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Response of vegetation pattern to different landform and watertable depth in Hailiutu River basin, Northwestern China

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Abstract The spatial distribution of vegetation pattern and vegetation cover fraction (VCF) was quantified with remote sensing data in the Hailiutu River basin, a semiarid area in North China. The moderate resolution imaging spectroradiometer normalized different vegetation index (NDVI) values for 4 years from 2008 to 2011 and field observation data were used to assess the impact of climate factors, landform and depth to water table on vegetation distribution at large scale. In the VCF map, 74 % of the study area is covered with low and low-medium density vegetation, 24 % of the catchment is occupied by mediumhigh and high-density vegetation, and 2 % of area is bare soil. The relationship between NDVI and climate factors indicated that NDVI is correlated with relative humidity and precipitation. In the river catchment, NDVI increases gradually from landform of sand dune, eolian sand soil to

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College of Water Resources and Environment, Hohai University, Nanjing 210098, China e-mail: danrong_zhang@hhu.edu.cn river valley; 92.4 % of low NDVI from 0.15 to 0.3 is mostly distributed in sand dunes and the vegetation type is shrubs. Crops, shrubs and some dry willows dominate in eolian sand soil and 82.5 % of the NDVI varies between 0.2 and 0.35. In the river valley, 70.4 % of NDVI ranges between 0.25 and 0.4, and grass, dry willow and some crops are the main plants. Shrubs development of *Korshinsk peashrub* and *Salix psammophila* are dependent on groundwater by analyzing NDVI response to groundwater depth. However, NDVI of *Artemisia desertorum* had little sensitivity to groundwater.

Keywords Vegetation patterns · Climate change · Remote sensing · MODIS NDVI · North China

Introduction

Spatial distribution of vegetation patterns, as an important index of ecosystems, can reflect eco-environmental variation in arid and semiarid areas; and it has been frequently illustrated by remote sensing data. Climate change, landform and groundwater depth play an important role in vegetation dynamics at large scale (Lucht et al. 2002; Naumburg et al. 2005; Nezlin et al. 2005; White et al. 2005; Eamus et al. 2006). Vegetation variation is generally sensitive to climate factors and the climate effect on vegetation in arid regions has been studied by many researchers (Nemani et al. 2003; Roerink et al. 2003; Zeng and Yang 2009; Hu et al. 2011). Some of them studied the effect of one or two climate factors, normally rainfall and temperature, on vegetation variation. The others used more variables to investigate climate change and vegetation response. Furthermore, time lag between vegetation and climate factors was also discussed in some studies and the result improved understanding of the response of vegetation to climate change (Richard and Poccard 1998; Zhang et al. 2003).

Landform effect on the ground surface is also important for vegetation change and the remote sensing technique was used widely in related analysis. Lunetta et al. (2006) studied landform impact on different vegetation pattern using multitemporal MODIS NDVI. Cuo et al. (2010) discussed vegetation response to topography based on Landsat Enhanced Thematic Mapper Plus images and provided a simplified topographic normalized method to reduce the topographic effect on land cover classification. In arid and semiarid regions, landform can influence vegetation pattern and further controls water redistribution in space.

Depth to water table is a key factor influencing vegetation growth in arid areas and the ecosystem can be groundwater-dependent characterized as vegetation (Eamus et al. 2006; Lv et al. 2012). However, different vegetation types are not impacted equally by groundwater depth changes. For example, some species collect groundwater occasionally when available and can survive without it; however, some plants could not survive without groundwater. Thus, the dependent relationship between groundwater and vegetation can be an indicator of land surface vegetation patterns (Stromberg et al. 1996; Wierda et al. 1997). Lichner et al. (2010) established the relationship between vegetation and soil moisture and further deduced the soil saturated hydraulic conductivity in different vegetation cover. Based on the response of grass and shrubs to groundwater depth, the effect of groundwater depth decrease on different vegetation types was discussed in Owens Valley, CA (Goedhart and Pataki 2011).

In arid and semiarid areas, the dependency of vegetation on climate change, landform and groundwater depth can be helpful for understanding of ecosystem response to land use change. However, our understanding is far from complete as vegetation distribution is mostly heterogeneous and can be controlled by multiple factors. In this study, MODIS NDVI and field observation data were used to investigate the influence of landform and groundwater depth on vegetation distribution pattern in Hailiutu catchment, a semiarid river basin in China. The correlations between vegetation and climate factors were discussed in analyzing NDVI response to climate change. Importantly, the authors address the twofold significance: (1) landform impact on vegetation distribution pattern and dominant vegetation type in difference landform; and (2) response of different vegetation types on groundwater depth variation.

Study area

Located in Erdos Plateau, Hailiutu River basin is a tributary of Wuding River in Shaanxi and Inner Monglia,



Fig. 1 Elevation and location of the Hailiutu River basin

China with an area of 2,606 km². The climate is typical inland arid to semiarid. The precipitation is scarce with annual average varying from 400 mm in the south to 200 mm in the north. Potential evaporation is very high ranging from 2,000 to 3,500 mm/a. The elevation decreases gradually from north to south as shown by digital elevation model (DEM) data (Fig. 1). An endorheic alkali lake occurs in the northern part of the basin, which is the discharge area of groundwater; and groundwater is the main resources of the watershed. Because of a harsh climate and fragile natural environment, desertification and soil erosion occur widely. Terrestrial ecosystems depend partially or completely on groundwater and are sensitive to climate change and groundwater levels and quality, especially changes in land use. Erdos Plateau is one of the new energy bases for China and is targeted as a priority area of western development strategy for China in the 21st century. Exploitation of coal, natural gas, oil and mineral resources has speeded up socioeconomic development in the region. The increasing water demand has been met by exploitation of groundwater resources in recent years. Increased groundwater abstraction has caused problems such as: decrease of groundwater levels, reduction of river flows, shrinking of lakes and degradation of ecosystems. To meet increasing water demand for natural resources exploitation, industrialization, urbanization and domestic water use while allocating groundwater use by ecosystem is a challenging task for the integrated water resources planning and management in Erdos Plateau.

Materials and methods

Normalized different vegetation index map

Normalized different vegetation index (NDVI) maps from the moderate resolution imaging spectroradiometer (MO-DIS), which were derived from monitoring the Earth's vegetation, can illustrate spatial and temporal variations of vegetation. These vegetation index maps have been corrected for ozone absorption, molecular scattering and aerosols (Zhan et al. 2000; Friedl et al. 2002). The MODIS NDVI data, with a 250-m spatial resolution, has been used in a wide range of disciplines, such as drought monitoring, global vegetation study, hydrologic modeling and agricultural activities (Jin and Sader 2005; Sakamoto et al. 2005; Knight et al. 2006; Lunetta et al. 2006; Wardlow et al. 2007; Caccamo et al. 2011; Hwang et al. 2011; Maire et al. 2011). For this study area, 32 MODIS NDVI images of the 16-day composites of June, July, August and September in 4 years from 2008 to 2011 were used as these 4 months are the most productive seasons for vegetation growth during a year in Northwest China. The pattern of the vegetation cover in these regions can be best reflected by the NDVI values of June, July, August and September.

Vegetation cover fraction map

Vegetation cover fraction (VCF) is one of the main quantitative indexes for forest management and vegetation community cover conditions, and it is also an important parameter in many remote sensing models, global vegetation change monitoring and regional climate modeling (Jiménez-Muñoz et al. 2009; Trimble 1990). VCF is defined as the percentage of vegetation covering the ground surface area, and it can be estimated from remote sensing data using the NDVI (Gutman and Ignatov 1998).

In this study area, the VCF is estimated by formulation as follows:

$$VCF = \frac{NDVI - NDVI_s}{NDVI_v - NDVI_s}$$
(1)

where NDVI_v and NDVI_s correspond to representative values of NDVI for 100 % vegetation and bare soil, respectively. In the Hailiutu River basin, the NDVI_v and NDVI_s correspond to NDVI values for 95 and 5 % of accumulative percentage, respectively.

Landform map

The elevation of the catchment increases from south to north (Fig. 1) and the land surface is dominated by sand covered with Xeric plants. The landform of the catchment contains valley, eolian sandy soil and sand dune



Fig. 2 Map of landform in the Hailiutu River basin

(Fig. 2). The elevation increases gradually from valley to sand dune. All the water, except in the lake, in the north discharges to the Hailiutu River formed the landform of the river.

Groundwater depth map

Based on 540 measurements of groundwater level in the Hailiutu River catchment, which includes 46 sites of field measurements of groundwater level during July 2010 (Lv et al. 2012) and 494 historical observation data, the contour map of groundwater depth was constructed by interpolating field measurements to the same spatial resolution grid as MODIS NDVI using ordinary kriging (Isaacs and Srivastave 1989; Fig. 3). It is shown that the groundwater depth in most of the study area is less than 5 m, and the depth of river valley in the south and the depth in the north area are shallower than 2 m. The regional groundwater flows to the river in the south, and it discharges to a lake in the north.



Fig. 3 The contour map of groundwater depth of 2010 in the Hailiutu River basin

Vegetation type map

The Landsat thematic image of 10 July 2010, with 30-m spatial resolution, was used for identification of vegetation types by combination of field vegetation survey. In this study, a false color composite of 3-4-5 (red–infrared–middle infrared) band was applied for further analysis. Unsupervised was selected in the image classification process and the algorithm used in classification was the ISODATA technique (iterative self-organizing data analysis). The advantage of unsupervised classification is that this method can be used without having prior knowledge of the ground cover in the study area.

The accuracy assessment of unsupervised classification can be made through a confusion matrix. The confusion matrix includes actual and predicted classification information in the classification system. The accuracy assessment can provide an overall accuracy of the map and the accuracy of individual class in the map. The classification accuracy of individual classes was evaluated by user's accuracy and producer's accuracy. The user's accuracy measures the probability that a pixel classified into a given category actually represent that category on ground. The producer's accuracy can indicate how well a certain area was classified.

The ground verification was conducted based on field sampling in July 2011. Fifteen samples were designed and located at different landforms with different vegetation cover types. The area of each sample was $1 \times 1 \text{ km}^2$. Seven to ten plots of $1 \times 1 \text{ m}^2$, $5 \times 5 \text{ m}^2$, $10 \times 10 \text{ m}^2$ were measured in each sample based on different vegetation status. To reflect the total feature of vegetation in samples, the plots were distributed randomly in each



Fig. 4 The spatial distribution of annual average NDVI from 2008 to 2011

Table 1 Statistics of VCF in Hailiutu River basin

VCF (%)	Classification	Area percentage
0–5	Bare soil	2
5-20	Low density	14
20–40	Low-medium density	33
40–60	Medium density	27
60–80	Medium-high density	15
>80	High density	9

sample. Vegetation characters of species composition, numbers, diameter and height of canopy were recorded in each plot. To improve the accuracy of VCF by field samples, the visual estimated results of seven to ten plots were averaged and the arithmetical mean value was taken as the measured VCF of this sample.

To discuss the dependency of different vegetation types on groundwater depth, the vegetation type map was upgraded to the same 250-m spatial resolution grid using the arithmetic mean, and the new vegetation type map matches the NDVI map and water table depth map. A pair



Fig. 5 Map of vegetation cover fraction in the Hailiutu River basin

 Table 2 Correlations between NDVI and meteorological factors

of NDVI and groundwater depth values can be obtained for each grid cell of different vegetation types. Generally, the water table depth has little effect on vegetation growth when the depth is larger than 8 m. Therefore, 957 pairs of water table depth and NDVI with water table depth smaller than 8 m were used in this research in total. The water table depth values were grouped by 0.1 m value ranges, and the corresponding NDVI values were averaged.

Results and discussion

The spatial distribution of annual average NDVI from 2008 to 2011 (Fig. 4) shows that the catchment is mainly covered by lower NDVI values (0.1 < NDVI < 0.3) which cover 73.2 % of the total basin area. Typical vegetation in Hailiutu River basin is dry willow, *Artemisia desertorum*, *Salix psammophila*, *Korshinsk peashrub* and crops. Most of them are arid vegetation.

Meanwhile, the statistics of VCF are shown in Table 1, and it is indicated that 74 % of the study area is covered by low and low-medium density vegetation, 24 % of the river basin is occupied by medium-high and high-density vegetation, and 2 % is bare soil (Fig. 5).

 Table 3
 Percentage statistics of NDVI groups, mean, median and standard deviation in different landforms

NDVI	Landform/percent (%)					
	Sand dune	Eolian sandy soil	Valley			
0.1–0.15	1.6	1.1	0.7			
0.15-0.2	19.6	7.1	1.2			
0.2-0.25	33	20.8	8.3			
0.25-0.3	26.3	27.8	16.7			
0.3–0.35	13.5	22.1	18.4			
0.35-0.4	4	11.8	19.2			
0.4–0.45	1.2	5.2	16.1			
0.45–0.5	0.4	2.6	9.7			
0.5-0.55	0.3	1.3	7.7			
0.55-0.6	0.1	0.3	2.1			
Average	0.219	0.283	0.366			
Median	0.213	0.276	0.363			
Standard deviation	0.048	0.065	0.093			

	0					
Air temperature	Relative humidity	Precipitation (current year)	Precipitation (1-year lag)			
-0.204	0.786	0.686	0.469			
0.449	< 0.001	0.003	0.067			
16	16	16	16			
	Air temperature -0.204 0.449 16	Air temperature Relative humidity -0.204 0.786 0.449 <0.001	Air temperature Relative humidity Precipitation (current year) -0.204 0.786 0.686 0.449 <0.001			

* Correlation is significant at the 0.01 level (2-tailed)



Fig. 6 Landuse map of the Hailiutu River basin in July 2010

Vegetation and meteorological factors

Meteorological factors, such as temperature, precipitation and relative humidity, have important impact on the spatial distribution of vegetation cover. To correspond with the NDVI data, monthly values of air temperature, precipitation, 1-year lag of precipitation and relatively humidity of June, July, August and September in Wu Shenqi meteorological station during 2008–2012 were used to discuss the impact of these four meteorological factors on vegetation.

Bivariate correlation analysis in SPSS was used to determine if NDVI and climatic factors are linearly related to each other. The correlation of the NDVI values with meteorological factors in the study area was shown in Table 2. The correlation is significant at the 0.01 level (2tailed). The result indicated that there is a significant correlation between relative humidity and NDVI; the Pearson correlation coefficient is 0.786; and the *p* value is smaller than 0.001. As observed in Table 2, precipitation of current year is also correlated with NDVI by higher correlation coefficient and low p value. However, it can be noted that p values of air temperature and precipitation of 1-year lag are generally high. These high p values indicated that these two climatic factors have little correlation with NDVI in the Hailiutu catchment. Thus, air temperature has little impact on vegetation growth.

Vegetation and landform

The NDVI values were grouped by 0.05 value ranging from 0.1 to 0.6. The corresponding NDVI pixel numbers in each interval for different landforms of river valley, eolian sandy soil and sand dune were calculated, respectively. The percentage statistics of each group in NDVI pixel numbers for different landforms is shown in Table 3.

It can be seen that the low NDVI is mainly distributed in sand dune and 92.4 % of NDVI ranges between 0.15 and 0.3. The vegetation cover is relatively low and the main vegetation type is shrubs. The mean NDVI is 0.219 and the median is 0.213. In eolian sandy soil, 82.5 % of the NDVI values vary between 0.2 and 0.35, with the vegetation types

Table 4 Confusion matrix of the unsupervised classification image

Classified data Land cover classes	Reference data									
	FL	DW	AD	KP	SP	WB	UA	S	Row total	User's accuracy (%)
Farm land (FL)	13	1	0	0	1	0	0	1	16	81.25
Dry willow (DW)	1	8	0	0	2	0	0	0	11	72.73
A. desertorum (AD)	0	0	7	1	0	0	0	1	9	77.78
K. peashrub (KP)	0	0	0	7	1	0	0	0	8	87.50
S. psammophila (SP)	3	2	1	3	60	0	0	1	70	85.71
Water body (WB)	0	0	0	0	0	2	0	0	2	100
Urban area (UA)	0	0	0	0	0	0	2	0	2	100
Sand (S)	0	0	1	0	2	0	0	9	12	75.00
Column total	17	11	9	11	66	2	2	12	130	Overall accuracy 83.08 %
Producer's accuracy (%)	76.47	72.73	77.78	63.64	90.91	100	100	75		

1

2

3

4

5

6

7

8

Groundwater depth(m)







C S. psammophila

of crops, shrubs and some dry willows. The mean NDVI and median are 0.283 and 0.276, respectively. The higher NDVI is dominated in river valley and 70.4 % of NDVI ranges from 0.25 to 0.4. The vegetation types are crops, dry willow and grass. The river valley has the largest mean NDVI of 0.366, variation about the mean is 0.093. The mean NDVI is thus a representative value over the landform. In general, the NDVI decreases gradually from river valley, eolian sandy soil to sand dune in the Hailiutu River basin.

Vegetation types and groundwater depth

Vegetation classification and accuracy assessment

All vegetation types were classified and eight general vegetation types were distributed in the Hailiutu catchment: farmland, dry willow, A. desertorum, S. psammophila, K. peashrub, water body, urban area and bare soil (sand) (Fig. 6). A. desertorum, S. psammophila, K. peashrub are the dominant vegetation types in the study area. Fig. 8 The ecological section of dominant vegetation type in different landforms in the Hailiutu River basin



The accuracy of the vegetation classification from unsupervised technique was evaluated and presented as a confusion matrix table. The result of the confusion matrix is presented in Table 4. The accuracy assessment generated from the unsupervised classification technique showed an overall classification accuracy was 83.08 % with Kappa statistic of 0.75. The accuracy of water body and urban area in both producer's and user's accuracies were 100 % due to better spectral discrimination from other classes. The followed by *S. psammophila* class, which accuracy ranged from 85.71 to 90.91 %. However, the accuracy value on dry willow and *K. peashrub* was lower with producer's accuracies of 72.73 and 63.64 %, respectively.

Vegetation types and groundwater depth

NDVI is an index of the vegetation growth in the river catchment, and it is affected by vegetation types present at a location. Thus, NDVI is an index influenced by all vegetation species present at an area. The relationship between NDVI and water table depth can reflect the average behavior of all vegetation types to groundwater depth. Some of the vegetation species are very sensitive to groundwater depth and others may be intensive. To examine different dependency of vegetation types to groundwater, typical species as *K. peashrub, A. desertorum* and *S. psammophila* were selected based on above vegetation classification. The scatter plots and fitted lines of NDVI for different species against water table depth are shown in Fig. 7.

The result showed that the frequency distributions of NDVI for *K. peashrub* were dense when the water table depth is smaller than 5 m (Fig. 7a). When groundwater depth is getting deeper (>5 m), the frequency distributions of NDVI were less dense, indicating less vegetation growth. The fitted line also reflected that the NDVI decreases with the increase of groundwater depth when the depth is deeper than 6 m. Figure 7c illustrated that the points of density of *S. psammophila* NDVI were higher when water table depth varies between 1 and 5 m. The

NDVI points of density were low when the water table depth is larger than 5 m. The NDVI decreased when the groundwater depth is deeper than 5 m in the fitted line. As shown in Fig. 7a, c there were similar trends of decreasing NDVI values with increasing water table depth when the depth is larger than 5 m, indicating the dependence of *K. peashrub* and *S. psammophila* on the groundwater. This result matches well with field surveys; the density and growth of vegetation are higher in lowland where groundwater is shallow than those grow in the upper land.

However, the relationship between water table depth and NDVI of *A. desertorum* (Fig. 7b) showed a different trend when compared with the above two types of vegetation. The cluster of data points concentrated in the area of groundwater depth in 3–8 m. The NDVI is relatively stable and has no big change with water table depth increase. Combined with the field observation, *A. desertorum* is intensive to groundwater, and it is mainly occupied in sand and sand dune where the water table depth is relatively deeper.

The ecological section of dominant vegetation type in different landforms is shown in Fig. 8 according to field observation. Crops, dry willow, grass and some populus are developed in river valley where the water table depth is shallow. In eolian sandy soil, the main vegetation types are crops, dry willow and some shrubs (*K. peashrub* and *S. psanmophila*), which are dependent on groundwater. The deep water table area of sand dune is mainly occupied by *S. psanmophila* and *A. desertorum*, which is intensive to groundwater. *A. desertorum* is developed in the north and east boundary of the Hailiutu River basin where the water table depth is relatively deep.

Conclusion

The vegetation distribution and its impact factors in the Hailiutu River basin were discussed using NDVI, groundwater depth, landform and meteorological data. The NDVI variation is correlated with precipitation and relative humidity to some extent. The landform is an important impact factor for vegetation change, and the NDVI decreases gradually from river valley, eolian sandy soil to sand dune in the river basin.

The dependence of different vegetation types on groundwater depth were investigated in the catchment. The result indicated that *K. peashrub* and *S. psammophila* develop in response to groundwater, and the NDVI value of these two types of shrubs decreases with the increase of water table depth when the depth is larger than 5 m. However, NDVI of *A. desertorum* showed little sensitivity to groundwater because of the deep water table depth.

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