,M) \) and \( s(L,M) \) are the luminance comparison function, contrast comparison function and structure comparison function, respectively; \( \alpha, \beta \) and \( \gamma \) are parameters that are used to adjust relative importance of three components, originally set to \( \alpha = \beta = \gamma = 1 \); \( \mu_x \) and \( \mu_y \) are mean VTCI values of two images; \( \delta_x \) and \( \delta_y \) are standard deviations of VTCI values of two images; \( \delta_{xy} \) is the covariance of the VTCI values of two images; and \( C_1 \) and \( C_2 \) are constants that are used to avoid instability.

RMSE is often used to measure the deviation between the assessment data of up-scaled image and the reference data of MODIS-VTCI image.

\[ RMSE = \sqrt{\frac{1}{m\times n} \sum_{i=1}^{m} \sum_{j=1}^{n} (VTCI_i(x,y) - VTCI_{ij}(x,y))^2} \]  

(14)

We assessed the effects of up-scaling by comparing the SSIM, \( r \) and RMSE between MODIS-VTCIs and up-scaled Landsat-VTCIs, the greater the value of SSIM and \( r \), the smaller the value of RMSE, the better the up-scaling.

3. Test Results and Discussions

3.1. Analysis of spatial distribution characteristics of drought

We have compared the texture features and the spatial distributions of drought extent between the MODIS-VTCI images and the up-scaled Landsat-VTCI images. The up-scaled images using TSA and TSA+PSF were darker in the eastern Guanzhong Plain, the same as the corresponding regions of MODIS-VTCI images. The up-scaled images using this two methods were lighter in the western Guanzhong Plain and the same as MODIS-VTCI images. In conclusion, the up-scaled images and MODIS-VTCI images have the consistent spatial distribution and texture characteristics of drought. This finding indicates that up-scaled Landsat-VTCI images and the corresponding MODIS-VTCI images at the coarser resolution were relatively comparable. In Fig. 2, up-scaled images and MODIS-VTCI images showed consistent characteristics in terms of the geographical distribution and level of image brightness. Moreover, the up-scaled images basically matched MODIS-VTCI images in terms of texture feature gradient, the Wei River in the middle of study area of up-scaled images on 15 March 2014 and 28 April 2015 and the Yellow River in the eastern study area of up-scaled images on 17 March 2014 could be easily recognized.
Fig. 2 Comparison of the texture features and the spatial distribution characteristics of MODIS-VTCI images and up-scaled Landsat-VTCI images

We further used SSIM to compare and analyse the characteristics of luminance, contrast and structure between MODIS-VTCI images and up-scaled Landsat-VTCI images (Table I). SSIM values between MODIS-VTCI images and up-scaled images were larger, this indicates that the brightness characteristics, contrast characteristics and structural features of up-scaled images were all similar with the MODIS-VTCI images. Meanwhile, most of the SSIM values from TSA+PSF were larger than those from TSA, this imply that up-scaled Landsat-VTCI images using TSA+PSF were better matched MODIS-VTCI images with respect to the image structure than those using TSA, TSA+PSF has a stronger capacity than TSA in characterizing the dominant features of luminance, contrast and structure in up-scaling, so TSA+PSF has a certain improvement effect compared to TSA.

3.2. Comparing SVF of MODIS-VTCI images and up-scaled Landsat-VTCI images

We further compared up-scaled images by SVF (Table I), results shows that all the up-scaled Landsat-VTCI images had larger SVF values than MODIS-VTCI images in terms of their spatial autocorrelation and variability. When the Landsat-VTCI images up-scaled to a coarser spatial resolution, the dominant
spatial characteristics of drought information of images would be smoothed. Meanwhile, SVF values of up-scaled images were very small, except for the results on 17 March 2014 and 23 May 2015 because these two images were all located at the L8 orbits of 126/36 in the eastern Guanzhong Plain where the landform is complex. SVF values using TAS were relatively small, this indicates that up-scaled images were resampled from a finer to a coarser spatial resolution, TSA produced relatively stronger smoothing towards the dominant spatial variability in the data aggregation.

Table 1. Comparison of MODIS-VTCI images and up-scaled Landsat-VTCI images based on SSIM, SVF, r and RMSE.

| Date     | Data Source | Scaling Method | SVF  | SSIM  | R     | RMSE  |
|----------|-------------|----------------|------|-------|-------|-------|
| 2014-03-15 | M-VTCI      | TSA            | 0.0004 |
|          | L-VTCI      | TSA+PSF        | 0.0012 | 0.7170  | 0.4483 | 0.1581 |
| 2014-03-17 | M-VTCI      | TSA            | 0.0029 |
|          | L-VTCI      | TSA+PSF        | 0.0089 | 0.4698  | 0.5539 | 0.1593 |
| 2014-05-18 | M-VTCI      | TSA            | 0.0010 |
|          | L-VTCI      | TSA+PSF        | 0.0015 | 0.6809  | 0.5144 | 0.2132 |
| 2015-04-28 | M-VTCI      | TSA            | 0.0014 |
|          | L-VTCI      | TSA+PSF        | 0.0007 | 0.5015  | 0.6277 | 0.0858 |
| 2015-05-23 | M-VTCI      | TSA            | 0.0027 |
|          | L-VTCI      | TSA+PSF        | 0.0106 | 0.4331  | 0.6921 | 0.1359 |
| 2016-03-13 | M-VTCI      | TSA            | 0.0012 |
|          | L-VTCI      | TSA+PSF        | 0.0010 | 0.5462  | 0.5557 | 0.1081 

3.3. Comparing the correlation and RMSE between MODIS-VTCI images and up-scaled Landsat-VTCI images

Correlation analysis was performed between MODIS-VTCIs and up-scaled Landsat-VTCIs (Table I). All up-scaled Landsat-VTCI images using TSA and TSA+PSF had better correlations with the corresponding MODIS-VTCI images, the r values were all larger which ranged 0.4382 to 0.6928. And TSA+PSF produced greater r value than TSA, this implies that TSA+PSF method has more obvious and significant improvement in up-scaling Landsat-VTCI images from a finer to a coarser resolution.

We also quantitatively compared TSA with TSA+PSF by RMSE between up-scaled Landsat-VTCI images and the corresponding MODIS-VTCI images. RMSE can express the systematic error between Landsat-VTCIs and MODIS-VTCIs, and based on this to evaluate the up-scaling effects (Table I). RMSE values between MODIS-VTCIs and up-scaled Landsat-VTCIs ranged from 0.0862 to 0.2132, and the values were smaller except for 18 May 2014. The results shows that the systematic error between up-scaled Landsat-VTCIs by the two methods and the corresponding MODIS-VTCIs were small, up-scaled Landsat-VTCI images and MODIS-VTCI images showed similar degree of drought. Meanwhile, RMSE values from TSA+PSF were slightly lower than those from TSA, which implied that the up-scaled results when using MODIS-VTCI were closer to the quantitative drought monitoring results of MODIS-VTCI images, and TSA+PSF was more suitable for up-scaling Landsat-VTCI images of the Guanzhong Plain from finer to coarser resolutions.
4. Discussion

The innovation of this research lies in the application of TSA to construct a trend surface. The trend surface is constructed by mathematical polynomial model to simulate the spatial distribution of drought and its regional variation, while considering the influence of the high spatial variation and random factors in natural scenes. The spatial analyzing problem was solved by mathematical statistics method, and the spatial analysis has been quantified and modeled, which has potential promotion effect on the aspect close to the actual drought surface. On the other hand, the up-scaling models using PSF built upon the foundation of the trend surface, PSF can better characterize the dominant distribution features, variability, patterns and processes of Landsat-VTCI images. The formation of drought is a complicated process. VTCIs in Guanzhong Plain varies with structural factors and shows regional differences. At the same time, spatial heterogeneity is one of the main causes of errors in up-scaled results. PSF took the influence of adjacent pixels on VTCI of the central pixel as the main factor of up-scaling, which fully considered the spatial variability and the local spatial autocorrelation of the drought information in local window. Therefore, the up-scaled model TSA+PSF is better to aggregate Landsat-VTCIs of Guanzhong Plain from a finer to a coarser spatial resolution, and TSA+PSF has a significant improvement over TSA.

5. Conclusion

In this study, we compared and evaluated up-scaled Landsat-VTCI images using TSA and TSA+PSF in a case study. Up-scaled images using TSA and TSA+PSF generally matched the MODIS-VTCI images with respect to the spatial distribution and texture characteristics of droughts. The SSIM and r between MODIS-VTCI images and up-scaled Landsat-VTCI images using TSA+PSF was relatively greater than that using TSA. This finding implies that TSA+PSF is better at up-scaling spatial drought variables than that only using TSA. TSA+PSF also performed better than TSA in terms of RMSE between up-scaled Landsat-VTCIs and MODIS-VTCIs. In conclusion, the up-scaling model based on the new algorithm TSA+PSF has higher accuracy, and is more effective and robust than TSA. In contrast, algorithm that using PSF to analysis trend surface constructed by TSA is an improvement for up-scaling Landsat-VTCI images of the Guanzhong Plain from finer to coarser resolutions.

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