Temporal and spatial variations of net primary productivity and its response to groundwater of a typical oasis in the Tarim Basin, China Postprint

Authors: Sun Lingxiao, In recent years, machine learning, especially deep learning, has achieved remarkable success in areas such as image classification, natural language processing, speech recognition, etc. These successes typically rely on large-scale, high-quality datasets. However, in many practical applications, obtaining large-scale annotated data is often costly or even infeasible. For example, in fields such as medical diagnosis, rare species identification, industrial defect detection, etc., annotated data is scarce and difficult to obtain. This data scarcity severely limits the performance and application scope of machine learning models. To address the issue of data scarcity, researchers have proposed various methods, among which Few-shot Learning has emerged as a prominent research direction. Few-shot Learning aims to enable models to learn from extremely few (e.g., 1 or 5) annotated samples and generalize to new classes. Meta-learning, as an effective few-shot learning method, trains models on multiple tasks by "learning to learn," enabling them to quickly adapt to new tasks. Among them, metric-based meta-learning methods are popular due to their simplicity and effectiveness. These methods learn an embedding space where new classes are identified through a simple nearest-neighbor classifier. Prototypical Networks are a classic metric-based meta-learning method. It calculates the feature mean of each class in the support set as the prototype for that class, and then classifies query samples based on their distances to each prototype. Although Prototypical Networks have achieved good performance in few-shot learning, they still have some limitations. First, Prototypical Networks use simple mean calculation to obtain class prototypes, which is very sensitive to sample quality and distribution. When there are noisy samples or uneven sample distribution in the support set, the calculated prototype may not accurately represent the class. Second, Prototypical Networks typically use a fixed distance metric (e.g., Euclidean distance) for classification, which may not be optimal. To overcome these limitations, this paper proposes a novel Adaptive Prototypical Network (APN). APN dynamically assigns weights to different samples by introducing an attention mechanism, thereby generating more representative class prototypes. Specifically, APN uses an attention module to calculate the contribution of each sample to prototype generation, so that high-quality samples receive higher weights while the weights of noisy samples are suppressed. Furthermore, APN also adopts a learnable distance metric function, which can adaptively adjust the distance calculation method according to task characteristics, thereby better adapting to different data distributions. We conducted experiments on multiple standard few-shot learning datasets, including miniImageNet, tieredImageNet, and CIFAR-FS. Experimental results demonstrate that APN outperforms existing mainstream methods under both 1-shot and 5-shot settings, verifying its effectiveness. The main contributions of this paper can be summarized as follows: (1) A novel adaptive prototypical network is proposed, which dynamically generates more robust class prototypes through an attention mechanism; (2) A learnable distance metric function is designed, which can adaptively optimize the distance calculation between classes; (3) Extensive experiments are conducted on multiple benchmark datasets, verifying the effectiveness of the proposed method and achieving state-of-the-art performance., GAO Yuting, Zhang Haiyan, YU Xiang, He Jing, Dagang Wang, Ireneusz Malik, Malgorzata WISTUBA, YU Ruide, YU Yang

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Abstract

Net primary productivity (NPP) of the vegetation in an oasis can reflect the productivity capacity of a plant community under natural environmental conditions. Owing to the extreme arid climate conditions and scarce precipitation in the arid oasis regions, groundwater plays a key role in restricting the development of the vegetation. The Qira Oasis is located on the southern margin of the Taklimakan Desert (Tarim Basin, China) that is one of the most vulnerable regions regarding vegetation growth and water scarcity in the world. Based on remote sensing images of the Qira Oasis and daily meteorological data measured by the ground stations during the period 2006–2019, this study analyzed the temporal and spatial patterns of NPP in the oasis as well as its relation with the variation of groundwater depth using a modified Carnegie Ames Stanford Approach (CASA) model. At the spatial scale, NPP of the vegetation decreased from the interior of the Qira Oasis to the margin; at the temporal scale, NPP of the vegetation in the oasis fluctuated significantly (ranging from 29.80 to 50.07 g C/(m2 • month)) but generally showed an increasing trend, with the average increase rate of 0.07 g C/(m2 • month). The regions with decreasing NPP occupied 64% of the total area of the oasis. During the study period, NPP of both farmland and grassland showed an increasing trend, while that of forest showed a decreasing trend. The depth of groundwater was deep in the south of the oasis and shallow in the north, showing a gradual increasing trend from south to north. Groundwater, as one of the key factors in the surface change and evolution of the arid oasis, determines the succession direction of the vegetation in the Qira Oasis. With the increase of groundwater depth, grassland coverage and vegetation NPP decreased. During the period 2008–2015, with the recovery of groundwater level, NPP values of all types of vegetation with different coverages increased. This study will provide a scientific basis for the rational

utilization and sustainable management of groundwater resources in the oasis.

Full Text

Preamble

Temporal and Spatial Variations of Net Primary Productivity and Its Response to Groundwater in a Typical Oasis of the Tarim Basin, China

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Abstract

Net primary productivity (NPP) of vegetation in an oasis reflects the productive capacity of plant communities under natural environmental conditions. Due to extreme arid climate and scarce precipitation, groundwater plays a key role in constraining vegetation development in arid oasis regions. The Qira Oasis, located on the southern margin of the Taklimakan Desert in the Tarim Basin of China, represents one of the world' s most vulnerable regions regarding vegetation growth and water scarcity. Based on remote sensing imagery of the Qira Oasis and daily meteorological data from ground stations during 2006–2019, this study analyzed the temporal and spatial patterns of NPP and its relationship with groundwater depth variations using a modified Carnegie Ames Stanford Approach (CASA) model. At the spatial scale, NPP decreased from the interior to the margin of the Qira Oasis. At the temporal scale, NPP fluctuated significantly (ranging from 29.80 to 50.07 g C/($m^2 \cdot$ month)) but generally exhibited an increasing trend, with an average rate of 0.07 g C/($m^2 \cdot$ month). However, regions with decreasing NPP occupied 64% of the total oasis area. During the study period, NPP of both farmland and grassland showed increasing trends, while forest NPP showed a decreasing trend. Groundwater depth was deep in the southern part of the oasis and shallow in the north, gradually increasing from south to north. As a key factor in surface change and evolution of arid oases, groundwater determines the succession direction of vegetation in the Qira Oasis. With increasing groundwater depth, grassland coverage and vegetation NPP decreased. During 2008-2015, with groundwater level recovery, NPP values of all vegetation types with different coverages increased. This study provides a scientific basis for rational utilization and sustainable management of groundwater resources in the oasis.

Keywords: net primary productivity; Carnegie Ames Stanford Approach; groundwater depth; land use; NDVI; Qira Oasis

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1 Introduction

Net primary productivity (NPP) is an important component of the terrestrial carbon cycle and a significant indicator reflecting changes in global climatic conditions (Gao et al., 2013; Yang et al., 2016; Xu et al., 2020). Analyzing temporal and spatial variation patterns of NPP in regional vegetation ecosystems is not only crucial for understanding ecosystem responses to climate change, but also provides a scientific basis for eco-environmental protection, plant productivity estimation, effective natural resource management, and formulation of corresponding social and economic development strategies.

In recent years, numerous models have been developed to estimate NPP, which can be summarized into three categories (Ruimy et al., 1994): statistical models, process models, and parametric models. Statistical models estimate NPP based on climatic factors, while process models introduce additional parameters such as temperature and moisture based on parametric models. Parametric models are expressed by two factors: the photosynthetically active radiation absorbed by vegetation and solar energy conversion efficiency. Currently, the Carnegie Ames Stanford Approach (CASA) is a widely applied solar energy utilization efficiency model for regional NPP estimation (Hadian et al., 2019).

The CASA model, developed by Potter et al. (1993), is a global estimation model for terrestrial vegetation NPP based on Monteith's method for calculating plant productivity. The model offers several advantages: (1) it is relatively simple and requires few parameters; (2) vegetation and photosynthetically active radiation information can be obtained from remote sensing data, enabling vegetation coverage classification; and (3) dynamic temporal and spatial monitoring of NPP can be realized based on multitemporal remote sensing data (Field et al., 1995; Chen et al., 2003; Li et al., 2018; Guo et al., 2020).

Due to its simplicity and accuracy, the CASA model has become a mature approach widely used in NPP estimation (Mao et al., 2014). For example, Ren et al. (2020) explored NPP variation characteristics through spatial autocorrelation, while Wang et al. (2020) used process models and satellite data to calculate

NPP change processes in China over multiple years. Yu (2020) analyzed temporal and spatial variations of grassland NPP using a vegetation photosynthetic efficiency model. Moreover, NPP can serve as an indicator to evaluate regional eco-environmental systems (Taelman et al., 2016), reflecting states of ecological change such as crop yield (Jaafar and Ahmad, 2015; Hadian et al., 2019; Zhang et al., 2019), eco-environmental sensitivity (Nayak et al., 2010; Xing et al., 2010), and surface carbon storage and accumulation (Thevs et al., 2013). Numerous studies have used vegetation productivity as an index to assess land degradation and restoration (Fay, 2008; Wairiu, 2017; Kang et al., 2019). Additionally, various external factors have been combined with NPP to analyze influences of climate change (Nemani et al., 2003; Wang et al., 2020), human activities (Zhou et al., 2015; Wang et al., 2016), environmental variables (Zhang et al., 2019; Koju et al., 2020), and other factors on NPP, as well as NPP responses to these factors.

Most previous studies focused on temporal and spatial variation trends of NPP at large or medium scales, while changes in NPP and its interaction with restrictive factors at small scales were often ignored.

The Qira Oasis is located in the Tarim Basin, China. Due to its distinct arid climatic conditions and geographical location, the eco-environment of the Qira Oasis is extremely vulnerable. Protecting the eco-environment of the Qira Oasis plays a vital role in local sustainability. In arid regions, although NPP is a significant indicator reflecting regional vegetation conditions, groundwater is also an important factor influencing surface process changes (Wu et al., 2010; Zhao et al., 2020). Groundwater impacts meadow vegetation in the oasis transition zone and directly determines economic development and vegetation growth in the oasis. In recent years, as groundwater fluctuation in the Qira Oasis has been relatively large, its impact on oasis vegetation has become increasingly evident (Ding et al., 2003). Therefore, the aims of this study are to: (1) adopt the CASA model modified by Feng et al. (2014) to simulate temporal and spatial variation characteristics of vegetation NPP in the Qira Oasis during 2006–2019; and (2) analyze the relationship between vegetation NPP and groundwater in the oasis based on inversion of high-precision Normalized Difference Vegetation Index (NDVI) data. To achieve these goals, we carried out research in three aspects: (1) calculating vegetation NDVI of the Qira Oasis based on remote sensing data in June of 2006–2019; (2) analyzing temporal and spatial variations of vegetation NPP using the modified CASA model; and (3) identifying the relationship between vegetation and groundwater depth in the oasis.

2.1 Study Area

The Qira Oasis, with geographical coordinates of 35°18 –39°18 N and 80°03 –82°10 E, is located on the southern margin of the Taklimakan Desert in the Tarim Basin of China. The terrain of the Qira Oasis is high in the south and low in the north, with elevations between 1296.5 and 1370.5 m; the middle part has developed into an inclined piedmont plain. Farmland occupies a significant proportion of the oasis, followed by grassland and forest (Fig. 1 [Figure 1: see original paper]). The oasis is characterized by an arid desert climate, with an annual average temperature of 11.9°C, an extreme maximum temperature of 42.0°C, and an extreme minimum temperature of 23.9°C. Mean annual precipitation is only 35.1 mm, while evaporation is close to 2595.3 mm. The annual frost-free season is about 230 days, and annual total sunshine duration exceeds 2868 hours. The mean annual runoff of the Qira River flowing through the oasis is 1.28$×10^{8}$ m^3.

Fig. 1 Land use classification of the Qira Oasis

2.2 Research Data and Sources

Meteorological data used in this research, including daily temperature, precipitation, evaporation, humidity, and solar radiation from 2006 to 2019, were obtained from a ground meteorological station in the Qira Oasis. Groundwater data were measured from 23 monitoring wells in the Qira Oasis in June of 2008–2015. Due to difficulty in obtaining groundwater data, this study lacks data for 2012 and 2013. These groundwater data were provided by the Qira National Station of Observation and Research for the Desert-Grassland Ecosystem, China.

Land use data were accessed on 11 December 2020 from the Cloud Platform for Resource and Environment Data of the Chinese Academy of Sciences (http://www.resdc.cn/). Land use types were divided into six categories: forest, grassland, farmland, water body, construction land, and unused land (Fig. 1), with grassland further classified into three sub-categories: low-coverage grassland, medium-coverage grassland, and high-coverage grassland. Low-coverage grassland refers to natural grassland with coverage of 5%–20%. This type of grassland is sparse, highly water-deficient, and poorly utilized. Medium-coverage grassland refers to natural grassland and improved grassland with coverage of 20%–50%. High-coverage grassland refers to natural grassland, improved grassland, and mowed grassland with coverage exceeding 50%, which usually has adequate moisture conditions and thick grass cover. Land use types were interpreted, classified, and digitized according to the land classification system of the Chinese Academy of Sciences, and the interpretation results were verified through field investigation.

Remote sensing data consisted of 14 Landsat 5 and Landsat 7 images from 2006 to 2019, accessed on 5 December 2020 from the United States Geological Survey (https://earthexplorer.usgs.gov/), with a spatial resolution of 30 m and cloud content less than 10%. ENVI software was used to conduct preprocessing such as radiometric calibration, atmospheric correction, and clipping on the remote sensing data before calculating vegetation NDVI. We estimated vegetation NPP based on NDVI using the CASA model.

2.3.1 Calculation of the NDVI

The formula for calculating NDVI is as follows: (NIR - R) / (NIR + R), where R refers to the red band of visible light and NIR refers to the near-infrared band. For the TM sensor, the red band is Band 3 and the near-infrared band is Band 4; for the ETM+ sensor, the red band is Band 4 and the near-infrared band is Band 5. The calculation result shows a single-band image expressed in gray level with pixel values generally ranging from -1 to 1.

2.3.2 Calculation of Vegetation NPP

The CASA model has been widely applied among currently available models for remote sensing estimation of vegetation NPP. In addition to habitat characteristics affecting vegetation, it also incorporates characteristics of the internal action mechanism of vegetation. The model is mainly determined by photosynthetically active radiation and solar energy utilization efficiency of vegetation (Piao et al., 2001):

$$NPP = APAR \times \varepsilon$$

where NPP refers to net primary productivity of vegetation (g C/m^2); APAR refers to solar radiation absorbed by vegetation (MJ/m^2); and refers to solar energy utilization efficiency of vegetation (g C/MJ).

The restrictive factor APAR can be calculated as follows:

$$APAR = SOL \times FPAR \times 0.5$$

where SOL refers to total solar radiation (MJ/m^2), obtained from measured data of local meteorological stations; FPAR refers to the proportion of photosynthetically active radiation absorbed by vegetation, determined by maximum and minimum NDVI values and maximum and minimum solar radiation of different vegetation types.

Solar energy utilization efficiency refers to vegetation' s capacity to convert solar radiation into organic matter, which is related to actual vegetation type, temperature, precipitation, and other environmental conditions. Its calculation formula is:

$$\varepsilon = \varepsilon_{max} \times T_{\varepsilon 1} \times T_{\varepsilon 2} \times W_{\varepsilon}$$

where $T_{\varepsilon 1}$ and $T_{\varepsilon 2}$ refer to restrictive effects of temperature; W_{ε} refers to restrictive effect of moisture; and ε_{max} refers to maximum solar energy utilization efficiency corresponding to different vegetation types (g C/MJ). The ε_{max} value was obtained from the maximum solar energy utilization efficiency table proposed by Fang et al. (2003), taking into consideration the characteristics of arid regions. Temperature is expressed in Celsius (°C).

2.3.3 Slope Trend Analysis

One-dimensional linear trend analysis was adopted to investigate the trend and magnitude of temporal and spatial NPP variations during 2006–2019. Fitting of NPP variation trends was conducted at the pixel scale. Temporal variation characteristics and regional spatial variation of each pixel were summarized to reveal long-term temporal and spatial trend patterns of NPP in the region. Since one-dimensional linear trend analysis can eliminate impacts of accidental abnormal factors on vegetation growth during the study period, it can more reliably reflect NPP variation trends over a long time series. The calculation formula is as follows (Wang et al., 2020):

$$\theta_{slope} = \frac{n \times \sum_{i=1}^{n} i \times NPP_i - \sum_{i=1}^{n} i \times \sum_{i=1}^{n} NPP_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where θ_{slope} refers to the trend line slope of the pixel regression equation; n refers to the time duration of the research data (years); and NPP_i refers to the average NPP value in the ith year. If $\theta_{slope} > 0$, NPP variation shows an increasing trend during the study period; if $\theta_{slope} < 0$, NPP variation shows a decreasing trend.

2.4 Data Analysis

NDVI calculation primarily relied on the NDVI function of ENVI software. Additionally, NPP distribution of different land use types in the Qira Oasis was calculated using the ArcGIS spatial overlay tool. Variation in groundwater depth was calculated by the Kriging interpolation method, a regression algorithm for spatial modeling and interpolation of random processes based on covariance functions, implemented using ArcGIS software.

3.1.1 Temporal and Spatial Distribution Characteristics of NPP

Temporal and spatial distribution of NPP in June of 2006–2019 calculated with the CASA model is shown in Figure 2 [Figure 2: see original paper]. At the temporal scale, NPP range of vegetation in the oasis fluctuated across different years, with maximum values occurring in 2007 and minimum values in 2016. Results revealed that distribution characteristics of vegetation NPP were basically similar each year. Spatial distribution of vegetation NPP was obtained by calculating the average NPP value pixel-by-pixel during the study period.

NPP distribution in the Qira Oasis exhibited relatively significant spatial heterogeneity and was closely related to land use types. Farmland and forest with relatively high vegetation coverage were distributed inside the Qira Oasis, while grassland and unused land with relatively low vegetation coverage were distributed on the margin. Therefore, at the spatial scale, NPP in the Qira Oasis was consistently higher in internal areas than on the margin (i.e., decreasing from center to edge), with maximum NPP values scattered in distribution.

3.1.2 Temporal and Spatial Variations of NPP

As shown in Figure 3 [Figure 3: see original paper], temporal variation of NPP in the Qira Oasis generally showed a slightly increasing trend (average increase rate of 0.07 g C/($m^2 \cdot$ month)) during the entire study period. Specifically, NPP values fluctuated significantly in recent years, ranging between 29.80 and 50.07 g C/($m^2 \cdot$ month) with an average value of 38.87 g C/($m^2 \cdot$ month). The maximum value reached 50.07 g C/($m^2 \cdot$ month) in 2006, while the minimum value was only 29.80 g C/($m^2 \cdot$ month) in 2016.

Pixel-by-pixel variation trends of NPP in June of 2006–2019 calculated with the one-dimensional linear regression model are shown in Figure 4a [Figure 4: see original paper]. At the temporal scale, variation characteristics of NPP differed across spatial regions of the Qira Oasis. Based on temporal NPP variation, nearly 70% of the oasis area showed positive NPP variation, while 30% showed negative variation. At the spatial scale, relatively high temporal variation occurred on the eastern and western margins of the oasis (increase rate mostly exceeding 0.50 g C/($m^2 \cdot$ month)). Regions with negative variation were scattered inside the oasis, with increase rates mostly between -0.50 and 0.00 g C/($m^2 \cdot$ month).

To further determine increasing and decreasing conditions of NPP in the Qira Oasis during the study period, we calculated NPP differences between June 2006 and June 2019 and produced a spatial distribution map of NPP difference in ArcGIS (Fig. 4b [Figure 4: see original paper]). Regions with decreasing NPP in the Qira Oasis were relatively extensive over the 14 studied years, covering a total area of 163.21 km^2 (accounting for 64% of the oasis). These regions were mainly distributed on the oasis margin, indicating that compared with the initial study year (2006), vegetation productivity in the Qira Oasis declined and vegetation was degraded.

Fig. 4 Spatial distribution of trend slope of NPP in June of 2006–2019 (a) and spatial distribution of NPP difference between June 2006 and June 2019 (b)

3.2 Distribution Characteristics of NPP for Different Land Use Types

Figure 5 [Figure 5: see original paper] shows average NPP values of four different land use types during 2006–2019, in decreasing order as follows: forest (82.95 g C/($m^2 \cdot$ month)), farmland (61.51 g C/($m^2 \cdot$ month)), grassland (58.39 g C/($m^2 \cdot$ month)), and unused land (10.37 g C/($m^2 \cdot$ month)). Land use types showing obvious NPP fluctuation during the study period were classified into two groups. Specifically, NPP fluctuation of farmland and forest was basically identical, with maximum values appearing in 2012 (76.96 and 115.13 g C/(m^2 · month), respectively) and minimum values in 2010 (44.92 and 62.16 g C/(m^2 · month), respectively). Eventually, forest NPP variation showed a decreasing trend, while farmland NPP variation showed a slightly increasing trend. NPP fluctuation of grassland and unused land was basically similar, with maximum values appearing in 2017 (92.53 and 15.20 g C/(m^2 · month), respectively) and minimum values in 2009 (40.35 and 5.53 g C/(m^2 · month), respectively). NPP fluctuation of both grassland and unused land showed an increasing trend during the research period.

Fig. 5 NPP variation trend for different land use types in June of 2006–2019

3.3.1 Temporal and Spatial Distribution Characteristics of Groundwater in the Oasis

Based on groundwater data measured at 23 monitoring wells in the Qira Oasis in June of 2008–2015 (excluding 2012 and 2013), we obtained spatial distribution of groundwater depth using the Kriging interpolation method (Fig. 6 [Figure 6: see original paper]). Significant spatial variability in groundwater depth occurred in the Qira Oasis during these years. Groundwater depth was deep in the southern part of the oasis and shallow in the north, showing a gradual increasing trend from south to north, which was basically consistent with the topographic distribution of the oasis.

After unified classification of groundwater depth in these regions, we found that within the same range of groundwater depth, oasis area changed greatly over the years.

3.3.2 Relationship Between Grassland NPP and Groundwater Depth

Variation in vegetation NPP can reflect ecosystem capacity in a region. Many factors influence vegetation NPP variation, with water being the most important restrictive factor in arid oasis regions. However, the Qira Oasis receives little precipitation and surface water is mainly used for agricultural irrigation, so plant growth almost exclusively depends on groundwater. As shown in Table 1 , for grassland in the Qira Oasis, groundwater depth from deep to shallow was in the order of low-coverage grassland > medium-coverage grassland > high-coverage grassland, while NPP from high to low was in the order of high-coverage grassland > medium-coverage grassland > low-coverage grassland. With increasing groundwater depth, vegetation coverage declined and vegetation NPP also decreased. Among these, groundwater depth in low-coverage grassland exceeded 10.0 m, which is extremely unfavorable for plant growth.

To further analyze grassland response to groundwater depth in the Qira Oasis, we selected plants including sacsaoul, rose willow, reed, and grasses to analyze NPP variations during the groundwater observation period and explore correlations between vegetation NPP and groundwater depth. As shown in Figure 7 [Figure 7: see original paper], among the four vegetation types, reed had the highest NPP values from 2008 to 2015 (except for 2012 and 2013), with an average value of 47.97 g C/($m^2 \cdot$ month) (ranging from 38.17 to 58.94 g C/($m^2 \cdot$ month)). Grasses ranked second, with an average NPP of 33.51 g C/($m^2 \cdot$ month) (ranging from 26.68 to 40.72 g C/($m^2 \cdot$ month)). Rose willow had an average NPP of 21.55 g C/($m^2 \cdot$ month) (ranging from 16.22 to 39.04 g C/($m^2 \cdot$ month)). Sacsaoul had the lowest NPP, with an average value of 25.95 g C/($m^2 \cdot$ month) (ranging from 14.97 to 29.68 g C/($m^2 \cdot$ month)).

During the study period, reed contributed most to vegetation productivity in the Qira Oasis. As demonstrated in Figure 7 [Figure 7: see original paper], a negative correlation existed between NPP of all four vegetation types and groundwater depth, indicating that vegetation NPP declined with increasing groundwater depth. Correlation coefficients between vegetation NPP and groundwater depth were -0.29 (sacsaoul), -0.35 (rose willow), -0.89 (reed), and -0.98 (grasses), indicating stronger negative correlations of groundwater depth with NPP of reed and grasses.

Fig. 6 Spatial distribution of groundwater depth in the Qira Oasis in June of 2008 (a), 2009 (b), 2010 (c), 2011 (d), 2014 (e), and 2015 (f)

Table 1 Net primary productivity (NPP) and groundwater depth (GWP) of grassland with different coverages in the Qira Oasis in June of 2008–2015 (excluding 2012 and 2013)

Grassland type	NPP (g C/($m^2 \cdot$ month))	Groundwater depth (m)
High-coverage grassland	65.23	3.2
Medium-coverage grassland	48.17	5.8
Low-coverage grassland	25.41	12.4

Fig. 7 Variations of NPP of four different vegetation types and groundwater depth in June of 2008–2015

4.1 Degradation of the Qira Oasis and Decline of Vegetation Productivity

In arid regions surrounded by deserts, oases contain biological communities of certain scales that can form relatively stable heterogeneous ecological landscapes, exhibit obvious microclimate effects, and play vital roles in arid land development (Thomas et al., 2006; Yu et al., 2015). NPP of vegetation in an oasis can reflect the productive capacity of plant communities under natural environmental conditions. At the spatial scale, NPP was higher in the interior and lower on the margin of the Qira Oasis, decreasing from center to edge. At the temporal scale, NPP showed a slightly increasing trend during the entire study period. However, according to temporal NPP variation results, regions with decreasing NPP on the Qira Oasis margin increased to 163.21 km^2, accounting for 64% of the oasis area, indicating that vegetation productivity in the Qira Oasis declined over the studied years. In recent decades, due to rapid population growth, demand for water resources has sharply increased. Additionally, as agriculture is the main industry of the Qira Oasis, the agricultural irrigation region that relies heavily on water supplementation has continuously expanded (Zhang et al., 2019). However, the Qira Oasis is located in the Taklimakan Desert, one of the world' s driest places, where precipitation and surface runoff are inadequate (Yu et al., 2017; Bi et al., 2020). Lack of water resources is a possible reason for the decline in vegetation productivity in the Qira Oasis, leading to oasis degradation.

4.2 Impact of Regional Land Use Change on NPP Variation

Land use change directly influences ecosystem type, structure, and function, thus affecting vegetation productivity (Liu and Gao, 2009). In the Qira Oasis, vegetation NPP variation for different land use types exhibited different characteristics. Specifically, NPP of farmland and grassland showed increasing trends, with grassland increasing faster than farmland. Forest NPP showed a decreasing trend, with peak values appearing in 2012. Overall, fluctuation in NPP of forest, farmland, and grassland was relatively large, indicating poor stability and large variation in these three land use types during the study period. Possible reasons for such fluctuation include climate change and human activities such as agricultural encroachment and illegal logging. Agricultural encroachment has been a serious problem throughout the oasis for a long time. Most people in this oasis are engaged in agriculture-related work, but the amount of land suitable for farming is limited, leading to encroachment on some natural forest and grassland (Sun et al., 2021). Climate change and water resource shortages are also possible causes of changes in land use types, exerting negative effects on NPP.

4.3 Response of Grassland NPP to Groundwater Depth

Due to extreme arid climate conditions and scarce precipitation in the Qira Oasis, precipitation has little effect on plant growth. Most water needed for vegetation growth comes mainly from groundwater, making groundwater a key factor restricting vegetation growth in the oasis. Variation in groundwater depth can determine the direction of vegetation succession in the Qira Oasis. Existing studies have shown that vegetation distribution patterns in the transitional zone on the Qira Oasis margin have certain regularity with groundwater depth variation (Helge et al., 2003; Qian et al., 2018; Zhao et al., 2020), suggesting that groundwater depth can significantly impact oasis vegetation.

In this study, we found that with groundwater level recovery in the Qira Oasis during 2008–2015, NPP values of all vegetation types with different coverages increased, indicating that groundwater depth affected vegetation productivity in the oasis. The deeper the groundwater depth, the smaller the NPP, and NPP is more sensitive to groundwater depth. These findings are consistent with research results of Zhang (2001) and Mao et al. (2012), demonstrating the applicability of this research.

In 2014, oasis area with groundwater depth between 40.0 and 70.0 m decreased significantly, indicating that groundwater depth increased to some extent in 2014. Groundwater, as one of the key factors in surface change and evolution of oases in arid regions, determines vegetation succession direction in the oasis. Groundwater depth variation in the Qira Oasis was relatively large, significantly impacting survival and growth of oasis vegetation that relies on groundwater.

5 Conclusions

In this study, we conducted a comprehensive analysis of temporal and spatial variations of NPP in the Qira Oasis from 2006 to 2019 based on the modified CASA model. NPP was higher in the interior and lower on the margin of the oasis, decreasing from center to edge. Vegetation NPP ranged from 29.80 to 50.07 g $C/(m^2 \cdot month)$ during the study period, with maximum values in 2006 and minimum values in 2016. Regions with decreasing NPP accounted for 64% of the oasis area, suggesting that vegetation productivity in the oasis declined over the years. For different land use types, forest NPP showed a decreasing trend, while farmland and grassland NPP increased. Groundwater depth was the main factor affecting vegetation characteristics in the oasis.

This study provides new ideas for research on oasis vegetation productivity and complements previous studies on the relationship between groundwater level and vegetation growth in the Qira Oasis. Future research should analyze influencing factors of NPP change in the Qira Oasis and quantify the influence degree of each factor to provide information for local environmental restoration.

Acknowledgements

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Note: Figure translations are in progress. See original paper for figures.