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Human-induced vegetation degradation and response of soil nitrogen storage in typical steppes in Inner Mongolia, China

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A B S T R A C T

The residuals trend (RESTREND) method was used to analyze spatial distribution and gradients of vegetation degradation over three time scales: short-term (2006–2011), medium-term (2001–2011), and long-term (1990–2011) and the responses of soil nitrogen storage at different vegetation degradation gradients were compared. The analyses used the 10-day synthetic normalized difference vegetation index of the advanced very high resolution satellite image (1 km^2, 1990–2011) and field surveys of typical steppes of Inner Mongolia, China to compare the responses of soil nitrogen storage at different vegetation degradation gradients. The results showed highly significant regression correlation between the maximum values of the normalized difference vegetation index and the natural logarithm of precipitation on pixel spatial series. Differences in the spatial distribution and gradients of human-induced degradation of vegetation were observed. Soil nitrogen storage decreased as vegetation degradation increased; whereas the impact of vegetation degradation on soil nitrogen decreased as soil depth increased. Thus, the modified RESTREND method can identify vegetation degradation gradients at a regional scale, and the response of soil nitrogen storage can be determined through experimental analysis.

1. Introduction

Degradation of steppe vegetation resulting from grazing and changes in the natural environment has become a serious problem in arid and semi-arid regions (Downing, 1978; Perevolotsky, 1991; Abule et al., 2007; Tefera et al., 2007; Verdoodt et al., 2009). Because of the more pronounced effects of precipitation, temperature, and limited mineralization of nitrogen on the productivity of steppe ecosystems, soil nitrogen storage is an essential source of this nutrient for vegetative growth, especially in the temperate arid and semi-arid steppe ecosystems. (LeBauer and Treseder, 2008; Gao et al., 2011). Soil nitrogen storage is lost when steppe vegetation degrades and nutrients are redistributed in the ecosystem (Bird et al., 2007; Turnbull et al., 2011; Chen et al., 2013). In addition to reducing the supply of nitrogen for vegetation, this loss of soil nitrogen may increase the rate of degradation of steppe vegetation and impede restoration. As a result, studies on the interactions between the degradation of steppe vegetation and soil nitrogen storage are significant for the identification of the ecological processes of ecosystem variation, monitoring, and management of steppe ecosystems (Bird et al., 2007). However, because the degradation of steppe vegetation is a long-term process, the natural and human factors that drive steppe degradation are usually coupled (Li et al., 2012), and nitrogen has many forms and is easily influenced by natural and human factors (de Vries et al., 2011), identifying the area and the degree of steppe degradation and the response of soil nitrogen is still a challenge at a broad spatial scale.

The residual trends (RESTREND) method, a relatively new method of evaluating degradation of vegetation based on the residuals of the regression between the normalized difference vegetation index (NDVI) and precipitation, has been advocated by Evans and Geerken (2004), Wessels et al. (2007), and Li et al. (2012).

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Wessels et al. (2007) and Li et al. (2012) calculated the residuals through the regression of inter-annual precipitation variability and ΣNDVI and $NDVI_{max}$ on pixel time series, respectively. This time series is constituted with pairs of pixels from the $NDVI_{max}$ and the natural logarithm of precipitation images at a given pixel spatial location during a period of time. However, different time scales produce different regression equations, yield different residuals on pixel time series, and significantly affect the results. On different time scales, the feasibility of building regression of precipitation and ΣNDVI or $NDVI_{max}$ on pixel spatial series remains unclear. This spatial series consisted of pairs of pixels, each with the same spatial location, chosen randomly from the maximum values of the normalized difference vegetation index and natural logarithm of precipitation images at a given time.

The effect of steppe vegetation degradation on the physicochemical properties of soil has been observed in sample plots. Conant and Paustian (2002) found that vegetation degradation leads to the reduction of organic matter in soil. Given that 95% of nitrogen is stored in soil organic matter, this indicates that vegetation degradation leads to the reduction of soil nitrogen storage. By comparing pastures subjected to different conditions, Snyman and du Preez (2005) found that the total soil nitrogen content within the 0–100 cm depth of pastures that have experienced five years of degradation is considerably less than that of pastures without degradation. Verdoodt et al. (2009) also found that the organic carbon content and total nitrogen storage in topsoil in enclosed pastures of a degraded steppe are higher and more amenable to restoration compared with those of open pastures. Although these studies reveal the response of soil nitrogen storage to steppe degradation with controlled experiments, few studies have investigated the response of soil nitrogen storage to the degradation of vegetation driven by human activity in natural steppe ecosystems with long-term grazing.

China has four million hectares of steppe vegetation, accounting for 11.8% of the world's steppe area (Zhao et al., 2005). Typical Inner Mongolia steppes represent a major steppe type, accounting for 10.5% of the China's total steppe area and are an important production base for animal husbandry in China. In recent decades, however, frequent droughts and overgrazing caused by increasing demand for livestock products have resulted in the degradation of 90% of Inner Mongolia steppes (Gao et al., 2008; Gong et al., 2008; Schiborra et al., 2009; Dong et al., 2012), resulting in serious social, economic, and environmental problems (Nelson, 2006). Quantitative studies on the degradation of steppe vegetation and the corresponding responses of soil physicochemical properties are urgently needed to promote the sustainable use of steppes by steppe users and governments.

This paper documents how the RESTREND method was modified by building regression of precipitation and $NDVI_{max}$ on pixel spatial series to analyze the response of soil nitrogen storage to vegetation degradation. The objectives were to explore the feasibility of using the RESTREND method on pixel spatial series to reveal the spatial distribution characteristics of vegetative degradation, and to study the response of soil nitrogen storage to the different gradients of vegetation degradation in a typical steppe of Inner Mongolia, China.

2. Study area and sample plots

2.1. Study area

Located in a typical steppe in Inner Mongolia, China, the study area covers 97,000 km^2 (lat 43°2′–46°44′, long 113°27′–119°12′) within the Northeast China Transect of the International Geosphere Biosphere Programme (Zhang and Zhou, 2011) and includes Abag Banner, Xilin Hot, West Ujimqin Banner, and majority of East Ujimqin Banner in the administrative division (Fig. 1). This area is dominated by a temperate semi-arid climate and has average annual precipitation ranging from 200 mm to 350 mm, mainly falling in June through August. The mean annual temperature is 2.2 °C (varying between −2.3 °C and 5.6 °C) (Li et al., 2012), with the lowest mean monthly temperatures in January (−15.4 °C to −22.4 °C) and the highest temperatures in July (18.2 °C–23.4 °C). The main vegetative ecosystem is typical steppe and the dominant vegetation includes *Stipa grandis*, *Stipa krylovii*, *Leymus chinensis*, *Cleistogenes squarrosa*, *Artemisia frigida*, *Caragana microphylla*, and *Agropyron cristatum*. The growing season is from April to August. The soil is mainly composed of zonal soils, such as light chernozem, meadow chestnut, dark chestnut, chestnut, light chestnut, and gray desert soils, which have the same characteristics as climate transition. Scattered azonal soils, such as aeolian sandy, bog, fluvo-aquic, salinization chestnut, meadow, calcareous meadow, meadow saline, meadow brown and regosols, are also present. Animal husbandry is the primary industry in the region and grazing and mowing are the main utilization patterns on the steppe.

2.2. Sample plots

Natural factors affecting soil nitrogen storage include soil type, vegetation type, annual precipitation, and average daily temperature. To ensure the comparability of soil nitrogen storage in sample plots with different stages of vegetative degradation, we selected sample plots for their uniformity in terms of soil type, vegetation, and climatic conditions. To emphasize the influence of spatial heterogeneity on soil nitrogen storage, we ensured the sample plots were somewhat scattered. After preliminary evaluation of vegetation degradation, we selected 21 sample plots in the study area (Fig. 1), including nine sample plots with serious vegetation degradation (SD), nine with moderate vegetation degradation (MD), and three with no vegetation degradation (NVD). The natural features of the different sample plots are shown in Table 1.

3. Materials and methods

3.1. Remote sensing data

We used remote sensing data obtained from China's advanced, very high resolution (AVHRR) 1 km data set, which were based on high resolution picture transmissions (HRPT) 1B format data from the sensors of AVHRR/2 on the NOAA-11, NOAA -12, and NOAA-14 satellites, and AVHRR/3 on the NOAA-15, NOAA-16, NOAA-17, and NOAA -18 satellites. The basic images from 1990 to 2011 were consistently calibrated to correct for sensor degradation and satellite changes. The radiation calibration, geometric registration, cloud detection, and atmospheric correction were processed by the China Satellite Meteorological Center and Institute of Remote Sensing Applications, Chinese Academy Sciences (Wu et al., 2004). We calculated the NDVI from the red (0.55–0.68 μm) and near infrared (0.73–1.1 μm) bands as described by Wu et al. (2004). By examining each NDVI value pixel by pixel for each observation during the growing season, we produced a 10-day NDVI composite, which allowed us to determine the seasonal maximum value. We then composited the seasonal maximum of NDVI to determine the yearly maximum value of NDVI using the band math of ENVI (version 4.8; ITT VIS, 2010). Taking advantage of image series continuity, we pre-processed the synthesized primary images using Jakubauskas et al.'s (2001) harmonic analysis of time series (HANTS) to reduce the influence of cloud contamination.

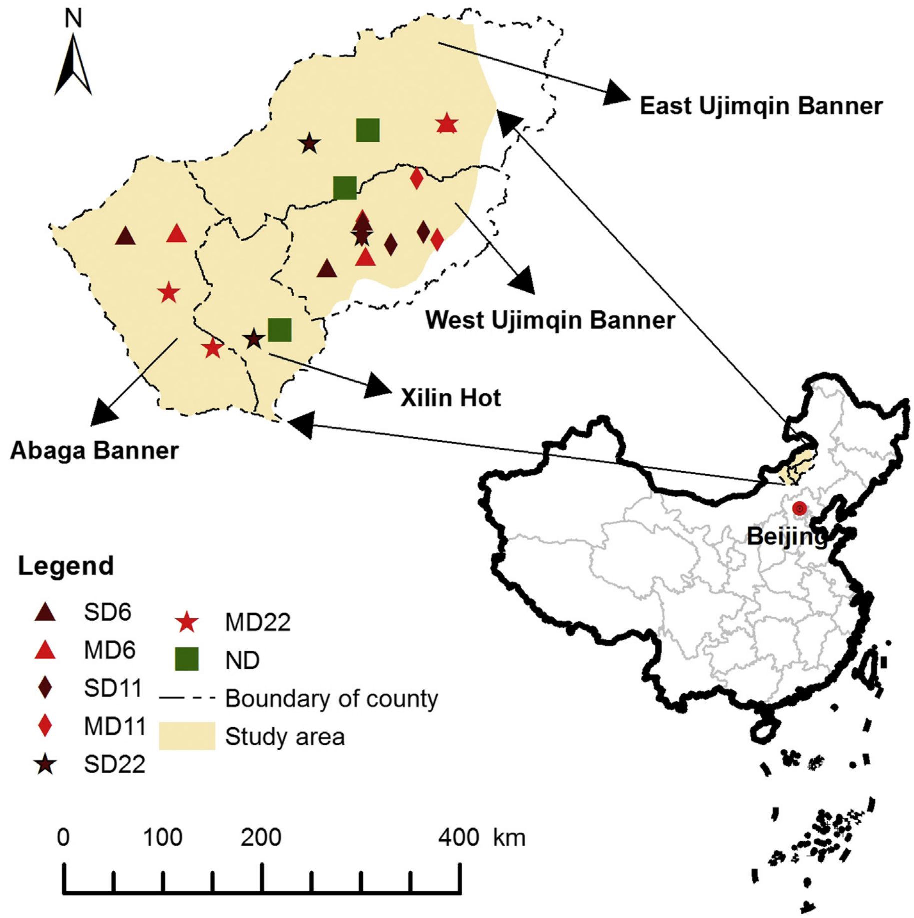

Fig. 1. Study area and sample plots. Note: SD6, SD11, and SD22 refer to three sample plots with serious vegetation degradation gradient as determined with residuals trends of $NDVI_{max}$ on short-term (2006–2011), medium-term (2001–2011), and long-term (1990–2011) scales, respectively; MD6, MD11, and MD22 refer to three sample plots with moderate vegetation degradation gradient determined on short-term (2006–2011), medium-term (2001–2011), and long-term (1990–2011) scales, respectively. ND refers to the no vegetation degradation sample plot.

3.2. Soil data

We determined soil type using the Second National Soil Survey of China, augmented with data from field surveys conducted in 2011. We collected soil profiles (0–50 cm depth) in every sample plot, sampling five layers (0–10 cm, 10–20 cm, 20–30 cm, 30–40 cm, and 40–50 cm). As described by Abdollahi et al. (2014), we measured soil bulk density using a stainless steel cylinder of 98.18 cm^3 (5 cm diameter, 5 cm height) and measured soil particle composition using the pipette method as described by Day (1965). We measured total soil total nitrogen using a Vario EL Cube CHNOS Elemental Analyzer (ELEMENTAR, Hanau, Germany) and calculated soil nitrogen storage using the bulk density, the proportion of total nitrogen, the thickness of the soil layer, and the volume of the fraction of fragments greater than 2 mm at the soil profile as described by Batjes (1996).

3.3. Meteorological data

The National Meteorological Information Center of China provided the monthly precipitation and temperatures from 1990 to 2011, as recorded by 51 weather stations in Inner Mongolia, China. We generated the precipitation spatial distribution maps with the Ordinary Kriging spatial interpolation tool of ArcGIS (version 9.3; ESRI Institute, 1993), transformed to raster images with a resolution of 1 km. We carried out the projection transformation and correction by referring to corrected NDVI image data.

3.4. Vegetation data

We obtained vegetation data from field surveys conducted from July to August, 2011. We randomly set three quadrats in each sample plot and recorded species composition and height in each quadrat to determine the vegetation type and dominant species in each sample plot.

3.5. RESTREND method and implementation

The RESTREND method determines vegetation degradation based on the vegetation's ability to transform precipitation into primary productivity. After precipitation, the main natural constraining factor, is removed, the primary influence on vegetative productivity is human factors (Wessels et al., 2007). Application of the RESTREND method implies two premises: (1) the key factor influencing vegetation productivity is precipitation, and (2) human factors significantly affect vegetative productivity. Our study area is located in a semi-arid region where precipitation is an important limiting factor in vegetative productivity (Chen et al., 2012; Yuan et al., 2006). Human activities (mainly grazing) in the study area also have important effects on vegetative productivity. These two

Table 1
Sample plots in the field survey.

Type	Sample plot name	Location	Soil type	Dominant species	Annual precipitation (mm)	Average daily temperature (°C)
Serious vegetation degradation (SD)	SD6_1	44°25′58″N; 117°0′47″E	Chestnut soil	*Leymus chinensis, Achnatherum splendens*	293.78–309.39	2.36–2.83
	SD6_2	44°42′10″N; 114°26′4″E	Chestnut soil	*Stipa krylovii*	222.66–241.84	1.60–1.95
	SD11_1	44°38′24″N; 117°49′26″E	Dark chestnut Soil	*Stipa krylovii*	324.22–338.30	2.83–3.37
	SD11_2	44°43′45″N; 117°27′17″E	Chestnut Soil	*Stipa grandis, Leymus chinensis*	309.39–324.22	2.36–2.83
	SD11_3	44°45′9″N; 118°14′35″E	Dark chestnut soil	*Achnatherum nakaii*	324.22–338.3	3.99–4.70
	SD22_1	43°47′9″N; 116°5′24″E	Dark chestnut soil	*Stipa grandis*	260.05–277.35	2.83–3.37
	SD22_3	45°34′10″N; 116°46′52″E	Chestnut soil	*Stipa krylovii*	260.05–277.35	2.36–2.83
Moderate vegetation degradation (MD)	MD6_1	44°32′12″N; 117°30′13″E	Chestnut soil	*Achnatherum splendens*	309.39–324.22	2.36–2.83
	MD6_2	44°44′16″N; 115°5′15″E	Chestnut soil	*Artemisia frigida*	222.66–241.84	1.95–2.36
	MD6_3/ SD22_2[a]	45°44′33″N; 118°34′1″E	Chestnut soil	*Cleistogenes squarrosa*	324.22–338.80	3.99–4.7
	MD11_1	44°40′37″N; 118°24′54″E	Chestnut soil	*Stipa grandis, Leymus chinensis*	338.30–351.68	3.99–4.7
	MD11_2/ SD6_3[a]	44°51′32″N; 117°27′52″E	Fluvo-aquic soil	*Stipa krylovii, Cleistogenes squarrosa*	293.78–309.39	2.36–2.83
	MD11_3	45°14′33″N; 118°9′53″E	Chestnut soil	*Stipa grandis, Leymus chinensis*	324.22–338.3	3.37–3.99
	MD22_1	44°11′59″N; 115°0′42″E	Chestnut soil	*Stipa krylovii*	222.66–241.84	1.95–2.36
	MD22_3	43°41′58″N; 115°34′34″E	Chestnut soil	*Artemisia Mongolia*	241.84–260.05	2.83–3.37
No vegetation degradation (NVD)	ND_1	45°40′41″N; 117°32′24″E	Chestnut soil	*Stipa grandis*	293.78–309.39	2.83–3.37
	ND_2	45°9′21″N; 117°14′27″E	Chestnut soil	*Stipa grandis, Cleistogenes*	277.35–293.78	2.36–2.83
	ND_3	43°51′35″N; 116°25′16″E	Chestnut soil	*Stipa grandis*	277.35–293.78	2.83–3.37

Note: SD, MD and NVD refer to serious, moderate and no vegetation degradation gradient types; Sample plots were named by the connection the sample plot type and serial number with an underscore character, the former is sample plot type and the later is the serial number of sample plot.
[a] Refers to overlapping sample plots at the same geographical location.

factors are usually regarded as the main factors for the degradation of vegetation in this region (Zha and Gao, 1997; Sneath, 1998; Conant and Paustian, 2002; Li et al., 2012). Therefore, the premises for the application of the RESTREND method in the region are satisfied and have been verified by Li et al. (2012). Vegetation degradation is determined by referring to the trend of residuals of net primary productivity (or ΣNDVI or $NDVI_{max}$). The detailed process can be found in Evans and Geerken (2004), Geerken and Ilaiwi (2004), Wessels et al. (2007), and Li et al. (2012).

We fitted regression equations between the pixel-level $NDVI_{max}$ and the log-transformed cumulative precipitation variable with 482 sample pixels from 1990 to 2011, which were randomly selected using ArcGIS's spatial analysis tool for creating random sample points. For the complex influence of precipitation time lags on changes of vegetation (Wessels et al., 2007), we selected six log-transformed cumulative precipitation variables with different time steps (Li et al., 2012) to explore the best fitted statistical relationship, and selected the corresponding regression equation with the highest R^2 and a $p < 0.05$ for generating annual residuals.

Using the optimal linear regression model, we obtained the predictive value of $NDVI_{max}$ with precipitation within a corresponding period in every pixel and obtained the residual with the real $NDVI_{max}$ from remote sensing images. We determined changes in vegetation with the residuals interannual trend of $NDVI_{max}$ during a given period. The residuals trend may change for different lengths of time, bringing uncertainty to the results, but this result difference helps analyze the changes to vegetation and the impacts of human activities during different periods. We selected three time scales – short-term (2006–2011), medium-term (2001–2011), and long-term (1990–2011) – to conduct regression analysis on residuals and time. Based on the development of grassland management policy in China, the short-term scale represents a period of stable grassland protection policy implementation; the medium-term scale covers the launch and implementation of grassland protection policy; and the long-term scale includes the period before and after the implementation of grassland protection policy (Li et al., 2012).For every time period, we determined the coefficient of determination (R^2) and probability of regression significance (p) based on pixel-level regression analysis of residual and time, and determined the changing trends of vegetative growth using the slope of the regression line of residuals.

Using the F-test, we divided the significance of the linear regression of residual and time into four levels (0.01, 0.025, 0.05, and 0.1) and identified nine variations in residual trends. We defined the downward trend as D1 ($p < 0.01$), D2 ($0.01 \le p < 0.025$), D3 ($0.025 \le p < 0.05$), and DNC ($0.05 \le p < 0.1$), and the uptrend as I1 ($p < 0.01$), I2 ($0.01 \le p < 0.025$), I3 ($0.025 \le p < 0.05$), and INC ($0.05 \le p < 0.1$). D1, D2, and D3 represent obvious decreases in vegetative productivity, whereas I1, I2, and I3 represent increases. DNC and INC represent observable decreasing and increasing trends, respectively, with statistical significance between 0.05 and 0.1. The ninth variation, NSC, refers to an insignificant statistical relationship in the trend of residual variation ($p > 0.1$). To study the response of soil nitrogen storage to vegetation degradation, we designated the sample plots in the pixels with the residual variation types of D1, D2, and D3 as SD and sample plots in pixels with DNC and NSC residual variation types as MD and NVD, respectively.

3.6. Comparison of soil nitrogen storage in different vegetation degradation gradients

To determine the differences in soil nitrogen storage in sample plots, we averaged sample plots numbered SD6, SD11, SD22, MD6, MD11, MD22, and ND, respectively. To reveal the difference of the soil nitrogen storage in vegetation degradation gradients (SD, MD and NVD), we averaged sample plots at the same vegetation gradient (e.g. SD6, SD11 and SD22 have serious vegetation, SD). We determined variations in soil nitrogen storage with soil depth (0–50 cm) by averaging the soil nitrogen storage of different soil layers of sample plots belonging to the same vegetative degradation gradient.

4. Results

4.1. Correlation between $NDVI_{max}$ and precipitation

Table 2 suggests a significant statistical relationship between $NDVI_{max}$ and precipitation in each year. Inter-annual differences in the coefficient of determination (R^2) exist in all years studied.

4.2. Correlation between $NDVI_{max}$ residual and time

For short-term, medium-term, and long-term scales, areas with high coefficients of determination were found mainly in the northeastern, southeastern, and northern parts of the region (Fig. 2). The coefficients of determination for most of the region (such as the middle, southern, and western parts) were always low (Fig. 2, Table 3), indicating that the $NDVI_{max}$ residual in the corresponding pixel has no obvious trend over time.

At the 0.05 significance level, no more than 10.29% of the pixels showed a significant statistical relationship on the three time scales and 93.7% of the pixels showed an insignificant statistical relationship on the medium-term scale (Table 3). The spatial distribution of regression significance was similar to that of the coefficient of determination: the area with a high coefficient of determination usually showed high regression significance and the area with a low coefficient of determination usually showed low regression significance (Fig. 3).

4.3. Characteristics of degradation

The percentages of pixels in I1, I2, and I3 were 5.01%, 2.05%, and 5.66%, respectively, and the percentages of pixels in D1, D2, and D3 were 4.59%, 4.05%, and 4.29%, respectively. Including INC and DNC, the percentages of pixels that exhibited an increasing trend in residuals were only 8.2%, 4.5%, and 9.06%, whereas the percentages of pixels that exhibited a decreasing trend of residuals were 8.2%, 6.69%, and 7.68% (Table 3). In the study area, the residuals of over 80% of the pixels did not show a specific trend over time.

In terms of spatial distribution, vegetation degradation occurred mainly in the southeast and west central parts of the study area, and vegetative restoration was found mainly in the northeast, north, and southwest. The areas with vegetation restoration or degradation were typically scattered and intermixed. Over the short-term, the pixels with increasing residuals were concentrated in the northeast, whereas the pixels with vegetation degradation were scattered from the southeast to the northwest. Over the medium-term, the pixels indicating vegetation degradation were found mainly in the southeast, whereas pixels indicating vegetation restoration were scattered from northeast to southwest. Over the long-term, pixels indicating vegetation degradation and pixels indicating vegetation restoration were scattered to the south and north, respectively (Fig. 4).

4.4. Soil nitrogen storage of different degradation gradients

The order of soil nitrogen storage for vegetation degradation gradients determined with the residuals trends of $NDVI_{max}$ on short-term, medium-term, and long-term scales were SD < MD < NVD, MD < NVD < SD, and SD < NVD < MD, respectively

Table 2
Pixel-level regression relations between $NDVI_{max}$ and precipitation in 1990–2011.

Year	x	a	b	R^2	F	Sig.
1990	$\ln(Precipitation_{March–July})$	0.2232	−0.8807	0.1555	88.37	<0.0001
1991	$\ln(Precipitation_{January–December})$	0.4766	−2.4047	0.4562	402.77	<0.0001
1992	$\ln(Precipitation_{January–December})$	0.5993	−3.2378	0.1454	81.67	<0.0001
1993	$\ln(Precipitation_{March–July})$	0.3683	−1.546	0.3564	265.77	<0.0001
1994	$\ln(Precipitation_{January–August})$	0.607	−2.9833	0.4346	368.99	<0.0001
1995	$\ln(Precipitation_{March–July})$	0.4987	−2.165	0.4038	325.12	<0.0001
1996	$\ln(Precipitation_{March–July})$	0.2793	−1.0901	0.1728	100.31	<0.0001
1997	$\ln(Precipitation_{March–July})$	0.4867	−2.1465	0.3937	311.69	<0.0001
1998	$\ln(Precipitation_{January–December})$	0.2074	−0.7714	0.2727	13.45	0.0003
1999	$\ln(Precipitation_{January–December})$	0.5667	−2.7509	0.1338	74.13	<0.0001
2000	$\ln(Precipitation_{January–December})$	0.5347	−2.6401	0.5099	499.33	<0.0001
2001	$\ln(Precipitation_{April–July})$	0.3475	−1.4092	0.4557	401.89	<0.0001
2002	$\ln(Precipitation_{January–December})$	0.3712	−1.7458	0.3271	191.01	<0.0001
2003	$\ln(Precipitation_{March–August})$	0.3324	−1.419	0.1535	87	<0.0001
2004	$\ln(Precipitation_{March–July})$	0.828	−3.757	0.4262	356.46	<0.0001
2005	$\ln(Precipitation_{April–August})$	0.3158	−1.2538	0.4609	410.42	<0.0001
2006	$\ln(Precipitation_{January–December})$	0.5404	−2.5616	0.4147	340.03	<0.0001
2007	$\ln(Precipitation_{April–July})$	0.1348	−0.398	0.0363	18.07	<0.0001
2008	$\ln(Precipitation_{April–August})$	0.6877	−3.4023	0.4737	432.04	<0.0001
2009	$\ln(Precipitation_{January–December})$	0.5463	−2.8220	0.3692	230.04	<0.0001
2010	$\ln(Precipitation_{March–July})$	0.3544	−1.4099	0.3502	211.82	<0.0001
2011	$\ln(Precipitation_{March–August})$	0.2983	−1.1704	0.5259	418.79	<0.0001

Note: To conduct linear regression according to the model of $y = ax + b$, where y represents $NDVI_{max}$, x is the logarithm of precipitation accumulated in different periods, and b is a constant of regression equation. R^2, F, and Sig. are the coefficient of determination, value of F in the F test, and statistical significance of the regression model, respectively.

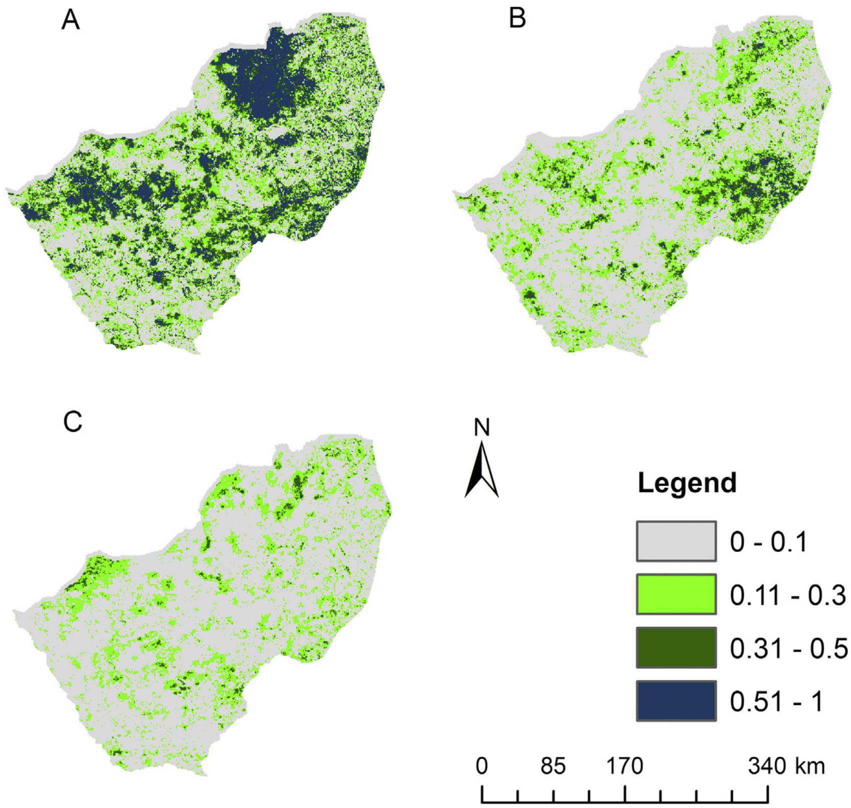

Fig. 2. Spatial distribution of coefficient of determination (R^2) of the regression between $NDVI_{max}$ residual and time at pixel level on short-term (A), medium-term (B), and long-term (C) time scales.

Table 3
Percentages of pixels with different R^2, p, and residual trends on the three temporal scales.

Type		2006–2011(%)	2001–2011(%)	1990–2011(%)
R^2	0–0.1	39.49	63.32	76.14
	0.1–0.3	26.08	26.88	19.62
	0.3–0.5	15.31	7.39	4.15
	0.5–1	19.12	2.40	0.08
p	0.05–0.1	6.80	5.10	6.80
	0.025–0.05	4.27	2.73	4.30
	0.01–0.025	3.01	1.89	3.13
	0.001–0.01	2.33	1.48	2.52
	<0.001	0.29	0.20	0.34
Residual trend	INC	3.19	2.46	3.40
	I3	2.13	1.07	2.29
	I2	1.58	0.61	1.77
	I1	1.29	0.36	1.60
	D1	1.04	1.12	0.92
	D2	1.42	1.28	1.35
	D3	2.13	1.66	2.01
	DNC	3.60	2.64	3.40

(Fig. 5A). We observed a large standard deviation in soil nitrogen storage in sample plots (Fig. 5A) and generally found that the order of nitrogen storage was SD < MD < NVD (Fig. 5B).

The soil nitrogen storage at each layer was typically SD < MD < NVD and the soil nitrogen storage of SD, MD, and NVD decreased with increasing soil depth; however, the decreasing rate was characterized by NVD > MD > SD (Fig. 6D). Degradation of vegetative productivity may have a significant impact on soil nitrogen storage, especially for soil nitrogen storage at the soil surface; this influence decreases with increasing soil depth. The soil nitrogen storage at the vegetation degradation gradient determined on the short-term scale exhibits a similar variation trend to the average value of all sample plots at the same vegetation degradation gradient in different depths (Fig. 6A and D). The soil nitrogen storage at the vegetation degradation gradients determined over medium- and long-term scales exhibits a similar decreasing rate with the average value of all sample plots on the same vegetation degradation gradient with increased soil depth (Fig. 6B–D). At the vegetation degradation gradient determined at the medium-term scale, the minimum soil nitrogen storage on each layer appears in MD, and the soil nitrogen storage of SD was higher than that of NVD, except on the layer with depth of 10 cm–20 cm (Fig. 6B). At the vegetation degradation gradient which was determined on the long-term scale, the soil nitrogen storage at each

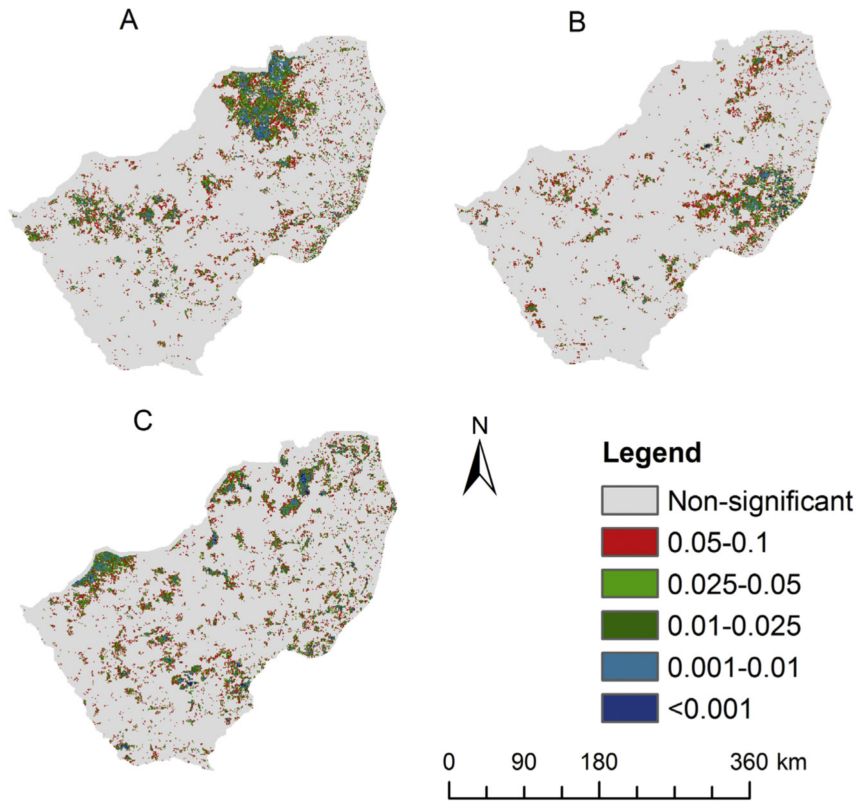

Fig. 3. Spatial distribution of the regression significance (p) of $NDVI_{max}$ residual and time at pixel level on short-term (A), medium-term (B) and long-term (C) time scales.

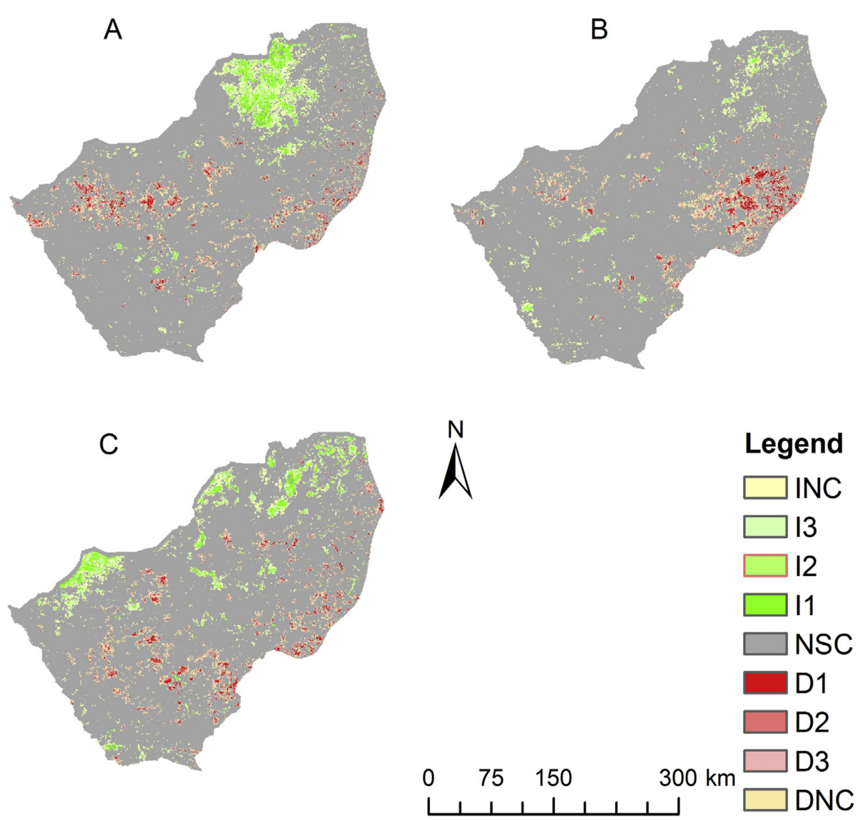

Fig. 4. Spatial patterns of steppe vegetation variation on the short-term (A), medium-term (B), and long-term (C) scales. Note: D1, D2, and D3 denote decreasing trends; I1, I2, and I3 represent increasing trends. Numbers 1 to 3 denote the different degrees of statistical significance.

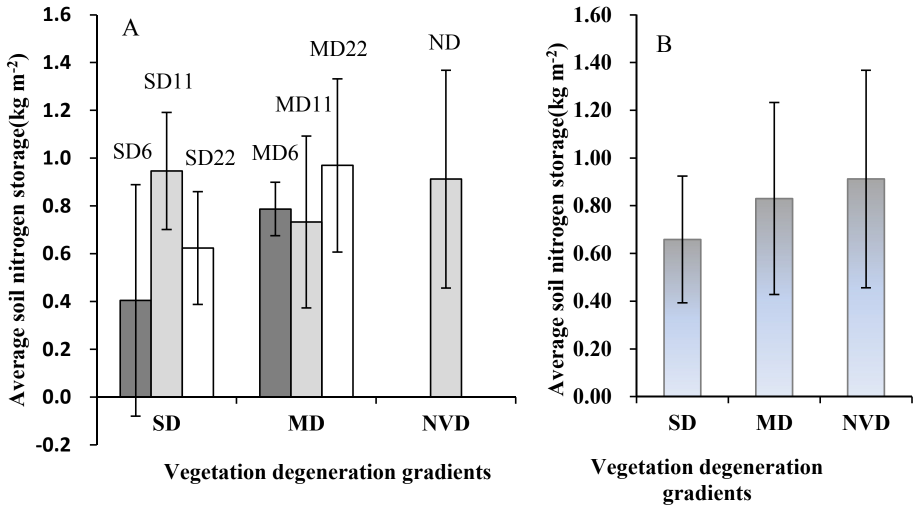

Fig. 5. Average soil nitrogen storage of sample plot types at vegetation degradation gradients (A) and average soil nitrogen storage of vegetation degradation gradients (B).

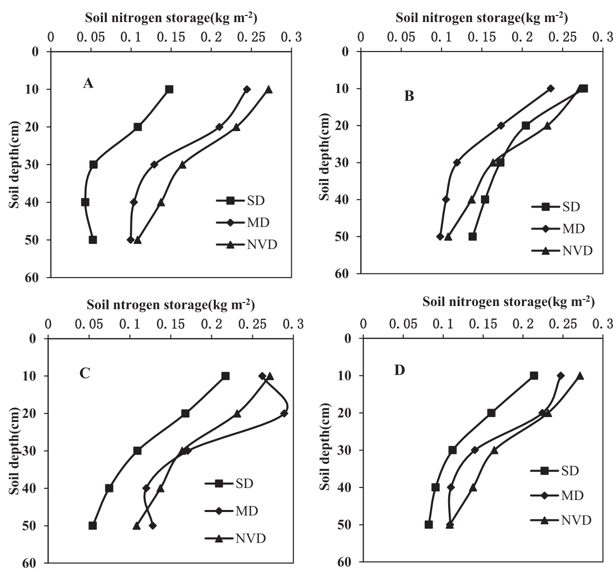

Fig. 6. Variation in soil nitrogen storage with soil depth (0 cm–50 cm) at vegetation degradation gradients (SD, MD, and NVD) determined with residuals trend of $NDVI_{max}$ on the short-term (A), medium-term (B), and long-term (C) scales, respectively, and the average soil nitrogen storage of all sample plots with a similar vegetation gradient (D).

layer was characterized by MD > NVD, except on the layers with depths of 0 cm–10 cm and 30 cm–40 cm.

5. Discussion

5.1. Effect of precipitation on the linear regression equation

The linear regression equation predicts $NDVI_{max}$ with precipitation and incorporates this value when calculating the residual and analyzing the residual trend. Time and the effects of precipitation have important impacts on vegetative production (Du Plessis, 1999; Wang et al., 2001; Evans and Geerken, 2004). Furthermore, translation and the time lag effect of precipitation in different years will affect vegetative production in the subsequent growing season (Goward and Prince, 1995; Wiegand et al., 2004). Obtaining the proper regression relationship is difficult when accumulated precipitation in a specific period is used as the variable to predict $NDVI_{max}$ for different regions. An effective method for choosing the optimal variable for predicting $NDVI_{max}$ is to compare multiple cumulative precipitation variables with different time lags or intervals. The method has been validated by Li et al. (2012).

5.2. Uncertainty in response of residual trend to variation degradation

The RESTREND method builds a regression equation on pixel spatial series to obtain the relative value of different pixels in the same year, increasing the spatial comparability of residuals. Simultaneously, it weakens the temporal comparability of residuals in different years because the temporal comparability is calculated using different regression models. Therefore, a potential hypothesis for judging the degree of steppe vegetation degradation or restoration with the RESTREND method is that the precipitation spatial distribution in a given time scale remains unchanged. If the annual precipitation spatial distribution varies greatly in different years, estimating human-induced vegetation degradation using the residuals trend is difficult. In addition, the regions of degradation and restoration should actually exist in the study area at the same time scale. On the contrary, if all steppe vegetation is experiencing restoration or degradation and the rate of restoration or degradation differs greatly, the RESTREND method will overestimate or underestimate vegetation degradation when building the regression model based on the spatial series of pixels.

A comparison of $NDVI_{max}$ variations in the pixels showing SD, MD, and NVD vegetation degradation over short-, medium-, and long-term scales, indicated a decreasing $NDVI_{max}$ value for SD and MD pixels over the medium- and long-term scales (Fig. 7B and C); the downward trend of residuals indicates decreasing vegetative productivity. However, on the short-term scale, the $NDVI_{max}$ for SD and MD exhibited an increasing trend (Fig. 7A), which was inconsistent with the conclusion derived from the residual trend. A possible reason for this inconsistency is that the steppe protection and restoration measures implemented since 2000 (Li et al., 2012) began to restore steppe vegetative productivity over the short-term and vegetation degradation was overestimated by the RESTREND method. Moreover, the residual trend reflects the efficiency of vegetation in transforming moisture into productivity, which is different from the variation trend of $NDVI_{max}$ in terms of content.

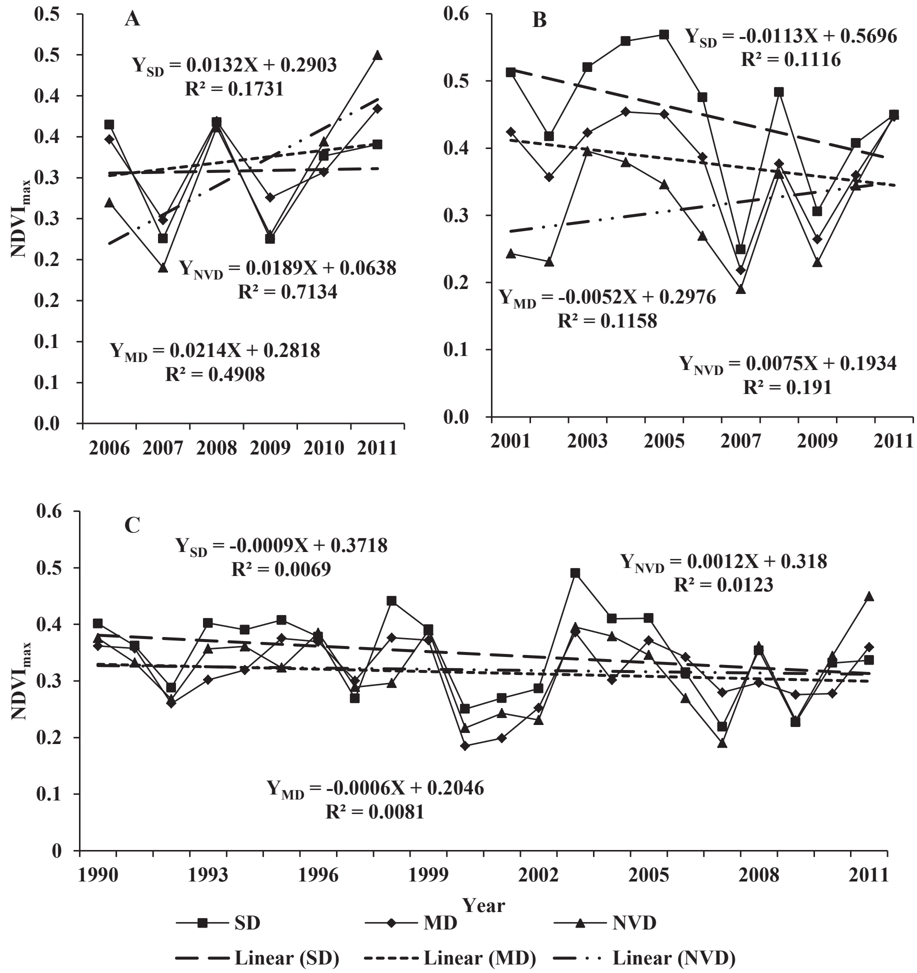

Fig. 7. Variation trend of $NDVI_{max}$ on short-term (A), medium-term (B), and long-term (C) scales.

Even if the efficiency of moisture use decreases, $NDVI_{max}$ may still increase. Wessels et al. (2007) adopted the RESTREND method, building a regression model on pixel time series, and also found that the accumulated NDVI actually increased in an area with a declining residual trend. Therefore, results obtained with the RESTREND method should be handled with caution and analyzed carefully.

5.3. *Temporal–spatial scale effects in terms of time duration and pixel size*

The residual trend in the RESTREND method on pixel time series is influenced by both vegetation degradation gradients and time of degradation. Monitoring of vegetation degradation becomes difficult when it occurs in the first or last two years of the time-series (Wessels et al., 2007). Therefore, when analyzing degradation of steppe vegetation in a specific period, the specific period must be placed in the middle of the selected time-series. Li et al. (2012) also stated that the time-series should be selected cautiously, and influencing factors, such as research objective, time series of vegetation data, precipitation, land use, and land use policies should be considered. In this study, we examined residual trend analysis of multiple time scales, which allowed the comprehensive analysis of residual trends on different time scales. Thus, vegetation degradation occurring at different time periods can be monitored more closely and the influence of defects in the time series analysis can be decreased.

The spatial resolution difference of $NDVI_{max}$ remote sensing data, which are used in the RESTREND method to indicate the status of vegetative production, also has important effects on the evaluation results. Li et al. (2012) conducted a regression analysis on $NDVI_{max}$ and precipitation with 30 randomly selected pixels in the remote sensing image of the 8 km resolution global inventory modeling and mapping studies (GIMMS) dataset, which yielded the coefficient of determination (R^2) for their linear regression on Inner Mongolia steppes. They obtained a value of 0.49, with more than 90% of all pixels displaying significant regression relationship ($p < 0.05$) between residual and time. This differs from the results obtained in our study. Due to insufficient data, analysis of results with image data were not compared on different spatial scales, but different spatial scales definitely influenced the analysis results (Jelinski and Wu, 1996; Wu, 2004). Future studies should explore the optimal pixel scale or patch scale of the RESTREND method.

5.4. *Response of soil nitrogen storage to vegetation degradation*

Human-induced degradation of vegetation is mainly ascribed to high-intensity use of steppe vegetation. Overgrazing and mowing remove nitrogen from the steppe ecosystem without external nitrogen input; livestock production has been regarded as the main source of nitrogen loss (Hoekstra et al., 2007; Li et al., 2008). The loss of soil nitrogen storage inevitably reduces vegetative productivity, leading to further consumption of stored soil nitrogen by root absorption, which means a smaller amount of nitrogen is returned to the soil. Even though changing weather pattern have an overwhelming influence on ecosystems (Yu et al., 2004; Zhang et al., 2011), overgrazing remains the primary cause of steppe vegetation degradation (Sneath, 1998). Therefore, high vegetation degradation corresponds to low soil nitrogen storage and is consistent with the results of our study. In addition, the difference in soil nitrogen storage corresponding to vegetation degradation gradients is probably related to the similarity of soil type, vegetation type, and climate conditions in the selected sample plots. The relationship between vegetation degradation and soil nitrogen storage under varying conditions with large differences in soil type, vegetation type, and climate still warrant further research.

6. Conclusion

In this study, the degradation of typical steppes and the variation in soil nitrogen storage in Inner Mongolia were evaluated using the RESTREND method over short-, medium-, and long-term time scales. Our results indicated that a significant regression relationship exists between $NDVI_{max}$ and precipitation on pixel spatial series. Evaluating less than 10% of the study area using the residual trend method showed significant increases or decreases in steppe vegetative productivity and over 80% of study area did not exhibit a significant change in productivity, indicating that the major vegetation changes can be attributed to climatic factors rather than human factors. The soil nitrogen storage corresponding to vegetation degradation gradients and the decreasing rate of soil nitrogen storage with increasing soil depth both followed the trend SD < MD < NVD. Overall, the RESTREND method, which calculates residuals on pixel spatial series, can predict the status of vegetation degradation for typical steppes, but some uncertainties in the method demand further research.

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