Availability analysis of the Chen NDVI model in MOD13 Q1 validation

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Abstract. The MODIS normalized difference vegetation index (NDVI) product plays an important role in the eco-environmental monitoring of natural disasters. However, its validation has been a long standing and important scientific problem. The paper proposed a method to integrate accurate classification information for medium-high spatial resolution remote sensing images to improve the traditional Chen NDVI scale conversion model and perform MOD13 Q1 validation. The authors had verified the method in the research area of Xiamen, Fujian Province, China, and the experimental results proved its effectiveness. This paper focuses on the availability research of the model in different experimental areas. Taking Fuzhou City of Jiangxi Province, China, as the study area, the MOD13 Q1 validation experiment was implemented. The conclusions are obtained from the experimental results: the Chen NDVI scale transformation model is not robust, and in some experimental areas there is significant transformation error when the conversion factor is too large (such as eightfold from 30 m OLI NDVI to 240 m up-scaled NDVI). In these bad cases, other more robust scale transformation models should be elected for the validation of the low-resolution land surface parameter images.

1. Introduction
The normalized difference vegetation index (NDVI) is an optimal indicator for vegetation growth and coverage and has been widely applied in the fields of environmental (climate) change, crop yield estimation, and others. While there are currently numerous vegetation index products, MODIS is of particular interest because it is not only cost-free and stable, but also offers global coverage and phase continuity. Specifically, it has been applied in various studies of eco-environmental monitoring, including forest fires [1-3], grassland vegetation growth [4, 5], droughts [6, 7], and desertification [8-10]. One limitation of MODIS is that its highest spatial resolution is only 250 m. Thus, validating remotely sensed land surface parameters [11-16] is very important, which is generally achieved through scale transformations. To this end, this study utilized the representative MODIS NDVI product MOD13 Q1.

The scale transformation of remotely sensed land surface parameters is a fundamental and important issue in quantitative remote sensing. Several researchers have studied various land surface parameters, including NDVI, and proposed a number of scale transformation methods, such as statistical [17-19], physical model [20-24], and analytical [25-28] methods. Moreover, fractal theory was used in the scale transformation of remotely sensed land surface parameters by some researchers.
[29-32]. Every model has its advantages and disadvantages, and is not perfect. To date, the scale transformation of remotely sensed land surface parameters based on ground object categories has emerged as a new trend. For example, Chen [33], Zhang et al. [26], and Shi et al. [34] constructed NDVI and leaf area index (LAI) up-scaling models based on integrating ground object categories. These categories intuitively presented land surface spatial heterogeneity, which was the fundamental cause of the scale effect of remotely sensed surface parameters. Thus, research ideas from these studies were adopted here.

As a representative moderate resolution satellite sensor, Landsat 8 OLI offered numerous advantages in ground object identification and element extraction due to its spectrum and radiation features. Thus, it has been widely applied in related studies [35, 36]. Ground object identification was first performed using the 30 m Landsat 8 OLI images. The NDVI up-scaling model integrated with ground object categories was constructed, and the validation of a MODIS NDVI product (MOD13 Q1) was conducted. Luan et al. [37] has already experimented with this method in the research area of Xiamen, Fujian Province, China. This paper focuses on the availability research of the model in different experimental area, Fuzhou City of Jiangxi Province, China.

2. Study area and data sources
Fuzhou City, located in the eastern part of Jiangxi Province, China, is an important member of the urban group in the middle reaches of the Yangtze River. It is between 26°29′ N ~ 28°30′ N and 115°35′ E ~ 117°18′ E, and governs two districts, nine counties, and a high-tech industrial park. The selected study area is located at the junction of Nancheng, Lichuan, and Nanfeng counties in Fuzhou. The Fuzhou Landsat8 OLI and MOD13Q1 data were downloaded, as shown in Table 1.

Table 1. List of Fuzhou remote sensing data.

| Data          | Row Number/Tile | Spatial Resolution/m | Temporal Resolution/d | Day of Year (DOY) |
|---------------|-----------------|----------------------|-----------------------|-------------------|
| Landsat8 OLI  | 121041/121043   | 30                   | 16                    | 7/15/2018         |
| MOD13Q1       | H28v06          | 250                  | 16                    | 7/12/2018         |

The images were preprocessed as follows.

2.1. Pre-processing of the OLI image
Firstly, the OLI image of Fuzhou was pre-processed with atmospheric and geometric corrections. The OLI land reflectance image was used for the NDVI and calculated histogram of the image, as shown in Figure 1 and Figure 2.

Figure 1. The 30 m OLI NDVI image.

Figure 2. Histogram of the 30 m OLI NDVI image.
The original images from Fuzhou City were classified, and the modified normalized difference water index (MNDWI) proposed by Xu [38] could clearly distinguish water from buildings. The MNDWI can be used to divide water and land [38] as follows:

\[
\text{MNDWI} = \frac{\text{band}_{2\text{TM}} - \text{band}_{5\text{TM}}}{\text{band}_{2\text{TM}} + \text{band}_{5\text{TM}}}.
\]  

In formula (1), the \(\text{band}_{2\text{TM}}\) and \(\text{band}_{5\text{TM}}\) are, respectively, the green and short-wave infrared bands of the TM sensor, corresponding to band 3 and band 6 of the OLI sensor. The MNDWI of the Fuzhou OLI image was calculated, as shown in Figure 3.

![Figure 3. Fuzhou OLI classification image.](image)

### 2.2. Pre-processing of the MOD13 Q1 product

The MOD13 product has a different coordinate system and projection method from the OLI image. Therefore, it is necessary to perform reprojection prior to MOD13 validation; the MODIS Reprojection Tool (MRT) software from the National Aeronautics and Space Administration (NASA) website was used to this end. The MOD13 product was then clipped following re-projection with respect to the OLI image. For the post-preprocessed 240 m MOD13 Q1 product, the abnormal pixels (set to be -3000) were replaced with the corresponding values from the 240 m resampled image for the OLI NDVI. The 240 m MOD13 Q1 image and its histogram were then obtained, as shown in Figure 4. The basic statistics of Figure 4(a) are shown in Table 2.

![Figure 4. The 240 m MOD13 Q1 image and its histogram (7/12/2018): (a) The MOD13 Q1 image; (b) Histogram of the MOD13 Q1 image.](image)

Table 2. Basic statistics of the 240 m Fuzhou MOD13Q1 image.
3. Methods

The traditional and modified Chen NDVI models [37] are expressed as:

\[ \rho_t = \sum_{i=1}^{N} R_{\text{class}}^i \rho_{ti}, \]  
\[ \rho_{nir} = \sum_{i=1}^{N} R_{\text{class}}^i \rho_{niri}, \]  
\[ \text{NDVI} = \frac{\rho_{nir} - \rho_t}{\rho_{nir} + \rho_t}, \]  

where \( \rho_t \), \( \rho_{nir} \), and NDVI represent, respectively, the surface reflectance of the red band, the near-infrared band, and the corresponding NDVI values in the up-scaled image obtained after the medium and high spatial resolution NDVI image is up-scaled at a specific conversion multiple; \( N \) represents the number of the types of ground objects recognition in the medium and high spatial resolution image; \( i \) represents the serial number of the category, and the value ranges from 1 to \( N \); \( R_{\text{class}}^i \) represents the proportion of the number of \( i \)-th category within the model calculation window (such as the 8 pixels × 8 pixels window of the OLI NDVI image up-scaled to 240m spatial resolution of MOD13 Q1 image); and \( \rho_{ti} \) and \( \rho_{niri} \) are, respectively, the average values of surface reflectance in the red band and near-infrared band of the \( i \)-th category in the calculation window. When the value of \( N \) is 2, one case is to divide the medium and high spatial resolution images into land and water bodies, and at this time Equations 2-4 is the traditional Chen NDVI model [33]; when the value of \( N \) is larger, it indicates that the images will be finely classified, and Equations 2-4 is the improved Chen NDVI model [37].

The Chen NDVI scale conversion model is also called the “first average and then inversion” method. The “first inversion then average” method [37] is introduced and compared to illustrate the effects of the method on the NDVI scale effect characterization.

\[ \text{NDVI}_i = \frac{\rho_{nir} - \rho_{ti}}{\rho_{nir} + \rho_{ti}}, \]  
\[ \text{NDVI} = \frac{\sum_{i=1}^{N} R_{\text{class}}^i \text{NDVI}_i,} \]

where, \( i \), \( \rho_{ti} \), \( \rho_{niri} \), \( N \) and \( R_{\text{class}}^i \) has the same meanings as them in formulas 2-4; \( \text{NDVI}_i \) represents the \( i \)-th category’s NDVI value corresponding to \( \rho_{ti} \), \( \rho_{niri} \); NDVI represents the NDVI value of the big pixel in the up-scaled image.

Luan et al. [37] found that the improved Chen NDVI model, incorporating fine ground information, had more advantages in the fine and quantitative description for the influence of different land types on the NDVI scale effects. In addition, the improved Chen NDVI could be considered as an expanded approximate Geometrical Optical (GO) model without consideration of shadows’ influences in the medium-resolution images such as OLI one, but with consideration of ground objects from two types to several types. Besides NDVI, for many other NDVI-like surface parameters, taking surface reflectance on different spectral bands as independent variables of the retrieval functions only, their
scale transformation models could be established like the improved Chen NDVI model. The general formulas were expressed as:

\[
\rho_{\text{band}_j} = \frac{\sum_{i=1}^{N} R_{\text{band}_{ji}}}{N},
\]

(7)

\[
y = f(\rho_{\text{band}_1}, \rho_{\text{band}_2}, \ldots, \rho_{\text{band}_n}),
\]

(8)

where, \(i\), \(N\), and \(R_{\text{band}_{ji}}\) has the same meanings as them in formulas 2-4; \(j\) represents the spectral band number of the image, and the value ranges from 1 to \(n\); \(\rho_{\text{band}_j}\) is the average value of surface reflectance of the \(i\)-th category in the \(j\)-th band in the calculation window; \(\rho_{\text{band}_j}\) represents the surface reflectance in \(j\)-th band of the big pixel in the up-scaled image; \(y\) represents the surface parameter’s estimated value of the big pixel in the up-scaled image with the retrieval function \(f\). The scale transformation model (formulas 7-8) could play significant role in quantitatively describing the influence of different land types on the scale effect of the land surface parameter.

However, according to Luan et al. [37], the improved NDVI model was not significantly different in the up-scale conversion results compared with the traditional Chen NDVI model, which incorporated rough information (land and water). Therefore, it was acceptable that the traditional Chen NDVI model was selected to analyze the availability of the NDVI scale transformation models in different experimental area, which made the implementation convenient.

4. Experimental process

4.1. Up-scaling of Fuzhou OLI NDVI image

The results in Ref. [37] show that the overall quality of the MOD13 Q1 is good, but there is an overestimation problem, especially for artificial ground objects. These issues should therefore be carefully considered in practical applications. New experiments were conducted to further verify the availability of the Chen NDVI model in different research area, Fuzhou of Jiangxi Province, China.

The red and near-infrared surface reflectance from the Fuzhou OLI image was used merging with the classification result of the two ground objects water and land (Figure 3), then based on the traditional Chen NDVI model the NDVI up-scaled images were obtained at different conversion multiples. The NDVI up-scaled images and their statistics were shown in Figures 5-11 and Table 3, respectively.

![Figure 5](image-url)  
Figure 5. 60 m NDVI up-scaled image (conversion multiple: 2): (a) the up-scaled NDVI image; (b) histogram of the up-scaled NDVI image.
Figure 6. 90 m NDVI up-scaled image (conversion multiple: 3): (a) the up-scaled NDVI image; (b) histogram of the up-scaled NDVI image.

Figure 7. 120 m NDVI up-scaled image (conversion multiple: 4): (a) the up-scaled NDVI image; (b) histogram of the up-scaled NDVI image.

Figure 8. 150 m NDVI up-scaled image (conversion multiple: 5): (a) the up-scaled NDVI image; (b) histogram of the up-scaled NDVI image.
Figure 9. 180 m NDVI up-scaled image (conversion multiple: 6): (a) the up-scaled NDVI image; (b) histogram of the up-scaled NDVI image.

Figure 10. 210 m NDVI up-scaled image (conversion multiple: 7): (a) the up-scaled NDVI image; (b) histogram of the up-scaled NDVI image.

Figure 11. 240 m NDVI up-scaled image (conversion multiple: 8): (a) the up-scaled NDVI image; (b) histogram of the up-scaled NDVI image.

Furthermore, the basic statistics were calculated for the 240m up-scaled NDVI image (Figure 11) and the 240 m MOD13 Q1 image (Figure 4(a)), as shown in Table 4.
Table 3. Basic statistics of the NDVI Up-scaled images with different spatial resolutions.

| NDVI Up-scaled Images | Conversion Multiple | Spatial Resolution / m | Maximum       | Minimum       | Mean     | Standard Deviation |
|-----------------------|---------------------|------------------------|---------------|---------------|----------|--------------------|
| Figure 5              | 2                   | 60                     | 0.919180      | -0.847900     | 0.714549 | 0.191522           |
| Figure 6              | 3                   | 90                     | 0.870350      | -0.765250     | 0.595803 | 0.182802           |
| Figure 7              | 4                   | 120                    | 0.809880      | -0.764980     | 0.403230 | 0.183108           |
| Figure 8              | 5                   | 150                    | 0.828450      | -0.640800     | 0.229759 | 0.160357           |
| Figure 9              | 6                   | 180                    | 0.788040      | -0.491800     | 0.103460 | 0.111690           |
| Figure 10             | 7                   | 210                    | 0.774090      | -0.330020     | 0.034322 | 0.055061           |
| Figure 11             | 8                   | 240                    | 0.694470      | -0.210400     | 0.006667 | 0.026174           |

Table 4. Basic Statistics of the 240 m NDVI Up-scaled Image and MOD13 Q1.

| 240m NDVI Up-scaled Image | MOD13 Q1 |
|---------------------------|----------|
| Correlation Coefficient   | 0.0174567|
| Covariance                | 0.000685057 4.91296e-05 4.91296e-05 0.0115621 |

By comparing Figure 11 with Figure 4(a), it was found that the 240 m up-scaled NDVI image, the MOD13 Q1 image, and their histograms differ significantly, which meant the MOD13 Q1 image had bad quality. The current conclusions on MOD13 Q1 (or MOD09GA) product quality [13, 39] by other scholars indicate the large errors of this experimental result in Fuzhou research area, which suggests the Chen NDVI model has certain application disadvantages in some experimental area.

4.2. Discussion

Taking Xiamen as experimental area, Luan et al. [37] verified the traditional and improved NDVI scale transformation models and validated the corresponding MOD13 Q1 product. The experimental results were shown in Table 5.

Table 5. The statistics comparison table of the up-scaled NDVI image and MOD13 Q1 one [37].

| NDVI Images                          | Maximum       | Minimum       | Mean     | Variance | Correlation Coefficient |
|--------------------------------------|---------------|---------------|----------|----------|-------------------------|
| up-scaled NDVI image based on Chen NDVI model (No.1 result) | 0.9538        | -0.6909       | 0.3150   | 0.1886   | 0.9312                  |
| MOD13 Q1 image (abnormal pixels processed based on No.1 result) | 0.9991        | -0.6909       | 0.3822   | 0.1822   | ——                      |
| difference image (MOD13 Q1 image - up-scaled NDVI image) based on No.1 result | 1.0664        | -0.6364       | 0.0672   | 0.0256   | ——                      |
| up-scaled NDVI image based on the improved Chen NDVI model (No.2 result) | 0.9538        | -0.6909       | 0.2982   | 0.1911   | 0.9233                  |
| MOD13 Q1 image (abnormal pixels processed based on No.2 result) | 0.9991        | -0.6909       | 0.3803   | 0.1829   | ——                      |
| difference image (MOD13 Q1 image - up-scaled NDVI image) based on No. 2 result | 1.0664        | -0.6030       | 0.0821   | 0.0288   | ——                      |

(Note: the correlation coefficient is that between the up-scaled NDVI image and the MOD13 Q1.)

According to Luan et al. [37], the experimental results such as Table 5 proved that the traditional and improved NDVI models had creditable scale transformation results, and the models were rather accurate for Xiamen area. While the experiment in Fuzhou of Jiangxi Province showed opposite results as above. Therefore, it could be concluded that the Chen NDVI model was not robust, and it has rather large error in some experimental areas. In these bad cases, other more robust scale
transformation models (such as the Taylor series expansion model [40]) should be elected for the validation of the low-resolution land surface parameter images.

Furthermore, some issues in this study are further addressed, as described below.

(1) The time phase of the OLI image is not fully consistent with that of the MOD13 Q1 product. The MOD13 Q1 product is a 16-day integrated image, whereas the OLI NDVI image and the up-scaled NDVI image are taken on a specific date within the 16-day range. Thus, the OLI image is limited in time phase resolution (16 days). To implement a more accurate validation, follow-up studies should cover the 16-day range of the MOD13 Q1 product using images from different sensors with different time phases.

(2) There is a geometric inconsistency between the OLI image and the MOD13 Q1 image. Strictly speaking, geometric normalization should be performed first for NDVI image validation. Normalization can be achieved by calculating the bidirectional reflectance distribution function (BRDF) for typical land types in the study area and then correct the land surface reflectance of the OLI NDVI image. Follow-up research will focus on achieving this goal.

5. Conclusions
In this study, land type classification of OLI images was performed in the Fuzhou research area, and based on the OLI NDVI the Chen normalized difference vegetation index (NDVI) model, integrating the classification information, was used to validate the corresponding MOD13 Q1 product. It was concluded from the experimental results that the Chen NDVI scale transformation model was not robust, and the up-scaled image of NDVI had rather large error at large conversion factor in some experimental areas. In these bad cases, other more robust scale transformation models should be utilized for the validation of land surface parameters.

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Conflicts of Interest
The authors declare that they have no conflicts of interest.

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