Assessment of Aeolian Desertification in Korqin Sand, China

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ABSTRACT

Desertification is a worldwide concern and the assessment of aeolian desertification has become one hotspot in global ecosystem research. In this paper, hyperspectral data acquired from modular OMIS-I imaging spectrometer, combined with ETM data and field survey data, was used to assess the aeolian desertification in Korqin Sand, Inner Mongolia, China by pixel-level. The results indicated that hyperspectral image, combined with ETM image and little field works, is capable to monitor and assess desertification through quantitative retrieval of assessing parameters directly from hyperspectral data or indirectly from the encoding map by visual interpretation of hyperspectral image and ETM image. For the retrieval of vegetation biomass and coverage, polynomial fit curve is suitable to regions where shrubs and grasses coexist, while linear fit curve is suitable to single vegetation type and was highly restricted by region. The retrieval of surface soil water content based on soil thermal inertia is suitable in flat terrain and sparse vegetation, and it can resist vegetation disturbance. The algorithms for numerical evaluation and quantitative retrieval for hyperspectral image are also practicable for aeolian desertification in Korqin Sand, China.

Keywords: desertification assessment, hyperspectral image, quantitative retrieval, Modular OMIS-I, Korqin Sand

1. INTRODUCTION

Desertification and its increasing rate have aroused more concerns in the world \textsuperscript{1,2}, which have also become one of the research hotspots in global change science. Though its definition is controversial \textsuperscript{3-5}, desertification is certainly the results of climate-related changes and human-induced alterations \textsuperscript{6,7}. The basic aim of desertification research is to control and govern desertification, and monitoring is the key \textsuperscript{8,9}. However, few efforts have been made to devise diagnostic and monitoring techniques for assessing the status and trend of desertification, and to use indicators to develop a system of desertification evaluation \textsuperscript{10}.

Most scholars believe that advanced technique and newly research results must be introduced in order to improve the monitoring efficiency and accuracy \textsuperscript{11-13}. Remote sensing, as a tool which can rapidly and reliably collect data about a variety of ground conditions \textsuperscript{14}, has been applied to discriminate the sand bodies with vegetation as well as to identify and characterize sand dunes and their temporal dynamism \textsuperscript{2,15-21} with its advantage of multitemporal or hyperspectral coverage, extensive view and digital form available to further process \textsuperscript{22}. Several algorithm for monitoring vegetation using satellite data in arid area were brought forward, such as SAVI \textsuperscript{23} and OPVI \textsuperscript{24}, the relationship among vegetation index and physical parameters of vegetation was evaluated \textsuperscript{25}, and attempts to quantify geophysical parameters by using TM or SPOT sensor were made \textsuperscript{26,27}. However, high accuracy is difficult to get because of the separation between bands, atmospheric effects, soil background and inherent characteristics of vegetation \textsuperscript{28,29}, especially in arid and semiarid environments, traditional multispectral classification approaches and most vegetation indices have been problematic because vegetation cover is sparse \textsuperscript{30}.

The advent of imaging spectrometer made a great breakthrough of human earth-observation \textsuperscript{31}. Imaging spectrometry is defined as the quantitative analysis of the spectral properties of different earth surface materials registered in contiguous spectral bands in the optical wavelength. For each picture element (Pixel) it is possible to derive a complete reflectance spectrum \textsuperscript{32} and meets directly with the spectrum curve from database of standard spectrum to recognize the type of vegetations and land cover, which make it possible to analyze fine spectrum and quantitative retrieval of the geographic parameters \textsuperscript{33} based on waveform analysis techniques \textsuperscript{34}. Many attempts to retrieve geographic parameters from

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hyperspectral remote sensing images were conducted, such as retrieval of water quality parameters \textsuperscript{35,36} subpixel snow-covered area and effective grain size \textsuperscript{37} equivalent water thickness (EWT) of vegetation \textsuperscript{38}, and so on, but the retrieval of desertification parameters with hyperspectral remote sensing images in arid and semi-arid environments is rare. The objectives of this study were to develop the algorithms for quantitative retrieval of geophysical parameters needed to desertification monitoring and assessment and to assess the aeolian desertification degree in Korqin Sand, China.

2. DATASETS AND ASSESSMENT SYSTEM

2.1 Study Area
The study area is located in the south Jirem Meng, inner-Mongolia Municipality, China with geographic coordinates of 120.33°~122.23°E and 42.24°~43.54°N. It belongs to the continentally semi-arid monsoon climatic zones with an average annual precipitation of 364mm, falling mostly in July and August. The average annual evaporation is 1973 mm. Surface runoff change greatly between years and the ratio of maximum to minimum is 7:1. The surface runoff within a year is also uneven, much concentrating in flooding seasons. Soils are Loess, castanozem, meadowsoil and aeolian sandy soil, with aeolian sandy soil accounting for 65% of total soil area. Vegetations are steppe vegetation, meadow, and artificial vegetation. This region was selected because it showed clear characteristics of a typical aeolian desertification. Moreover, a field research station belonging to Cold and Arid Regions Environmental and Engineering Research Institute (CAREERI), CAS was set up here, which has longer research history and has collected a lot of research data, so it is convenient to the field work and benefit to the study.

2.2 Image Data

2.2.1 Airborne hyperspectral data
Images of upward spectral radiance was measured at June 17 and 18, 2000 using a modular OMIS-I imaging spectrometer, which manufactured by Shanghai Institute of Technical Physics, Chinese Academy of Sciences. It has 128 bands with a spatial resolution of 5×5m and the data format is BSQ. A strip-sampling method was adopted and 6 navigation strips with each width of 3.8km paralleled each other and equally distributed in the study area. After radiometric calibration and geometric correction, images of upward spectral radiance were obtained.

2.2.2 ETM data
The Enhanced Thematic Mapper (ETM) image was acquired on June 3, 2000, on board Landsat-7 satellite, with a spatial resolution of 15×15m. It was used to select sites with relatively consistent ground targets or with a uniform hue on image for fieldworks, and combined with hyperspectral data for visual interpretation to encode some geophysical parameters hard to retrieve from hyperspectral data. In this study, 27 study sites were pre-selected according to different desertification type, land use type, vegetation type and coverage, and the geographic coordinate of each site was input into GPS for locating in field.

2.3 Field Data
Fieldworks, including field spectrometry and sample plot investigation, were carried out on the day and the next day of the OMIS-I data acquisition for the ground spectrum analysis and reconstruction, and the retrieval of some desertification parameters.

2.3.1 Field spectrometry
Two kinds of spectra were measured in each point: one acted as the scalar for the ground spectrum reconstruction, and its measure time is same to that of aircraft overhead. A special area of asphaltic surface, blind creek, water body and barren sands was pre-selected on TM images and the spectra were measured. The other was selected to analyze the spectral characteristics of all kinds of ground targets for ground target recognition and quantitative analysis, and it was measured in the last ten-day of June, 2000. Different natural conditions, such as aspect, solar zenith and azimuth angle, surface characteristics, were selected to analyze the spectral variability of ground target. Moreover, some different conditions, such as soil water content, mixed targets with different ratio, were artificially simulated. 271 spectral curves were measured in this study, of which 35 were used as the standard spectra, and the others were used to analyze the spectral characteristics.

2.3.2 Sample plot investigation
Sample plot investigation is needed for quantitative analysis. Detailed data about natural indicator, vegetation indicator, soil indicator and surface indicator were acquired for each sample plot, starting from the day aircraft acquisition and extending to 12 July 2000, in imaging range. The investigation time was nearly synchronous to that of imaging so to make the data comparable to imaging data. In field, 2-4 sample plots were set in each site pre-selected on TM images.
The plot area of arbor is 10×10m², shrub is 5×5m², half-shrub is 2×2m² and herbage is 1×1m². Totally, 42 sample plots were investigated and all information gathered was georeferenced by GPS. The detail parameters investigated were as follows: (1) Natural indicator (common indicator): including altitude, gradient, aspect and desertification types. (2) Vegetation indicator: including vegetation types and their distributions, total vegetation coverage and arbor, shrub, herbage coverage respectively, total or annual vegetation biomass, crop yield, species number and individual number. (3) Soil indicator: including soil types, soil texture, soil thickness, soil erosion form, soil water content. (4) Surface indicator: including quicksand and crust conditions, dune and its size. Among those parameters, vegetation biomass and soil water content were measured by oven drying method.

2.4 Assessment System for Aeolian Desertification

According to the general conditions and research results 39, the evaluating indicators of aeolian desertification were expressed as Eq. (1):

\[ D = G + T + B \]  

Where, \( D \) is the degree of aeolian desertification, \( G \) is vegetation indicator, \( T \) is soil indicator and \( B \) is the earth’s surface indicator.

On image, the degree of aeolian desertification was calculated with below Eq. (2):

\[ D = \sum_{i=1}^{n} X_i Y_{ij} \]  

Where, \( D \) is the desertification degree of any cell, \( n \) is the number of assessing parameters, \( X_i \) is the weight of \( i^{th} \) assessing parameter and \( Y_{ij} \) is the grading value of \( i^{th} \) assessing parameter in \( j^{th} \) grade.

<table>
<thead>
<tr>
<th>Assessing parameter</th>
<th>Weight ((X_i))</th>
<th>Grade Value ((Y_{ij}))</th>
<th>Assessing parameter</th>
<th>Weight ((X_i))</th>
<th>Grade Value ((Y_{ij}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation Coverage(%)</td>
<td>3</td>
<td>1</td>
<td>Soil Texture</td>
<td>1.5</td>
<td>1</td>
</tr>
<tr>
<td>&gt;60</td>
<td>1</td>
<td></td>
<td>Clay loam</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>60-41</td>
<td>2</td>
<td></td>
<td>Loam</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>40-26</td>
<td>3</td>
<td></td>
<td>Sandy loam</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>25-10</td>
<td>4</td>
<td></td>
<td>Loamy sand</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>(\leq 10)</td>
<td>5</td>
<td></td>
<td>Sand</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>Vegetation Biomass (g/m²)</td>
<td>2</td>
<td>1</td>
<td>Surface Crust</td>
<td>1.5</td>
<td>1</td>
</tr>
<tr>
<td>&gt;500</td>
<td>1</td>
<td></td>
<td>High Crust</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>500-300</td>
<td>2</td>
<td></td>
<td>Medium Crust</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>300-150</td>
<td>3</td>
<td></td>
<td>No crust</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>150-50</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;50</td>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Soil Water Content(%)</td>
<td>1</td>
<td>1</td>
<td>Dune Form</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>&gt;3</td>
<td>1</td>
<td></td>
<td>Flat sand</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>3-2.3</td>
<td>2</td>
<td></td>
<td>Lower dune</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>2.2-1.5</td>
<td>3</td>
<td></td>
<td>Mid dune</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>1.4-0.7</td>
<td>4</td>
<td></td>
<td>Higher dune</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>(&lt; 0.7)</td>
<td>5</td>
<td></td>
<td>Exceptional</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>

Referred to other research results 39,40, assessing system on aeolian desertification degree was given in table 1. In this table, each assessing parameter was divided into 5 grades, and their values \((Y_{ij})\) were given respectively. The weighting summation of all parameters \((\sum X_i)\) was 10. Grade was acquired through quantitative retrieval from hyperspectral imaging data or calculation from TM data and hyperspectral imaging data through visual interpretation, code and imaging (detail explanations see later Quantitative calculation of other desertification parameters), its corresponding value \((Y_{ij})\) and assessing parameter weight \((X_i)\) were found from table 1. The aeolian desertification degree of each cell was calculated from Eq. (2) and was assessed according to table 2.
### Table 2. Degrees of aeolian desertification

<table>
<thead>
<tr>
<th>Degree</th>
<th>Non-desertification</th>
<th>Gentle</th>
<th>Moderate</th>
<th>Severe</th>
<th>Immoderate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>≤15</td>
<td>16-23</td>
<td>24-31</td>
<td>32-40</td>
<td>&gt;40</td>
</tr>
</tbody>
</table>

#### 3. METHODS AND RESULTS

After the analysis of the ground spectral characteristics, ground spectra were reconstructed with a few necessary ground measured data and hyperspectral data, now derivative action will be used to the hyperspectral data to quantitatively retrieve some parameters with pixel-level for desertification monitoring and assessment, such parameters include vegetation biomass, vegetation coverage and soil water content.

##### 3.1 Quantitative retrieval of vegetation biomass and vegetation coverage

For the sake of universality, the spectral reflectance of any pixel was assumed as:

\[ R = \alpha R_v + \beta R_s \]

where \( \alpha \) \( \beta \) is the weighting area in a pixel, \( R_v \) and \( R_s \) are the reflectance of vegetation and soil respectively. Moreover, \( \alpha \) can be expressed as a simple reflection model as following \(^4\):

\[ \alpha = 1 - e^{-2cL} \]

where \( L \) is leaf area index (LAI), \( c = a - s^2 \), \( a \) is absorptive coefficient, and \( s \) is scattering coefficient (note: some scholars express \( a \) as \( 1 - e^{-KL} \), and define \( K \) as attenuation coefficient of vegetation). So the spectrum of this pixel is:

\[ R = (1 - e^{-2cL}) \cdot R_v + e^{-2cL} \cdot R_s \]

After the derivative of above formula, we have below Eq.:

In spectral range of vegetation “red edge”,

\[ \frac{d^n R_v}{d^n \lambda} \to 0 \]

\[ \frac{d^n R_s}{d^n \lambda} \]

\[ \therefore \frac{d^n R}{d^n \lambda} = (1 - e^{-2cL}) \cdot \frac{d^n R_v}{d^n \lambda} + e^{-2cL} \cdot \frac{d^n R_s}{d^n \lambda} \]

So LAI can be figured out as below Eqs.:

\[ L = -\frac{1}{2c} \ln(1 - \frac{R_v}{R_s}) \]

Derivatives are notoriously sensitive to noise \(^4\), high frequency information was enhanced and the noise was enlarged through derivative, so the integral of derivative wave from \( \lambda_1 \) to \( \lambda_2 \) was applied to reflect vegetation information,

\[ \phi = \int_{\lambda_1}^{\lambda_2} \frac{d^n R}{d^n \lambda} d\lambda = (1 - e^{-2cL}) \cdot \phi_v \]

expressed as \( \phi \):

Where, bands \( \lambda_1 \) to \( \lambda_2 \) are the spectrum bands reflecting vegetation characteristics in “red edge” region, \( \phi_v \) is the integral of derivative spectrum in vegetation endmember from \( \lambda_1 \) to \( \lambda_2 \), namely, integral from \( \lambda_1 \) to \( \lambda_2 \) in full vegetation cover.

So the LAI was further calculated as:

\[ L = -\frac{1}{2c} \ln \left(1 - \frac{\phi}{\phi_v}\right) \]
If \( \phi = \phi_c, L \to \infty; \) if \( \phi = 0, L = 0. \)

\( \phi/\phi_c \) was defined as normalized vegetation factor (\( \Phi \)), so yield Eq. (7).

\[
L = -\frac{1}{2c} \ln(1 - \Phi)
\]  

(7)

According to the correlative model of biomass and LAI \(^{33}\), vegetation biomass is related to the ratio of leaf biomass to total biomass and also related to special LAI, and this relationship can be expressed as Eq. (8).

\[
MT = LT^{-1} \times LS^{-1} \times L
\]  

(8)

Where, \( LT \) is the ratio of leaf biomass to total dried above-ground biomass, and \( LS \) is the ratio of LAI to leaf biomass, namely special LAI. Substitution of Eq. (7) into Eq. (8) yields

\[
MT = -\left(2c\right)^{-1} \times LT^{-1} \times LS^{-1} \times \ln(1 - \Phi)
\]

\( LT \) and \( LS \) are parameters related to vegetation type, and they are hard to obtain directly from imaging spectral data. So we simulated the measured data in the field and get a semi-empirical biomass equation, as Eq. (9).

\[
M_T = \bar{A} \ln(1 - \Phi)
\]  

(9)

Figure 1 are the simulated results with fieldwork data of grass and shrub, and \( x \) is \( \ln(1 - \Phi) \), in which (a) is the simulated results with polynomial fitting and (b) is the results with linear fitting.

For one type of vegetation, assumed there is a direct proportion between biomass and vegetation coverage, so the retrieval of vegetation coverage should also be on the basis of vegetation type. According to above analysis, shrubs and grasses were also processed as one type here. Figure 2 is the simulating results of normalized vegetation factor (\( \Phi \)) and

![Figure 1. Semi-empirical fitting equation of vegetation biomass by (a) polynomial and (b) linear fitting](image1)

![Figure 2. Semi-empirical fitting equation of vegetation coverage by (a) polynomial and (b) linear fitting](image2)
vegetation coverage, with the fieldwork data of shrubs and grasses as basis. In equation, x is the normalized vegetation factor (Φ) defined before and equal to ϕ/ϕv.

From figure 1 and figure 2, we can see that the precision of polynomial fitting is obviously higher than that of linear fitting. We also found that in area with single vegetation type, linear fitting has a higher precision, but the applied region of this fitting is restricted and can only calculate in blocks. According to the spectral curves of shrubs and grasses measured in the field, the spectral curves of shrubs and grasses within the range of “red edge” have little difference, so in area where shrubs and grass coexist, the polynomial fitting model is used to retrieve vegetation biomass and coverage.

3.2 Quantitative retrieval of soil water content

In desertification area, vegetation coverage is lower, and according to the study results of Sui Hongzhi, et al.43, in bare soil or soil with low vegetation coverage,

\[ W = a + b \cdot P \]

Where, W is soil water content, P is soil thermal inertia, and P was defined as

\[ P = \sqrt{Kc\rho} \]

Where, K is thermal conductivity, c is thermal capacity, and \( \rho \) is density.

From the definition of thermal inertia, we can see that many physical characteristics concerned soil water content were contained in thermal inertia, so it is natural to convert the study of soil water content to that of the relationship between soil water content and thermal inertia. But soil thermal inertia is hard to acquired, because K, c and \( \rho \) are hard to correspond with remote sensing information. Eq.(10) was obtained theoretically by many scholars44,45 based on heat exchange equation:

Where, \( A \) is albedo, \( \Delta T \) is the temperature difference between day and night on the ground and P is thermal inertia.

\[ \frac{1 - A}{\Delta T} = f(P) \quad (10) \]

\( (1-A) / \Delta T \) was defined as apparent thermal inertia and its value monotonously rise along with the accretion of P. The value of \( (1-A) / \Delta T \) reflect the comparatively magnitude of thermal inertia.

From equation (10) we know, if the two parameters, albedo(4) and the difference in temperature between day and night( \( \Delta T \) ) was calculated, apparent thermal inertia will be calculated, so we will calculate \( A \) and \( \Delta T \) as follows.

3.2.1 Calculation of albedo(4)

Assumed that ground has the characteristics of a Lambert body, albedo(4) was defined as:

\[ A = \frac{\int_0^\infty \rho(\lambda)Q_{se}(\lambda)d\lambda}{\int_0^\infty Q_{se}(\lambda)d\lambda} \]

Where, \( \rho(\lambda) \) is spectroscopic reflectance of ground target, \( Q_{se}(\lambda) \) is the spectroscopic irradiance of sun. The sun energy mainly concentrates on a narrow range of 0.2-1.5 \( \mu \)m, so the albedo of visible light and near-infrared bands can approximatively be replaced with that of 0-\( \infty \) bands.

For Hyperspectral data,

\[ A = \frac{\sum_n Q_{se,n}(\lambda) \rho(\lambda)}{\sum_n Q_{se,n}(\lambda)} \]

Where, \( n \) is the serial number of wave band, \( Q_{se,n}(\lambda) \) is the ground solar spectroscopic irradiance in each wave band, \( \rho(\lambda) \) is the ground target’s reflectance in each wave band. Here we give a weighting coefficient:

\[ W_n = \frac{Q_{se,n}(\lambda)}{\sum_n Q_{se,n}(\lambda)} \]

so,
\[ A = \sum_n W_n \cdot \rho(\lambda) \]

This formula indicates that albedo(\(A\)) is the weighting mean of ground target’s spectroscopic reflectance in each wave band, the weighting \(W_n\) represents the ratio of incidence solar energy of \(n^{th}\) band to that of all bands on ground surface.

In this study, we can only find the total solar irradiation value outside atmosphere from the range of visible light to near-infrared, so

\[ A = 0.423V + 0.577N \]

Where, \(V\) is the bands sum within the range of visible light, \(N\) is the bands sum within the range of near-infrared.

3.2.2 Calculation of the difference in temperature between day and night(\(\Delta T\))

The difference in temperature between day and night(\(\Delta T\)) was obtained by subtracting the real temperature of day and night. The real temperature can be obtained through measuring each type of ground target, consulting weather observation station, acquiring from satellite image, though from satellite image can only acquire brightness temperature. But in this study, the real temperature data was acquired from local weather observation station.

3.3 Quantitative calculation of other desertification parameters

For other desertification parameters hard to quantitative retrieval, such as soil texture, surface crust and dune form, we can encode each parameter through visual interpretation of hyperspectral image and TM image, and then imaged with equation (11).

\[ g = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \times 255 \]

Where \(g\) is the gray value of each encoded parameter, \(I_{\min}\) and \(I_{\max}\) are the minimum and maximum of the encoded parameter in the whole image, \(I\) is the encoded value of each pixel.

3.4 Assessment of desertification

After the quantitative retrieval of vegetation biomass, vegetation coverage and soil water content from hyperspectral data, and the quantitative calculation of soil texture, surface crust and dune form from hyperspectral data and TM data, each pixel has its own value for all assessing parameters, so the quantitative assessment of desertification is possible. Take these six parameters as variables, the desertification degree was calculated with pixel-level by use of equation(2)(see...
assessing method to aeolian desertification), where their weight \( X_i \) and values \( Y_j \) corresponding to the grades in image were found from table 1. After partitioning the desertification degree with table 2, image reflecting the level of aeolian desertification was obtained. Calculating the minimum and maximum of the whole image and once again imaged the whole image with equation (11), we got the desertification level image. Figure 4 is the desertification degree image of one sampling strip, with the green is non-desertification, blue is gentle desertification, deep yellow is moderate desertification, buff is severe desertification and white is immoderate desertification. Here we can see that the non-desertification is nearly zero.

Figure 4. Desertification degree image of one sampling strip

4. CONCLUSIONS

Hyperspectral image, combined with ETM image and little fieldworks, is capable to quantitatively assess desertification, and has some practical significance. Through study of the relationships between hyperspectral data and ETM data in this area and in other different desertification regions by systematic sampling and typical sampling, we can use hyperspectral data to aid or improve ETM classification based on the study results. A second-order sampling can be designed to future desertification assessment, namely, with ETM images covering the overall regions and hyperspectral image covering the sensitive and important regions. Compared with traditional multi-spectral image, this can replace most of fieldworks and raise the efficiency and decrease expense.

On retrieval of vegetation biomass and coverage, we found that in area where the shrubs and grass coexist, the precision of polynomial model is obviously higher than that of linear model. In area with single vegetation type, linear mode has a higher precision, but the applied region of the model was restricted and can only compute in block. So in area with shrubs and grass concurrence, the polynomial model is advisable to retrieve.

The method to retrieve soil water content is suitable to flat terrain with no or sparse vegetation, and the soil water content model based on soil thermal inertia had some ability to resist vegetation disturbance. The reason about this is likely that the vegetation water content is higher correlate with its thermal inertia, and vegetation water content has relation to soil water content. Soil water content also has relation to vegetation transpiration and roots absorption, especially in area of higher vegetation coverage, the mechanism is complex and more research is needed.

Of course, the assessing accuracy is decided by the assessing methods in existence, including the rationality and objectivity of assessing parameters and their weights and grades, and the precision of acquired data, so the assessing methods should also be studied and improved.

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