A New Strategy for Comparison of Land Surface Temperature Retrieval Methods with Landsat Remote Sensing Images Considering Regional Consistency

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Abstract. Landsat remote sensing images are widely used in fields such as land surface temperature retrieval, urban expansion, and urban heat islands, due to their high spatial resolution and the availability of long time series data. Long-term land surface temperature (LST) change analysis usually requires comprehensive utilization of remote sensing data from different sensors, such as Landsat 7, Landsat 8. A LST retrieval algorithm with generalization for Landsat thermal infrared image can effectively improve the reliability of long-term analysis using multi-source images. In order to evaluate the performances of different LST retrieval methods for Landsat images, a new strategy based on regional consistency was proposed in this paper so that different LST retrieval algorithms can be compared with each other without utilizing reference data from ground observation. The general hypothesis is that there is a significant positive correlation between the obtained Landsat 7 and Landsat 8 LST products with adjacent imaging time, similar imaging environment for the identical area. Firstly, the Landsat 7 and Landsat 8 image pairs from Shenzhen were selected under aforementioned constraints. Secondly, four representative LST retrieval methods, radiative transfer equation method (RTEM), image-based method (IBM), mono-window algorithm (MWA) and single-channel algorithm (SCA) were used to generate the LST products from the Landsat 7 and Landsat 8 image pairs respectively. Lastly, the correlation between the Landsat 7 and Landsat 8 LST products from different methods can be calculated as different indexes, including the goodness of fit, Pearson correlation coefficient and Euclidean distance. It is convincing that the optimal LST retrieval method should exhibit a higher regional consistency between the Landsat 7 and Landsat 8 LST product pair given the certain area. The experimental results show that the radiative transfer equation method generates the highest correlation and it is considered as a suitable option for long-term LST research with multi-source Landsat datasets.

1. Introduction

LST is one of the important parameters to measure the status of urban green development, and it is of great significance to the study of hydrology, ecology, environment, urban planning and other fields[1]. With the rapid development of satellite technology, thermal infrared remote sensing has become an important means to obtain the LST[2]. Compared with the traditional method that obtains the surface temperature by arranging observation stations, satellite temperature retrieval technology has many advantages of broad coverage, intuitive images, and good synchronization, and it has been widely used in the fields of urban heat island research[3,4] and drought monitoring[5].
Domestic and foreign scholars have conducted a lot of research on the LST retrieval for Landsat thermal infrared images, such as radiative transfer equation method\cite{6}, mono-window algorithm\cite{7,8}, single-channel algorithm\cite{9,10}, image-based method\cite{11} and split window algorithm\cite{12}. In addition, due to satellite revisit period and other factors, it is inevitable to use images from different Landsat sensors in the research of long-term LST change. Shen et al. used the Landsat data (Landsat 5, Landsat 7, Landsat 8 etc.) of Wuhan from 1988 to 2013 for LST retrieval, and applied the result to the study of long time series heat island\cite{13}; Liu used different inversion algorithms on Landsat 5, Landsat 7, Landsat 8 and other data to obtain LST that was used to analyze the spatio-temporal evolution of the heat island and its influencing factors in Hefei\cite{14}. Therefore, the performance of the universal LST retrieval method for Landsat images on multi-source Landsat data is an important issue to be considered in the long time series analysis.

Currently, three methods are mainly used to evaluate the accuracy of Landsat LST retrieval algorithm. The first is a comparison method based on the synchronous measurement of near-surface temperature. For example, Wang used the infrared thermometer to obtain the real surface temperature synchronously at the transit time of the satellite, for the comparative analysis of different LST retrieval methods\cite{15}. Also, Liu got the true surface temperature by the hand-held infrared temperature sensor during the transit time of the satellite to compare the accuracy of various LST retrieval algorithms\cite{16}. Although this method has high precision, it is laborious and the available measured data is limited. The second is a comparison method based on the observation data of regional weather stations. For example, Tsou et al. used the mean daily air temperature obtained from 28 weather stations in Hong Kong to evaluate the surface temperature obtained by different retrieval algorithms using Landsat 8 data\cite{17}. However, the air temperature used in this method is a discrete point data, which is greatly affected by the number of weather stations and the surrounding environment, so it’s not suitable for the large-scale research. The third is cross-comparing with other satellite LST retrieval products. Song compared the results obtained by various Landsat image LST retrieval algorithms with MODIS LST products\cite{18}. Tu et al. also selected MODIS LST products that has similar imaging time with Landsat images as validation data to quantitatively compare and analyze the results of different surface temperature retrieval algorithms\cite{19}. However, compared with Landsat images, MODIS LST products used in this method have lower spatial resolution, and are usually analyzed by selecting the temperature at a finite number of points, which presents statistical contingency in some extent.

In this paper, we used multi-source Landsat data with similar imaging mechanism and same spatial resolution for cross-validation and comprehensively utilized all the temperature retrieval data of research areas to effectively evaluate the accuracy of different Landsat LST retrieval methods. The basis of this study is that the temperature products obtained by the same surface temperature inversion method using different Landsat sensor data acquired under similar imaging conditions at adjacent times in the same area should have a high correlation, and whether the imaging conditions are similar is mainly determined by the similarity between the data of ground weather stations at the imaging time of the sensors. Chen et al. conducted statistical analysis on the ground surface temperature retrieved by geostationary satellites and the measured temperature at ground stations, then they found that there is a good linear relationship between them\cite{20}. Zhang et al. carried out a regression analysis on the multi-year monthly mean temperature data of 64 weather stations in Hengduan Mountains from 2001 to 2007 and the multi-year monthly mean MODIS surface temperature, and also found that there is an excellent linear relationship between them\cite{21}.

Accordingly, this paper proposed a comparison strategy for Landsat remote sensing image LST retrieval methods based on regional consistency analysis, to solve the problem of how to select the Landsat temperature retrieval method suitable for the analysis of long time series surface temperature changes, and took Shenzhen as the study area to carry out our experiment. Firstly, the Landsat 7 and Landsat 8 image pairs were selected based on the similarity of ground weather station temperature and adjacent imaging time. Secondly, after image preprocessing, four representative LST retrieval methods, radiative transfer equation method, image-based method, mono-window algorithm and single-channel algorithm were used to generate the LST products from the Landsat 7 and Landsat 8 image pairs.
respectively. Lastly, the correlation between the Landsat 7 and Landsat 8 LST products from different methods can be calculated as different indexes, including the goodness of fit, Pearson correlation coefficient and Euclidean distance. Then, the most suitable LST retrieval method for Landsat was determined.

2. Data and Methods

2.1 Study area and data
Shenzhen is located in southern Guangdong province, between 113°46’ to 114°37’ E and 22°24’ to 22°52’ N. It has a subtropical maritime climate and the southeast wind prevails in summer, with high temperature and rain. The rainy season is from April to September each year, with an annual rainfall of 1933.3 mm. The other seasons are dominated by the Northeast monsoon, with relatively dry weather, mild climate, and an average annual temperature of 22.4°C. The city includes 9 administrative districts and 1 new district, with a total area of 1997.47 square kilometers.

In this paper, we mainly used Landsat 7 and Landsat 8 image pairs. According to the climate type of Shenzhen region and cloudiness, we selected two images with similar weather conditions and similar near ground temperature at the transit time of the satellite: Landsat 7 image on 31 October, 2017 and Landsat 8 image on 23 October, 2017, as shown in Table 1. A single standard scene of Landsat data can cover about 80% of Shenzhen. In order to avoid errors and uncertainties caused by the mosaic of images in different time phases, we only carried out the research on the area covered by a single Landsat image.

![Fig.1 Landsat thermal infrared images of Shenzhen](image)

(a) Landsat 7 image on 31 October 2017 (b) Landsat 8 image on 23 October 2017

| Date       | Satellite | Daily maximum temperature | Daily minimum temperature | Satellite transit time | Satellite transit temperature |
|------------|-----------|---------------------------|---------------------------|-----------------------|------------------------------|
| 2017.10.23 | Landsat 8 | 27°C                      | 17°C                      | 10:52                 | 23.89°C                      |
| 2017.10.31 | Landsat 7 | 25°C                      | 18°C                      | 10:54                 | 21.67°C                      |

2.2 Data preprocessing
The preprocessing of the data includes strip repair of Landsat 7 images and radiometric calibration. In this paper, ENVI plug-in was used to repair the strip. Also, radiometric calibration is one of the important preprocessing steps in satellite image processing. For Landsat 7 and Landsat 8 image pairs used in this paper, radiometric calibration was conducted according to their corresponding calibration coefficients respectively.
2.3 LST retrieval method

2.3.1 Radiative transfer equation method
The fundamental of the radiative transfer equation is that the thermal infrared radiance value $L_{Q}$ received by the satellite sensor includes three parts: the upwelling radiance $L_{μ}$ the true radiance of the ground reaches the satellite sensor after passing through the atmosphere; the downwelling radiance $L_{d}$ reaches the sensor after reflection from the ground and passing through the atmosphere. The specific realization equation is:

$$L_{T} = \frac{L_{λ} - L_{μ} - \tau(1-\varepsilon)L_{d}}{\varepsilon} \quad (1)$$

Where, $\tau$ is the atmospheric transmittance, which can be obtained with $L_{μ}$ and $L_{d}$ by inputting the imaging time, center longitude and latitude and other related parameters in the atmospheric correction tool provided by NASA’s official website (http://atmcorr.gsfc.nasa.gov); $\varepsilon$ is the surface emissivity; $L_{T}$ is the blackbody radiance at the same temperature, and then $L_{T}$ can be converted to the surface temperature by the Planck formula.

2.3.2 Image-based method
Compared with other inversion algorithms, the image-based method doesn’t need to simulate the atmospheric parameters during the satellite transit, which is simpler and more convenient. This method firstly needs to obtain the brightness temperature according to the following formula:

$$T_{s} = \frac{K_{2}}{\ln(1+(K_{1}/L_{s}))} \quad (2)$$

Where $T_{s}$ is brightness temperature, $K_{1}$ and $K_{2}$ are constants., which can be obtained in the Landsat meta file. Then, the brightness temperature can be converted to the surface temperature by Formula 3:

$$T = \frac{T_{s}}{1+(\lambda \times T_{s} / \alpha) \ln(e)} \quad (3)$$

Where T is the surface temperature; $\lambda$ is the wavelength of emitted radiance in meters; $\alpha = 1.438 \times 10^{-2} mK$; $\varepsilon$ is the surface emissivity.

2.3.3 Mono-window algorithm
The mono-window algorithm was proposed to retrieve LST using Landsat 5 thermal infrared images, and further modified to be suitable for Landsat 8 images.

$$T = \frac{a_{1}(1-C_{i} - D_{i}) + (b_{1}(1-C_{i} - D_{i}) + C_{i} + D_{i})T_{s} - D_{i}T_{a}}{C_{i}} \quad (4)$$

$$C_{i} = \tau_{i}\varepsilon_{i}; D_{i} = (1 - \tau_{i})[1 + (1 - \varepsilon_{i})\tau_{i}] \quad (5)$$

Where, $T_{s}$ is the light temperature and $T_{a}$ is the effective average atmospheric temperature, which can be calculated by the relevant empirical formula using the near-surface air temperature; $a_{1}$ and $b_{1}$ are the empirical coefficients; $\varepsilon_{i}$ is the surface emissivity; $\tau_{i}$ is the atmospheric transmittance.

The effective average atmospheric temperature can be calculated by the empirical formula obtained by Qin et al. [7] using the near-surface temperature $T_{0}$. Atmospheric transmittance is related to the water vapor content in the air and can also be calculated by empirical formula. But for different satellites, the empirical formulas of atmospheric transmittance and water content in the air are also different.

2.3.4 Single-channel algorithm
The single-channel algorithm was proposed to retrieve LST using Landsat 5 thermal infrared images[9], which was then gradually extended to Landsat 7 and Landsat 8 after improvement[10]. The main formula is:
$T = \frac{1}{\varepsilon_i} (\psi_1 L_\lambda + \psi_2) + \psi_3 + \delta$  \hfill (6)

$\gamma \approx \frac{T^2_S}{b_\gamma L_\lambda}; \delta \approx T_S - \frac{T^2_S}{b_\gamma}; b_\gamma = \frac{c_2}{\lambda}$  \hfill (7)

Where $\varepsilon_i$ is the surface emissivity; $T_S$ is the brightness temperature, and $\lambda$ is the effective wavelength; for different satellite types, the value of $b_\gamma$ is different\textsuperscript{[15]}; $\psi_1$, $\psi_2$ and $\psi_3$ are the three function of atmospheric parameters related to the atmospheric water content, which can be calculated by empirical formula.

Fig. 2 LST inversion results using four algorithms. (a) Image-based method. (b) Mono-window algorithm. (c) Radiative transfer equation. (4) Single-channel algorithm.
2.4 Correlation evaluation indexes
In view of how to analyze the correlation between Landsat 7 and Landsat 8 LST products obtained by the different retrieval methods, this paper selects the goodness of fit R^2, Pearson correlation coefficient and Euclidean distance as evaluation indexes.

2.4.1 The goodness of fit
The goodness of fit refers to the fitting degree of the regression line to the observed value, and the statistic that measures the goodness of fit is the coefficient of determination R^2 calculated by the formula:

\[ R^2 = \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \]  

Where y is the value to be fitted, its mean value is \( \bar{y} \), and the fitted value is \( \hat{y} \). The larger the value of R^2 is, the better the fitting degree of the regression line to the observed value is. In this paper, the correlation between Landsat 7 and Landsat 8 temperature retrieval results was judged by linear fitting.

2.4.2 Pearson correlation coefficient
The Pearson correlation coefficient is a parameter that characterizes the degree of linear correlation between variables. The calculation formula is:

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

Where, X and Y respectively represent the temperature retrieval results of Landsat 7 and Landsat 8. The greater r is, the higher the correlation is, and the higher the consistency of the temperature retrieval results of Landsat 7 and Landsat 8 is.

2.4.3 Euclidean distance
The calculation formula of Euclidean distance is as follows:

\[ D(X, Y) = \sqrt{\sum_{i=1}^{n} (X_i - Y_i)^2} \]  

Where, X and Y respectively represent the temperature retrieval results of Landsat 7 and Landsat 8. The smaller D is, and the higher the consistency of the temperature retrieval results of Landsat 7 and Landsat 8 is.

3. Results
In this paper, the radiative transfer equation method, image-based method, mono-window algorithm and single-channel algorithm are used to retrieval the LST of the Landsat 8 image on 23 October, 2017 and the Landsat 7 image on 31 October, 2017, respectively. The results are shown in Figure 2.

From Figure 2, it can be seen that the LST products of Landsat 7 and Landsat 8 obtained by each method inversion have certain similarity, which also verifies our assumption that the surface temperatures of the adjacent dates in the study area with the same weather condition are similar. In order to further demonstrate and analyze this similarity, surface temperature of Landsat 7 and Landsat 8 retrieval results at corresponding pixel locations were extracted for statistical analysis, and the results were shown in Figure 3.
By statistical analysis, we found that there is an obvious linear relationship between the LST results of Landsat 7 and Landsat 8, and the linear fitting formulas corresponding to these four retrieval methods are approximate respectively, as shown in Table 2. Among them, the linear fitting formula between the retrieval results obtained by the radiative transfer equation method has the highest $R^2$, indicating that the linear relationship is more obvious.

### Table 2 The linear relationship between LST results of adjacent days under the same weather conditions obtained by different methods

| LST retrieval method | linear relationship          | $R^2$ |
|----------------------|------------------------------|-------|
| IBM                  | $T_B = 0.76T_7 + 5.52$       | 0.84  |
| MWA                  | $T_B = 0.78T_7 + 5.37$       | 0.87  |
| RTEM                 | $T_B = 0.80T_7 + 6.21$       | 0.89  |
| SCA                  | $T_B = 0.74T_7 + 4.77$       | 0.86  |

In addition, Pearson correlation coefficient and Euclidean distance are used as evaluation indexes to further evaluate the consistency of Landsat 7 and Landsat 8 LST retrieval products, as shown in Table 3.

### Table 3 Consistency indexes for Landsat 7 and Landsat 8 LST products

| LST retrieval method | Pearson correlation coefficient | Euclidean distance |
|----------------------|--------------------------------|--------------------|
| RTEM                 | 0.9412                         | 2266               |
| IBM                  | 0.9184                         | 2365.8             |
| MWA                  | 0.9311                         | 2337.3             |
| SCA                  | 0.9293                         | 4475.5             |
On the whole, the radiative transfer equation method performs best on the two consistency evaluation indexes, and the linear relationship between the retrieval results obtained by the radiative transfer equation method is more obvious, so we believe that the surface temperature obtained by this method has the strongest correlation on the two images. The second is the mono-window algorithm, both of which consider the parameters related to the atmosphere in detail.

4. Conclusion
In this paper, image-based methods, mono-window algorithm, radiative transfer equation method and single-channel algorithm are used to generate the LST products respectively from the Landsat 7 and Landsat 8 image pairs of adjacent dates in Shenzhen under the same weather conditions. Then the consistency of retrieval results was evaluated to compare the accuracy of different LST retrieval for Landsat images. Conclusions are as follows:

(1) there is an obvious linear relationship between Landsat 7 and Landsat 8 LST products of adjacent dates in the same area under similar imaging conditions.

(2) The linear relationship between Landsat 7 and Landsat 8 retrieval results obtained by radiative transfer equation method is the most obvious with the highest $R^2$, and performs best on the two consistency evaluation indexes.

(3) The radiative transfer equation method can effectively reduce the uncertainty caused by using multi-source Landsat data in the analysis of long-term surface temperature change to ensure the reliability of the research.

(4) The method proposed in this paper can provide a feasible solution for the accuracy comparison of different LST retrieval methods for Landsat data without utilizing reference data from ground observation.

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