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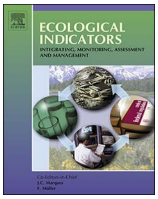

Vegetation response to climate conditions based on NDVI simulations using stepwise cluster analysis for the Three-River Headwaters region of China

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ABSTRACT

Located in the hinterland of the Qinghai-Tibet Plateau, the Three-River Headwaters region (THR) features unique eco-environmental conditions and fragile ecosystems, which are very vulnerable to climate change. To investigate the impacts of varying climate conditions, the Normalized Difference Vegetation Index (NDVI) was employed as an indicator to reflect the response of the vegetation dynamics. A series of pixel based VEgetation Dynamics Stepwise-cluster Prediction models (VEDSP) were proposed to establish the relations between NDVI and climate conditions through using the data series of remotely sensed precipitation and temperature. The obtained simulation results for training and testing showed very good agreements with the monthly NDVI observations. Rather than air temperature, the precipitation was identified as the critical climatic factor to result in various NDVI values, especially the 2-month consecutive average precipitation. The developed VEDSP models were further applied to predict the temporal and spatial distributions of NDVI values for five future years (2020, 2040, 2060, 2080 and 2100) according to climate projections of Euro-Mediterranean Center on Climate Change Climate Model (CMCC-CM) under the RCP4.5 scenario. The projected changes of NDVI indicated a slightly significant positive trend in annual average NDVI values, while the monthly peak values of NDVI for the entire THR would decrease by 5.34% in the future relative to the historical averages of the time period from 2000 to 2013. Distinct effects of precipitation and temperature on the response of NDVI were further demonstrated. Findings from this study would be used to help analyze the ecological effects of climate change and enhance the understanding of ecological changes in the future.

1. Introduction

Vegetation cover is one of the most important indices to evaluate the conditions of ecosystem (Wang et al., 2015) as its changes are closely related to livestock breeding, deforestation and desertification monitoring and anthropogenic activities (Purevdorj et al., 1998). However, how to effectively quantify long-term changes of land cover is still a dilemma in ecological studies and watershed management. As far as such issue is concerned, the Normalized Difference Vegetation Index (NDVI), which is derived from the difference between the reflectance ratio in the red band and the near-infrared band, was proved to be very efficient (Carlson and Ripley, 1997). Over the past decades, the relation between NDVI and vegetation cover has been well established theoretically and empirically (Pettorelli et al., 2005), and NDVI has been widely used as an effective indicator to quantify the vegetation cover in many studies (Field et al., 1995; Prince and Goward, 1995; Schloss et al., 1999; Fang et al., 2001; Xin et al., 2008; Vlek et al., 2010; Le et al., 2016; Rafique et al., 2016). It is agreed that strategies for ecosystem protection in a region would result in little effects without analysis of an adequate spatial resolution or length of ecological records. With the release of increasingly accessible products of long-term and high resolution satellites datasets, it has become very convenient to conduct ecological studies from NDVI at both regional and global scales since the early 1990s (Fensholt and Proud, 2012; Jia et al., 2016). Therefore, the knowledge of vegetation dynamics based on NDVI would substantially help to support decision making in local development and planning.

Correlation between NDVI and climatic factors provides a very

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practical way to explore the corresponding response of ecosystems to climate change (Potter and Brooks, 1998). It is well acknowledged that the spatial distribution of NDVI is a function of climate conditions, such as precipitation and temperature, and many studies have been undertaken to explore the response of NDVI to variations in precipitation and temperature at regional and global scales (Rundquist, 1994; Braswell et al., 1997; Kaufmann et al., 2003; Liang et al., 2015; Tian et al., 2015). Among these studies, complex correlation coefficient and partial correlation coefficient from linear regression were commonly used to reveal the relation between NDVI and climatic factors due to the simplicity of the methodology (Fensholt et al., 2009). These investigations aimed at determining the correlation and lag-correlation between climatic factors and NDVI, and thus identifying the main driving factors that force the changes of an ecosystem. Owing to the complexity of ecosystems and the uncertainty of the mechanisms driving the vegetation dynamics under climate change (Piao et al., 2006), the commonly used methods mentioned above were not capable of revealing the complex non-linear relation in the process of vegetation dynamics (Peng et al., 2012). As such, the linear assumptions based regression models would no doubt lead to distinct conclusions as presented in previous studies. For theses varying results, they might be attributed to such facts as different climate conditions of study areas, different land covers and climatic anomalies of the chosen years.

The Three-River Headwaters region (THR), also known as the “Chinese water tower”, is the source region of the Yangtze, Yellow, and Lancang Rivers and has been identified to be extremely sensitive to climate change (Liu et al., 2014). Many studies have focused on climate change, vegetation cover and ecological protection of this region (Liu et al., 2008; Xu et al., 2008; Fan et al., 2010; Li et al., 2011; Li et al., 2014; Liu et al., 2014; Cai et al., 2015), especially on the temporal and spatial distribution of NDVI values and the historical relation between climatic factors and NDVI. For example, a continuously decreasing trend of grassland was found in the THR based on the spatial characteristics of vegetation distribution in the late 1970s, early 1990s, and 2004 (Liu et al., 2008). Through using the residual analysis method and simple linear regression, Li et al. (2011) demonstrated that the contribution of climatic factors and human activities to vegetation growth were 79.3% and 20.7%, respectively. Liu et al. (2014) used linear regression analysis and Hurst exponent analysis to reveal an increasing trend in the spatial-temporal coverage of vegetation in the northern part of THR from 2000 to 2011 and a decreasing trend in the south, with a certain time lag in the response of vegetation coverage to precipitation and potential evapotranspiration. No matter that many interesting and significant findings were generalized based on the relation between NDVI and vegetation cover in the THR, it is noted that linear regression tools being applied would also result in high inaccuracy and uncertainties associated with the simulation and prediction. As a result, these obtained conclusions would be likely to be unreliable due to the limitations of the linear assumption. Thus, it is desired that more effective methods should be proposed to address the complex and nonlinear relations between climatic factors and NDVI in such area as THR. Accordingly, the knowledge of vegetation dynamics in response to climate change would need to be further reflected and expanded.

Besides the linear regression, some studies applied the Dynamic Global Vegetation Model (DGVM) to simulate the vegetation distribution of the THR under climate change, such as the modified Lund-Potsdam-Jena Dynamic Global Vegetation Model (LPJ model) with climate projections to analyze the changing tendency of vegetation distribution in the Qinghai-Tibet Plateau (Gao et al., 2016). The LPJ model is a biogeochemistry process-based model with climatic factors (precipitation, temperature, cloud amount, etc.), soil texture and CO_2 concentration as inputs to obtain the potential evapotranspiration and soil temperature, and then, calculate the seasonal plants functional types (Sitch et al., 2003). The results showed that the NPP was projected to increase by 79% and 134% under the RCP4.5 and RCP8.5, respectively, but the parameters used were not altered with the change of climate and vegetation conditions, which might reduce the accuracy of simulation.

As a potential approach to represent nonlinear relations between climatic factors and NDVI, stepwise cluster analysis (SCA) has the ability to capture the discrete and nonlinear relation between dependent and independent variables (Wang et al., 2013; Fan et al., 2015; Han et al., 2016). The SCA can clearly show the significance levels of different clustering branches., and hence the importance of different input indices can be presented (Sun et al., 2009). Based on the monovariate automatic interaction detection algorithm, Huang (1992) firstly proposed SCA method to analyze urban air quality. This study captured discrete and nonlinear relations between explanatory, such as industrial coal consumption, population density, traffic flow and shopping density, and response variables, such as SO_2, NO_x and dust fall. Li et al. (2015) proposed a hydrological inference model using the SCA method, and applied it to daily streamflow forecasting. The results showed that the model performed reasonably in capturing different hydro-climate behaviors in dry, medium, and wet years. Although many models have been developed based on SCA to explore the nonlinear relations between dependent and independent variables in the environmental field, few studies focus on the application of SCA in investigating the correlation between climatic factors and NDVI, and predicting NDVI variations with the changing climate.

Thus, this study aims at developing an integrated model based on SCA to establish the relation between NDVI and climate conditions, which is used to reveal the vegetation dynamics through predicting the temporal and spatial distributions of NDVI values across the THR. In this paper, the principles of the proposed model and model structures based on SCA are firstly presented. Then, The model performance for the simulations of monthly NDVI values, projected temporal and spatial changes of NDVI under climate change scenario, and the response of vegetation dynamics to climate change are sequentially analyzed and discussed. Conclusions are summarized at last.

2. Study area

According to “Plans for the National Comprehensive Experimental Zone for Ecological Conservation at the ‘Three-River headwaters region’, Qinghai” issued by China in 2005, the THR is mainly located in the hinterland of the Qinghai-Tibet Plateau, lying between 31.53–37.10°N and 89.41–102.40°E (Fig. 1). It covers an area of 312,000 km^2, of which the source regions of the Yellow (above Tangnaihai Station), Yangtze (above Zhimenda Station) and Lancang rivers (above Changdu Station) account for 30.2%, 49.4% and 9.8% of the THR, respectively. The remaining part is the internal drainage area, where rivers disappear or flow into inland lakes. The annual average runoff of THR is $47.5 \times 10^9\,m^3$, consisting of 20.1, 12.4, and $15.0 \times 10^9\,m^3$ from the Yellow, Yangtze and Lancang Rivers, respectively (Zhang et al., 2011).

In accordance with the Qinghai-Tibet plateau, the THR bears a climate with a wet and warm summer and a cool and dry winter, mainly due to high elevation (3335–6564 m) and the influence of the Asian monsoon. From 1965 to 2004, the annual average precipitation was 445 mm, approximately 85% of which occurring between May to September, and the annual average temperature was $-1.45\,°C$. Moreover, precipitation was found to decrease from east to west (Zhang et al., 2011). In addition to large spatial and temporal variations in precipitation and air temperature, the drought in this region was also found to become increasingly severe after 1990s with annual precipitation from 262 to 773 mm and annual evaporation ranging 730–1700 mm (Yi et al., 2011).

As shown in Fig. 2, there are large spatial variations in the monthly NDVI values across the region, while the vegetation types are mainly alpine grassland and alpine steppe (Hu et al., 2011). Generally, the THR could be further divided into three sub-regions: 1) the south-eastern sub-region with NDVI values from 0.3 to 0.5 is covered by evergreen