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Assimilating multi-source remotely sensed data into a light use efficiency model for net primary productivity estimation

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ABSTRACT

High spatiotemporal resolution satellite data are necessary for the retrieval of vegetation indexes, such as Normalized Difference Vegetation Index (NDVI), to be assimilated into the Carnegie-Ames-Stanford Approach (CASA) model for net primary productivity (NPP) estimation, especially in the growing season. However, current remotely sensed data cannot accurately monitor vegetation changes at high spatiotemporal resolution. To consider both temporal and spatial information, spatiotemporal fusion models have been developed to obtain the temporal information from high temporal resolution data (e.g., MODIS) together with the spatial information from high spatial resolution data (e.g., Landsat). In this paper, synthetic NDVI images with the spatial resolution of Landsat data and the temporal resolution of MODIS data were first produced using spatiotemporal fusion models. Next, phenological features were extracted from synthetic NDVI time series data to improve land cover classification accuracy. Finally, we evaluated the approach of assimilating the synthetic NDVI and land cover classification map into the CASA model for synthetic NPP estimation. The results revealed that the accuracy of the synthetic NPP was better than NPP estimation from non-fusion NDVI data, and improving the land cover classification accuracy could improve the accuracy of the synthetic NPP estimation. Furthermore, the monthly synthetic NPP showed a significant exponential relationship with the temperature, rainfall, and solar radiation of the current and previous month.

1. Introduction

As an important component of the terrestrial carbon cycle, net primary productivity (NPP) represents the amount of dry organic matter accumulated through the process of photosynthesis by vegetation per unit time and per unit area, and directly reflects the productivity of the vegetation under natural environmental conditions (Field et al., 1998; Lieth and Whittaker, 2012; Oke et al., 1989). It is worth noting that NPP acts not only as the driving force of the carbon cycle, but also as a primary factor in investigating carbon sources and sinks, and adjusting ecosystem processes (Field et al., 1998). Thus, the accurate monitoring of NPP can help explain the rising levels of atmospheric carbon dioxide (CO_2) and global climate change.

The completely manual measurement of NPP is almost impossible at a regional or global scale. With features such as observing large areas synchronously, as well as being timely and economical, remote sensing is considered a convenient means for mapping and monitoring the dynamic change of vegetation under no restriction of natural and socio-economic conditions. While modeling the NPP, the Carnegie-Ames-Stanford Approach (CASA) model, based on the concept of light use efficiency (LUE), has been widely used because of its capability to use remotely sensed biophysical parameters that reveal the spatiotemporal variations of vegetation growth conditions (Potter et al., 1993; Monteith, 1972; Piao et al., 2005; Potter et al., 2012; Pei et al., 2013; Yan et al., 2018). For instance, Normalized Difference Vegetation Index (NDVI) derived from remotely sensed data has been successfully assimilated into the CASA model. However, there are often contradictions between the spatial and temporal resolutions of optical sensors due to the limitations of their physical performance. In general, improvements in the spatial resolution of optical sensors are accompanied by decreases in temporal resolution. For example, data from AVHRR and MODIS can be acquired at high temporal resolution (e.g., 0.5 d), making them suitable for monitoring vegetation change in a continuous time series, but the coarse spatial resolution (e.g., 250 m or larger) of those sensors limit their ability to detect the subtle ecological processes. These subtle ecological processes, which occur at a sub-pixel scale, are more suited to sensors with high spatial resolutions (e.g., Landsat). However, especially during the growing season, the long revisit cycle of these sensors and frequent cloud contamination hinder the efforts to monitor vegetation change in a timely manner. To solve the

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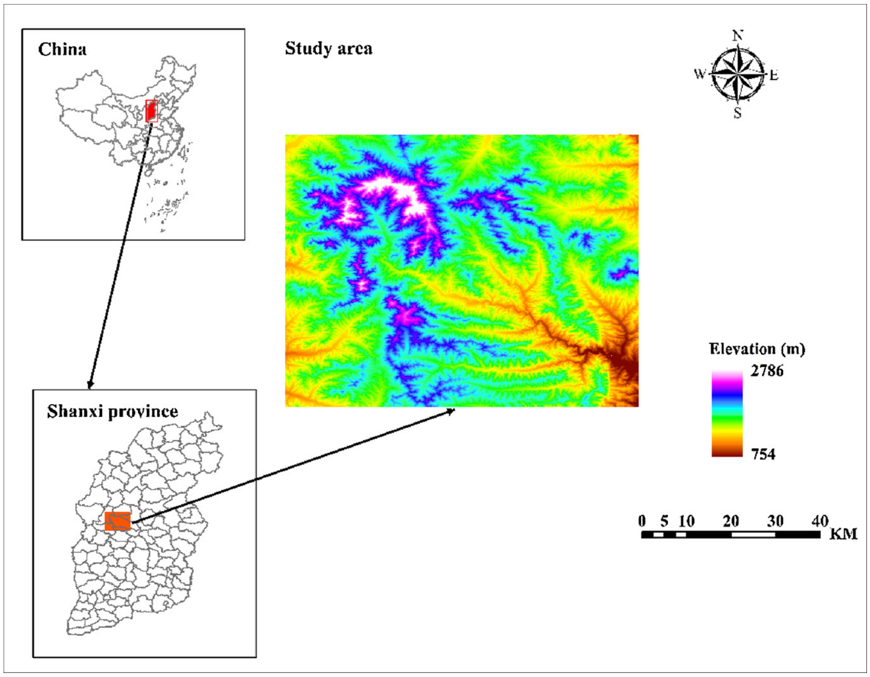

Fig. 1. Location of the study area.

"spatiotemporal contradiction" of remotely sensed data, an ideal approach is to integrate the advantages of these two different types of satellite sensors.

The spatiotemporal fusion method is an excellent technology that can integrate the superiority of multi-source satellites with fine spatial resolution or frequent temporal coverage, and generate high spatiotemporal resolution data characterized with spatial resolution that is same as high spatial resolution data, and with temporal resolution that is similar to high temporal resolution data. In this regard, Gao et al. (2006) developed the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM). The STARFM algorithm estimates surface reflectance values based on spatially and spectrally weighted differences between contemporaneous paired fine and coarse spatial resolution images, and a coarse spatial resolution image collected on the prediction day. To improve the applicability of STARFM in the spatial heterogeneity region, Zhu et al. (2010) developed an enhanced STARFM (ESTARFM) based on two pairs of contemporaneous fine and coarse resolution images. Compared to STARFM, the major difference of ESTARFM is the introduction of a conversion coefficient of similar pixels in the contemporaneous fine and coarse resolution images. These two models have been widely used in developing missing images in a time series, detecting phenology, inversing urban environment parameters, estimating gross primary production, evaluating biomass, and calculating land surface temperature (Bhandari et al., 2012; Chen et al., 2010; Liu and Weng, 2012; Singh, 2011; Walker et al., 2014; Dong et al., 2016; Weng et al., 2014; Shen et al., 2016). These results have shown that this kind of fusion model provides a feasible way to solve the "spatiotemporal contradiction" of different remotely sensed datasets. Given this, this paper seeks to produce a synthetic NDVI with high spatiotemporal resolution using the STARFM and ESTRAFM algorithms to improve the accuracy of NPP estimation.

Furthermore, land cover map is also the key parameter of the CASA model. An accurate land cover map is of great importance to obtaining accurate NPP estimation (Zhu, 2005; Yu et al., 2009). By providing multi-spectral and multi-temporal images, rapidly developed remote sensing technology has become a reliable way to classify different land cover types. The NDVI time series derived from the composition of spectral bands can characterize vegetation growth well, and has been widely applied to land cover classification (DeFries and Townshend, 1994; Hansen et al., 2000; Lunetta et al., 2006; Wardlow et al., 2007; Zhao et al., 2017). Nevertheless, it is always difficult to obtain NDVI data with high spatiotemporal resolution from remote sensing platforms, which greatly limits the improvement of classification accuracy at a finer scale. To solve this problem, researchers have used spatiotemporal fusion models to perform finer-scale land cover classification. For instance, Jia et al. (2014) extracted four temporal features (i.e., the maximum, the minimum, the mean and the standard deviation value) from fused time series NDVI data, and composited these features with Landsat spectral data to improve classification accuracy. Chen et al. (2017) and Chen et al. (2015) further integrated temporal and other features (e.g., angular and topographic features) to achieve better land cover classification accuracy. However, the features used in their studies are only the basic statistical variables. More significant features, such as phenological features, should be developed for land cover classification (Jia et al., 2014). Based on this, this study try to directly extract phenological features from a synthetic NDVI time series, and use them to improve classification accuracy.

The main goal of this study was to assess a way of combining the spatiotemporal fusion models and the CASA model for NPP estimation. This research mainly focuses on three focal points: (1) generating the synthetic NDVI time series via fusing Landsat and MODIS data; (2) extracting phenological features from the synthetic NDVI time series to conduct the land cover classification; and (3) assimilating the synthetic NDVI and land cover classification map into the CASA model for synthetic NPP estimation.

2. Materials and methods

2.1. Study area

The study area (37°20′–38°54′N, 110°18′–112°05′E) is located in the central region of the Luliang Mountain, Shanxi Province, China (Fig. 1). In this region, the primary climate type is temperate continental monsoon climate, characterized by four distinct seasons, high temperature and more rain in the summer, and low temperature and less rainfall in the winter. The annual average temperature is 3– 4 °C and the annual average rainfall is 830.80 mm. The elevation is 754–2786 m. The dominant land cover is forest, with scattered grassland, cropland,