Integration of multi-sensor data to assess grassland dynamics in a Yellow River sub-watershed

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Abstract
Grasslands form the dominant land cover in the upper reaches of the Yellow River and provide a reliable indicator by being strongly correlated with regional terrestrial ecological status. Remote sensing can provide information useful for vegetation quality assessments, but no single sensor can meet the needs for the high temporal–spatial resolution required for such assessments on a watershed scale. To observe long-term grassland dynamics in the Longliu Watershed located in the upper reaches of the Yellow River, Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat images were integrated to obtain Normalized Difference Vegetation Index (NDVI) data. The MODIS images were used to identify patterns of monthly variation. With the temporal dynamics of NDVI provided by the MODIS images, an exponential regression model was obtained that described the relationship between Julian day and NDVI. Four time-series data sets from multi-spectral sensors were constructed to obtain regional grassland NDVI information from 1977 to 2006 in the Longliu Watershed. Using the daily NDVI correlation coefficient, NDVI values for different days were obtained from Landsat series images, standardised to the same day and integrated into TM format by using NDVI coefficients between the four different sensors. Thus, the NDVI data obtained from multi-sensors on different days were integrated into a comparable format. A regression analysis correlating the NDVI data from two sensors with fresh grass biomass showed that the integration procedure was reliable.

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1. Introduction
Long-term observations of remotely sensed vegetation dynamics have held an increasingly prominent role in the study of terrestrial ecology (Budde et al., 2004; Prasad et al., 2007). A major limitation of such studies is the limited availability of sufficiently consistent data derived from long-term remote sensing (RS). The utility of most of these data sets is constrained by a lack of temporally replicated data due to the infrequent availability of cloud-free images or the short-term operation of the monitoring system. In many cases, this problem has been partially solved by combining information from different sensors. However, during the integration process, differences between the RS data are not always taken into account (Buheasier et al., 2003). Attempts to integrate diverse satellite data from different dates into a compatible format to identify terrestrial ecology dynamics over an extended period (e.g., thirty years) are still few. Such integrated satellite data are of great importance for vegetation assessments and the study of terrestrial ecology.

Investigating and monitoring the impact of climate change or human activities on vegetation dynamics is an important research field (Schaub and Paolletti, 2007). With the advance of RS technologies, vegetation characteristics on a regional or watershed scale can be identified efficiently. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) are frequently employed to provide useful time series data and are traditionally derived from multi-temporal satellite data with coarse spatial resolution (Sumfleth and Duttmann, 2008). These time series simulators are widely used to monitor the dynamics of spatial and temporal biophysical variables. The goal of these studies is to enhance the study of vegetation dynamics on regional and national scales, which is a key indicator in ecological analyses.

Medium to high spatial resolution sensors that allow detection of spatial vegetation patterns, such as MSS (Landsat Multi-Spectral Scanner), TM (Landsat Thematic Mapper), and ETM+ (Landsat Enhanced Thematic Mapper Plus), are limited in their temporal resolution (Rivero et al., 2007; Jones et al., 2008). On the other hand, high temporal resolution sensors such as MODIS (Moderate Resolution Imaging Spectroradiometer), which allow detailed monitoring
of the temporal change in vegetation, often lack sufficient spatial resolution (Weissteiner et al., 2011). Thus, both types of systems have their limitations when the goal is to assess vegetation dynamics over long periods. Higher resolution sensors provide spatial detail but do not offer sufficient temporal repetition, while low-resolution satellites offer high temporal repetition at the expense of spatial resolution.

Combining data derived from more than one kind of instrument can solve the problem of data gaps from any individual RS source (Duccio, 2007). Over the last two decades, studies of vegetation dynamics have explored several approaches to improve the spatial–temporal resolution of data from RS sources. Integrating medium to high spatial resolution data with high temporal resolution data can provide a means to detect most of the variation in vegetation (Jin and Steven, 2005). Because of their high-quality advantages, Landsat and MODIS are the most frequently applied RS images. The Landsat series data cover more than three decades, and the MODIS data have a 12-h temporal resolution (Ruelland et al., 2008).

The MODIS data are designed primarily for RS of the land surface with resolutions of 250 m in the red and near infrared bands and 500 m to 1 km for the other bands (Running et al., 1994). Compared with NOAA-AVHRR, MODIS provides high spatial resolution and, compared with Landsat, high temporal data. Thus, MODIS offers a good opportunity to monitor and analyse regional land surface processes. This is especially true for NDVI vegetation analysis, for which MODIS provides a standard product. MODIS has been applied in diverse applications for two reasons: (1) the advantage of daily data and (2) the possibility for high-quality data covering large land areas (Zhao et al., 2009). In the upper reaches of the Yellow River, the area of the current study, vegetation biomass is not as high as in south China and is susceptible to seasonal variation (Piao et al., 2006). Thus, the NDVI values provided by the MODIS at a 250 m spatial resolution will reveal regional vegetation properties for this watershed (Matsuoka et al., 2007).

One of the key factors in assessing vegetation dynamics and its response to climate change or human disturbances is the ability to make frequent and consistent observations (Thomas and Leason, 2005). The Landsat series images have the advantage of long-term high-resolution images, providing a resource for systematically assessing regional land cover in a retrospective manner (Luna-Ruiz and Berlanga-Robles, 1999). For example, Franklin et al. (2006) used images from MSS and TM to estimate the extent of land cover change to buffel grass in 1973, 1983, 1990, and 2000. However, the feasibility of finding sufficient medium spatial resolution images with no cloud cover to monitor long-term vegetation dynamics is quite low. Because of these disadvantages, medium resolution sensors like MODIS were developed and have been widely applied. At present, however, there are few cases where the Landsat series and MODIS data have been integrated to produce high-quality spatial and temporal data that can be used in long-term vegetation monitoring.

The purpose of the present study is to develop a new method that can be used to monitor and analyse vegetation dynamics over long time periods by utilising the standardised NDVI from diverse sensors and different observation dates. The main research objectives can be summarised as follows: (i) identify regional grassland NDVI relationships on different dates based on MODIS NDVI data and (ii) integrate NDVI data from Landsat MSS, TM, and ETM+ images for different dates into a comparable standard format.

2. Materials and methods

2.1. Study area description

This study was conducted in the Longliu watershed, which is located in the upper part of the Yellow River watershed (Fig. 1). The climate is continental with an average annual temperature of −2.3 °C. Precipitation is in the form of snow or heavy rainfall that typically occurs in short time periods (Feng et al., 2005). The vegetation is zoned according to elevation, and grassland covers approximately 62% of the watershed area. Villages and farmlands are found along the river and reservoirs. Desertification is a threat to the environment (Wang et al., 2006), leading to a reduction steppe and meadow vegetation cover as well as the drying of swamps.

2.2. General research framework

The approach used in integrating grassland NDVI time-series information from 1977 to 2006 is outlined in Fig. 2. The first step was to calculate the grassland NDVI from different Landsat sensor systems on different dates for four separate time periods (Table 2). These four years were selected because they provided favourable data availability and low percentages of cloud cover. The second step was to fit an exponential regression model with the day of the year as the explanatory variable and the value of the MODIS NDVI images on each of the 12 dates as response variables. This model allowed the interpolation of NDVI values for other dates and the conversion of the Landsat series NDVI on different dates into same day. Next, the NDVI values from MSS and ETM+ in 1997 and 2000 were standardised onto a TM format using the NDVI transformation model for different remote sensors. Finally, the grassland NDVI spatial characteristics and temporal variation principles were summarised. The grassland field investigation was carried out to calibrate the integration result.

2.3. Data set

The RSData used in our study were obtained from the following three sources:

(1) Land cover data. Around the year 2000, the Chinese Academy of Sciences organised several research institutions to construct and develop a nationwide land-cover database. This database was based on Landsat TM images with a spatial scale of 1:100,000 (Liu et al., 2005). In this study, the land-cover database was used to extract the grassland areas from MODIS images (Fig. 2). Grassland covers more than half of the study area, which is why it was selected as the focus for sampling vegetation (Table 1).

(2) MODIS dataset. The 250 m resolution, 16 day MODIS NDVI data (MOD13Q1) were downloaded from the Earth Observing System Data Gateway distributed archive (Olofsson et al., 2007). The NDVI from MODIS has been corrected for molecular scattering, ozone absorption, and aerosols. According to land cover and climatic characteristics, the monthly time series MODIS NDVI data starting from February 18 to December 18 were ordered for the years 2000, 2003, and 2006. Data were acquired from the MODIS tile (h26 v05) for state wide coverage. Next, the

| Table 1 Areas of the six types of land cover in the Longliu Watershed in 2000. |
|---------------------------------|-----------------|-----------------|-----------------|
| First level classes | Second level classes | Area (ha) | Ratio (% of total) |
| Farmland | Paddy land, dry land | 392,696 | 11.46 |
| Forestry | Forest, shrub, woods | 489,799 | 14.29 |
| Grassland | Dense grass, moderate grass, sparse grass | 2,125,454 | 62.01 |
| Water area | Stream, river, lake, reservoir and pond | 72,405 | 2.11 |
| Construction land | Urban built up, rural settlements | 19,701 | 0.57 |
| Bare land | Sandy land, swampland, bare soil, bare rock | 327,487 | 9.55 |
NDVI data was mosaiced and geo-referenced from its native SIN projection to the Universal Transverse Mercator (UTM) projection system by the nearest neighbour re-sampling method (Turner et al., 2006). All MODIS images acquired at different dates in the three years were assumed to be well co-registered; therefore, no further geometric correction was implemented. The MOD13Q1 is the maximum NDVI composition over a 16-day period and has been generally accepted for estimating the biomass green vegetation (Goetz et al., 2006). After deriving the NDVI fractional cover of all six land cover types in each MODIS NDVI pixel, the grassland areas in all 36 acquired images were extracted, and the grassland NDVI values were averaged. Based on these NDVI values, a model describing NDVI as a function of Julian day was explored to describe the daily NDVI variations. Furthermore, an exponential general regression model based on NDVI data for all three years combined was developed.

(3) Landsat data set. For each of the four periods analysed (mid 1970s, mid 1990s, approximately 2000 and approximately 2006), we selected five Landsat scenes that had minimal cloud cover and that covered the study area. The images were selected according to the following criteria: (i) cloud free, (ii) preferably from July and August (when the NDVI peaks), and (iii) preferably from a single year. Table 2 shows that these criteria were only partially met. The selected scenes were mosaiced after processing with a new approach (explained further below) to observe regional grassland biomass dynamics.

The images were atmospherically corrected using the ENVI Flash transfer code (Purkis et al., 2006) and geo-referenced by a 2nd order polynomial warping approach with reference to a number of ground control points on a 1:50,000 topographic map with a nearest-neighbour sampling method (Busetto et al., 2008). Finally, the regional NDVI distribution was masked within the study area boundary using ENVI 4.2 software.

After merging the regional Landsat-derived NDVI values into same date, a $7 \times 7$ pixel window ($28 \text{ m} \times 28 \text{ m}$) was applied to collect grassland NDVI from all sample sites. The plot size was determined by image temporal resolution and sample plot features; this procedure can exclude pixels located outside a given plot. Grassland NDVI values were extracted from different types of remote sensors (MSS, TM and ETM+) for 29 plots in the four observed years. The different sensors are sensitive to different wavelengths in the bands that were used to calculate NDVI values, such that there are systematic differences in the NDVI values derived from different sensors. Steven et al. (2003) found that the calculation of NDVI from different sensors had similar sensitivity to green vegetation, provided the bands exclude noisy regions and avoid the red-edge. Therefore, the NDVI from the different Landsat
sensors can be standardised with the aid of the following equations:

\[
\text{NDVI}_{\text{TMI}} = 1.052 \text{NDVI}_{\text{MSS}} - 0.021
\]

\[
\text{NDVI}_{\text{TMI}} = 0.979 \text{NDVI}_{\text{ETM+}} + 0.002
\]

2.4. Grassland biomass investigation

Many studies have noted the strong linear relationship that exists between NDVI and biomass and have used it in a wide range of applications (Huang et al., 2010). In our study, the correlation of NDVI and grassland biomass was used to assess the reliability of the integration procedure. In July and August of 2007, grassland biomass was harvested at 29 randomly selected sites located within the grassland area at elevations below 4500 m (Fig. 3). This is when the peak NDVI values occurred. A GPS was used to locate the sites in the field. At each site, the grassland homogeneously covered a 300 m × 300 m plot to ensure homogeneity within the corresponding pixel of the MODIS NDVI product. Within a 30 m × 30 m plot at the centre of each site, aboveground grassland biomass was clipped from five 1 m × 1 m subplots located at the centre and each of the four corners. Live plant material was separated from dead plant material, and the weight of the live plant material was recorded for each of the five subplots.

3. Results

3.1. NDVI temporal principle by MODIS

The monthly patterns of grassland NDVI and precipitation for the years 2000, 2003, and 2006 are shown in Fig. 4. The fluctuation in the NDVI curve coincides with the seasonal precipitation fluctuation for the Longli Watershed. The NDVI peak occurs at the end of July (Julian day = 210), when precipitation also reaches its maximum. Similarly, the minimum in the NDVI curve occurs between December and January, when precipitation and temperatures are lowest. These seasonal oscillations correspond to the vegetation status during the growing season. In 2000, a drought year, the peak NDVI value occurred at the end of June, which was a month earlier than for years with normal rainfall. The grassland NDVI for the years 2003 and 2006 had similar trends, and the peak and minimum values appeared at similar times.

The exponential regression models for each of the three years had similar coefficients with high correlations (Table 3). The annual precipitation was 249, 267, and 330 mm for the years 2000, 2003, and 2006, respectively. Compared with historical data, the year 2000 was a drought year, the year 2003 was a normal year, and the year 2006 was a rainy year. The general regression model can be used to estimate the grassland NDVI value under most climatic conditions, and the grassland NDVI on any day can be simulated. Thus, this regression model is the bridge between the high temporal resolution in the remotely sensed data and the high spatial resolution images.

3.2. Converting NDVI information from Landsat series to comparable dates

The selected MSS images from 1970 were obtained on four different dates (Table 2; 14 and 15 July were considered as the same date). Using the general regression model, the grassland NDVI for these four dates was converted to the expected NDVI value on 15 July. The second step was to obtain the coefficients for the time

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**Table 2**

<table>
<thead>
<tr>
<th>Path/Row</th>
<th>MSS</th>
<th>TM</th>
<th>ETM+</th>
<th>TM</th>
</tr>
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</table>

**Table 3**

<table>
<thead>
<tr>
<th>Year</th>
<th>Regression model</th>
<th>(R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>(y = 0.0842e^{0.007x})</td>
<td>0.9004</td>
</tr>
<tr>
<td>2003</td>
<td>(y = 0.1147e^{0.0074x})</td>
<td>0.8174</td>
</tr>
<tr>
<td>2006</td>
<td>(y = 0.1245e^{0.0071x})</td>
<td>0.8954</td>
</tr>
<tr>
<td>General</td>
<td>(y = 0.1063e^{0.0070x})</td>
<td>0.8405</td>
</tr>
</tbody>
</table>

*Note: When Julian day \(d\) ≤ 210, \(x = d\); when \(d > 210, x = 420-d.\)*

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![Fig. 3](image-url) Locations of biomass investigation samples in study area.
Fig. 4. Grassland NDVI and Precipitation of Longliu Watershed in 2000, 2003 and 2006.

Fig. 5. Time series NDVI distribution in 1977, 1996, 2000, and 2006 after integration and mergence of data.
periods between 4 January and 15 July and between 22 February and 15 July; these two coefficients were 0.6731 and 0.2403, respectively. With ArcGIS 9.2 tools, the NDVI distribution images on the two days (4 January and 22 February) were multiplied by the coefficient and converted into 15 July. After the conversion, the Landsat scenes were merged into one scene with NDVI values from the same date (Fig. 5a).

The TM images for 1996 occurred on 15 August, 16 August, 19 July and 10 May; their NDVI coefficients on 15 July were 0.9690, 0.9690, 0.9942, and 0.6021, respectively. With raster calculation and mergerence, the vegetation NDVI distribution in 1996 was standardised on 15 July (Fig. 5b). The ETM+ images in 2000 come from 5 July, 12 July, 12 August, and 9 October, and the coefficients expressing their relationship with 15 July were 0.9940, 0.9782, 0.9907, and 0.6633, respectively. Fig. 5c shows the NDVI distribution from ETM+ in 2000. The TM images in 2006 come from 5 August, 10 September, and 20 September, and their coefficients expressing their relationship with 15 July were 0.9961, 0.8775, and 0.8126, respectively. The merged regional NDVI distribution from TM in 2006 is shown in Fig. 5d.

3.3. Integration of NDVI

The sensor transformation equations were used to convert information from the MSS and ETM+ sensors into TM sensor format (Table 4). Applying this procedure, the grassland NDVI was integrated into a consistent format. The grassland NDVI for the region frequently peaked near the middle of July (Fig. 4); therefore, the data in Table 4 can be used to demonstrate the biophysical characteristics of fully grown grassland. The NDVI data for the fully grown grassland reflect the green biomass build-up over seven and a half months; this information can be used as an indicator of yearly grassland productivity. Therefore, the grassland NDVI on 15 July was used as a proxy of yearly grassland productivity.


With the integrated results obtained for 1997–2006, the vegetation in the four years had the same spatial distribution trends (Fig. 5). Relatively higher NDVI vegetation is observed in the southern and northern parts of the study region in all four maps. The terrestrial pattern can be identified according to the digital elevation model and the field investigation. Forest and dense grasslands are situated primarily in the top and middle elevations greater than 3800 m. The grassland vegetation areas (green patches) became smaller and more fragile through time, but dark green areas (forest) in the watershed boundary seem to be well conserved. The patches in the east and central parts of the study region with lower NDVI values were identified as the harvested farmlands. The bare lands in the west and southwest parts of the study region had the lowest NDVI values.

The statistical analysis based on the information obtained from the standardised treatment of the NDVI values was used to assess the detailed vegetation biomass dynamics over three decades (Table 5). The results revealed that the regional grassland NDVI range became more constrained in the recent ten-year period compared with the first twenty years because minimum values increased and maximum values decreased. Specifically, the minimum (Min) grassland NDVI increased from 0.0790 in 1977 to 0.1310 in 2006. Along with this increase, the maximum (Max) NDVI showed the opposite trend, starting at 0.5946 in 1977 and then decreasing to 0.4878 in 2006. In addition, the Standard Error (Std. Error) is smaller for the last ten years than in the first two decades, supporting the conclusion of a more narrow range. The decreased range and steady average suggests that the patches with abundant grass declined and the patches with less grass increased.

3.5. Assessment of the procedure reliability

The live grass biomass on each of the 29 sample plots was correlated with NDVI data from both TM and MODIS images in 2006. The NDVI from TM data are listed in Table 4. The NDVI data from the MODIS images were extracted from those 250 m × 250 m pixels that contained the sampling plots. The fitted regression model achieved an acceptable coefficient of determination (Fig. 6). The coefficient for the NDVI_{MODIS} Model (0.7582) is higher than the coefficient for the NDVI_{TM} model (0.6182), suggesting that the NDVI_{MODIS} explains grass biomass better than NDVI_{TM}. The main reason for this could be that MODIS has a coarser spatial resolution than Landsat, and the larger area per pixel averages across the variation. On the other hand, the NDVI_{MODIS} is maximised within a sixteen-day period. Therefore, the NDVI value derived from the MODIS sensor is larger than that from the TM system for an image of the same area, which would likely lead to a more reliable regression model.
Table 6
Statistical analysis of NDVI from two sensors.

<table>
<thead>
<tr>
<th>Model</th>
<th>Index</th>
<th>Sum of squares</th>
<th>df</th>
<th>Mean square</th>
<th>( F )</th>
<th>Sig.</th>
<th>( R^2 )</th>
<th>Adjusted ( R^2 )</th>
<th>Std. error</th>
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<tbody>
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<td>1,141,556</td>
<td>3</td>
<td>380518.6</td>
<td>39.73</td>
<td>0.001</td>
<td>0.688</td>
<td>0.671</td>
<td>97.868</td>
</tr>
<tr>
<td></td>
<td>Residual</td>
<td>517221.9</td>
<td>54</td>
<td>9578.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>1,658,778</td>
<td>57</td>
<td>–</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2b</td>
<td>Regression</td>
<td>1,141,256</td>
<td>2</td>
<td>570628.2</td>
<td>60.64</td>
<td>0.001</td>
<td>0.688</td>
<td>0.6717</td>
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<td></td>
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<tr>
<td></td>
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<td>–</td>
<td></td>
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<td>3c</td>
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<td>1,110,485</td>
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<td>57</td>
<td>–</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Predictors: (constant), intersection, NDVI, sensor.

b Predictors: (constant), intersection, NDVI.

c Predictors: (constant), NDVI.

A general regression model describing the relationship between grass biomass and all NDVI values (58 samples from both the TM and the MODIS sensors for 2006) was constructed, and the difference between the regression models of each of the two sensors was analysed. The NDVI values from the two sensors and their intersection were treated as predictors, and biomass was the dependent variable (Table 6). Multiple linear regressions show that the \( R^2 \) values for the three models are 0.688, 0.688, and 0.670, respectively. From this, we conclude that the multiple regression model that considers the difference of the two sensors is not significantly different from the model that neglects their difference. Consequently, the general regression model in Fig. 6 can be used to express the biomass data with NDVI values from either sensor for the time period in this study.

4. Discussion

4.1. Grassland temporal–spatial dynamics

The principal advantage of the data integration procedure developed in this study is that it provides a repeatable method that generates long-term spatial–temporal features of vegetation NDVI that removed systematic differences and thus can be compared. The link between precipitation and NDVI has been demonstrated previously by Udelhoven et al. (2009). The monthly MODIS NDVI data reveal the variation arising during the growing season (Fig. 4). Examining the data on a monthly scale, the NDVI trend is consistent with monthly precipitation. Particularly useful is the fact that NDVI data for the spring of 2000, a relatively dry year, are much lower compared with similar time periods in the other three years. The monthly variability trends indicate that the grassland NDVI fluctuation is primarily due to fluctuations in precipitation. On the yearly scale, the correlation coefficient (0.9065) for the relationship between grassland NDVI and precipitation reveals that precipitation is the key factor in grassland biomass fluctuation.

4.2. Application in terrestrial ecology

The NDVI has been widely used as an indicator in terrestrial ecology. With the integrated NDVI data, the long-term watershed vegetation quality was quantified and assessed, which will provide a useful method for terrestrial ecology and environmental management. In this underdeveloped area, the disturbance by human activity is low, and variation in NDVI comes primarily from natural variation. The long-term assessment of dynamic changes in grassland cover can provide important information for the quality and identification of terrestrial ecology variables. This information is quite important for sustainable development, particularly for biodiversity conservation.

4.3. Uncertainty analysis

The lack of a difference between the models from the NDVI data obtained directly from MODIS and the integrated TM data indicate that the integration process covered the information from both sensors. This provides a reliable method for characterising long-term spatial–temporal features of vegetation NDVI. However, there are still some uncertainties in the procedure, which is seen in the high scatter observed in Fig. 6. One hypothesis for this is that the NDVI does not express the vegetation status completely. A second hypothesis is that the geometric correction of all RS data is not completely accurate, which can be validated with field investigations at smaller scales.

5. Conclusion

In conclusion, this study constructs a methodology that integrates high temporal but low spatial resolution MODIS data with low temporal but high spatial resolution Landsat data. In the case study, the novel approach was used to summarise the temporal and spatial dynamics of grass biomass in a watershed in the upper reaches of the Yellow River. The study demonstrates that the combination of NDVI data from MODIS and Landsat sources can lead to a deeper understanding of large-scale vegetation dynamics over a time period of several decades. Compared with previous studies, this procedure provides more accurate quantitative NDVI information, which is helpful for regional environmental management. Although there are still some uncertainties, the innovative procedure provides information about watershed terrestrial ecology dynamics with both higher temporal and spatial resolution over a long period. The statistical analysis indicated that the integration model...
process is reasonable and can provide reliable information about vegetation NDVI. This procedure merits further study.

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References


