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SHORT COMMUNICATION

A rapid method for quantifying landscape-scale vegetation disturbances by surface coal mining in arid and semiarid regions

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Abstract
Context Quantifying landscape-scale vegetation disturbances by surface coal mining (SCM) is crucial for assessing and mitigating its negative impacts on the environment. Methods for detecting such disturbances in woody ecosystems exist, but these methods do not work well for deserts and grasslands in arid and semiarid regions because of their sensitive responses to precipitation variations.
Objectives The objective of this study was to develop a new index to reliably detect the locations and spatial extents of SCM-induced vegetation disturbances in dryland regions in the face of fluctuating precipitation.
Methods We have developed a vegetation disturbance index (VDI) that combines MODIS EVI data with precipitation data to detect vegetation disturbances by SCM on the Mongolian Plateau during 2000–2015. The VDI is computed by comparing vegetation production per unit precipitation for a given year with a multi-year mean, and by considering distances from coal-mining areas.
Results Our results show that the VDI was able to adequately distinguish vegetation disturbances by SCM from climate-driven vegetation changes in five selected sites across the Mongolian Plateau.
Conclusions The VDI provides an effective tool for quantifying the locations, spatial extents, and severity of vegetation disturbances by SCM in arid and semiarid regions.

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Keywords Vegetation disturbance · Surface coal mining · MODIS EVI · Precipitation · Mongolian Plateau

Introduction

Surface coal mining (SCM), also known as opencast coal mining, refers to activities that extract coal from the ground by first removing vegetation and topsoil when coal seams are near the surface (World Coal Institute 2005). About 40% of the global coal production comes from SCM, which contributes up to 80% of coal production in some countries (e.g., India and Australia) (Bian et al. 2010). Most coal producing countries with large-scale SCM are located in arid and semiarid regions, resulting in myriad ecological disturbances (Fernandez-Manso et al. 2012). SCM can profoundly transform landscape patterns and ecological processes, destroying large areas of land covers (Qian et al. 2014), exhausting or polluting surface and ground water (Tao et al. 2015), and reducing the biodiversity (Zeng et al. 2018). As the first step to assess and mitigate these negative ecological impacts, the locations and spatial extents of vegetation disturbances by SCM need to be determined at the landscape scale.

"Disturbance is a physical force or event that disrupts the physical or biological structure of an ecological system", and the geographic location and affected area of this structural disruption can be delimited from the adjacent undisturbed areas (Pickett et al. 1999). Spectral vegetation indices (e.g., Enhanced Vegetation Index, EVI) and midday radiometric land surface temperature (LST) have been used together to detect the locations and magnitudes of major disturbance events (e.g., wildfire, hurricane, or deforestation). Based on MODIS EVI and LST, MODIS Global Disturbance Index (MGDI) was developed to detect continental-scale disturbances (Mildrexler et al. 2007, 2009). The MGDI has been shown to be a computationally efficient and effective algorithm for monitoring large-scale ecosystem disturbances (Coops et al. 2009; Waring et al. 2011). However, it is mainly designed for detecting disturbances in woody ecosystems, and is not suitable for annual herbaceous plants (e.g., grasslands and croplands) in arid and semiarid regions. This is because herbaceous plants are generally shallow rooted and respond rapidly to precipitation fluctuations—making the MGDI difficult to distinguish disturbance events from precipitation anomalies (Mildrexler et al. 2007, 2009). Therefore, a new disturbance index with the low sensitivity to precipitation fluctuations is needed to quantify vegetation disturbances by SCM in arid and semiarid regions.

"Normalizing" vegetation growth by precipitation is a promising way to reduce the sensitivity to precipitation, because precipitation is recognized as the most important determinant of vegetation cover and biomass production in arid and semiarid regions among different climatic factors (Li et al. 2012; John et al. 2015; Zhao et al. 2015). Thus, the objective of this study was to develop a new vegetation disturbance index (VDI), which combines MODIS EVI with precipitation, to quantify spatial patterns of the landscape-scale vegetation disturbances by SCM in arid and semiarid regions.

Vegetation disturbance index (VDI)

Based on the disturbance detection algorithm developed by Mildrexler et al. (2007), we developed a vegetation disturbance index (VDI) using the following formula:

$$\mathrm{VDI} = \frac{\mathrm{EVI_{max}}/\mathrm{Precip_{cumulative}}}{\overline{\mathrm{EVI}}_{\mathrm{max}}/\overline{\mathrm{Precip}}_{\mathrm{cumulative}}} \tag{1}$$

where *VDI* is the vegetation disturbance index at the pixel level, EVI_{max} and $Precip_{cumulative}$ are the maximum value of EVI and the cumulative precipitation during the growing season (May to September) for one year (e.g., the year of 2015), and $\overline{\mathrm{EVI}}_{\mathrm{max}}$ and $\overline{\mathrm{Precip}}_{\mathrm{cumulative}}$ are the multi-year means of EVI_{max} and $Precip_{cumulative}$ for a period before the year (e.g., the period of 2000–2014).

The VDI is based on the general observations that rainfall is the determinant factor influencing vegetation growth without disturbance events in arid and semiarid ecosystems (John et al. 2015; Zhao et al. 2015), and vegetation production per unit precipitation (i.e., rain use efficiency) should keep within a range of natural variability because of fluctuations between wet and dry years (Mildrexler et al. 2007; Wessels et al. 2007; Bai et al. 2008). Here we used the ratio of EVI to precipitation, which "normalizes" vegetation growth by precipitation, to distinguish vegetation disturbances by SCM from vegetation changes due to precipitation anomalies in arid and semiarid regions. Without disturbances, the current-year vegetation production per unit precipitation (i.e., the value of $\mathrm{EVI_{max}}/\mathrm{Precip_{cumulative}}$) should approximate the multi-year mean (i.e., the value of $\overline{\mathrm{EVI}}_{\mathrm{max}}/\overline{\mathrm{Precip}}_{\mathrm{cumulative}}$), and thus the values of VDI are expected to be equal to 1 or within a range of natural variability including values larger than 1 (i.e., better than average vegetation conditions in wet years) or smaller than 1 (i.e., worse than average vegetation conditions in dry years) (Fig. 1). By contrast, when disturbance events occur, the current-year rain use efficiency will change greatly, making the value of VDI outside the natural variability range (Fig. 1). The impacts of disturbances on vegetation can be positive or negative. For example, irrigation can improve vegetation productivity, resulting in a larger current-year ratio relative to the multi-year mean and a divergence from the range of natural variability (Fig. 1), while SCM can not only

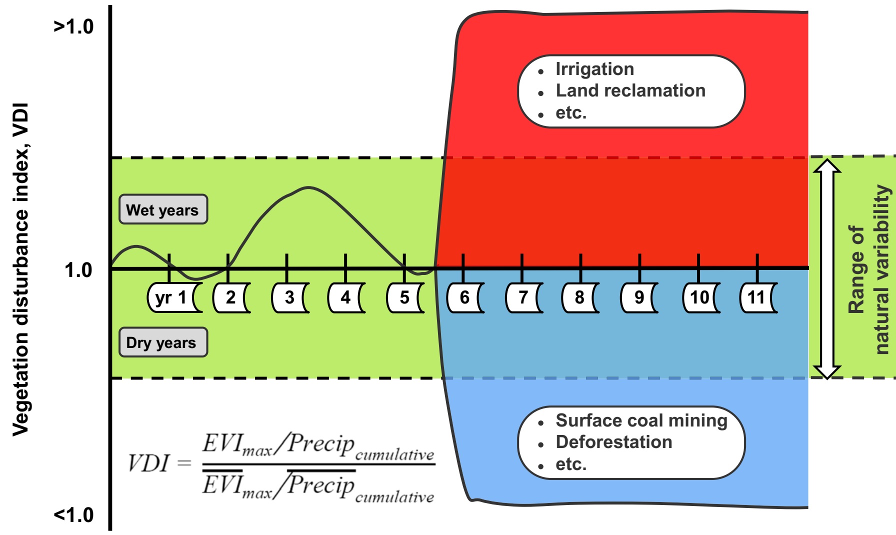

Fig. 1 The conceptual model of the vegetation disturbance index (VDI) illustrating vegetation changes under normal conditions and different types of disturbances over time (adapted from Mildrexler et al. (2007)). Normal conditions refer to conditions within the range of natural variability in precipitation

directly reduce vegetation cover by eradicating previous vegetation and soil, but also indirectly degrade the surrounding vegetation productivity through polluting soil, water, and air, causing a sharp decline in the current-year EVI_{max} and thus a much smaller current-year ratio relative to the multi-year mean.

Quantifying vegetation disturbances by surface coal mining with VDI

Study area and data acquisition

To test the effectiveness of VDI in detecting vegetation disturbances by SCM in arid and semiarid regions, we chose five SCM sites in the Mongolian Plateau, including four sites in Inner Mongolia and one site in Mongolia (Fig. 2a). The five sites were selected because they represented several different dryland vegetation types (including meadow steppes, typical steppes, desert steppes, cultivated lands, and deserts), and experienced extensive mining activities during 2000–2015 (Fig. 2b–k). The five vegetation types were chosen for three reasons: (1) they are the dominant vegetation types in the Mongolian Plateau, accounting for more than 70% of the total area of the plateau (Fig. 2a); (2) they are dominated by herbaceous plants with rapid responses of vegetation production to precipitation fluctuations (Mildrexler et al. 2007); (3) Most SCM sites of the plateau are located in grasslands, cultivated lands, and deserts (Zeng et al. 2018).

To implement the VDI for detecting vegetation disturbances caused by SCM in the selected sites, we first obtained Enhanced Vegetation Index (EVI) data, i.e., MODIS/Terra 16-day EVI data (MOD13Q1) with a spatial resolution of 250 m × 250 m, for the Mongolian Plateau between 2000 and 2015 from the Land Process Distributed Active Archive Center website (https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/). Then, we acquired daily precipitation data for Inner Mongolia during 2000-2015 from the China Meteorological Data Service Center website (http://data.cma.cn/), and monthly precipitation data (TRMM_3B43), with a spatial resolution of 0.25 × 0.25 degrees, for Mongolia between 2000 and 2015 from the Goddard Space Flight Center Distributed Active Archive Center website (https://mirador.gsfc.nasa.gov/collections/TRMM_3B43__007.shtml).

Google Earth images of high (e.g., QuickBird and SPOT) or medium (e.g., Landsat) spatial resolution across the plateau were used to obtain the actual spatial information on the five selected SCM sites. MODIS Gridded 1 km Annual Net Primary Productivity (NPP) data (MOD17A3) for the years of 2000 and 2015 (http://files.ntsg.umt.edu/data/NTSG_Products/MOD17/MOD17A3/) were used to evaluate the performance of VDI in identifying vegetation disturbances by SCM.

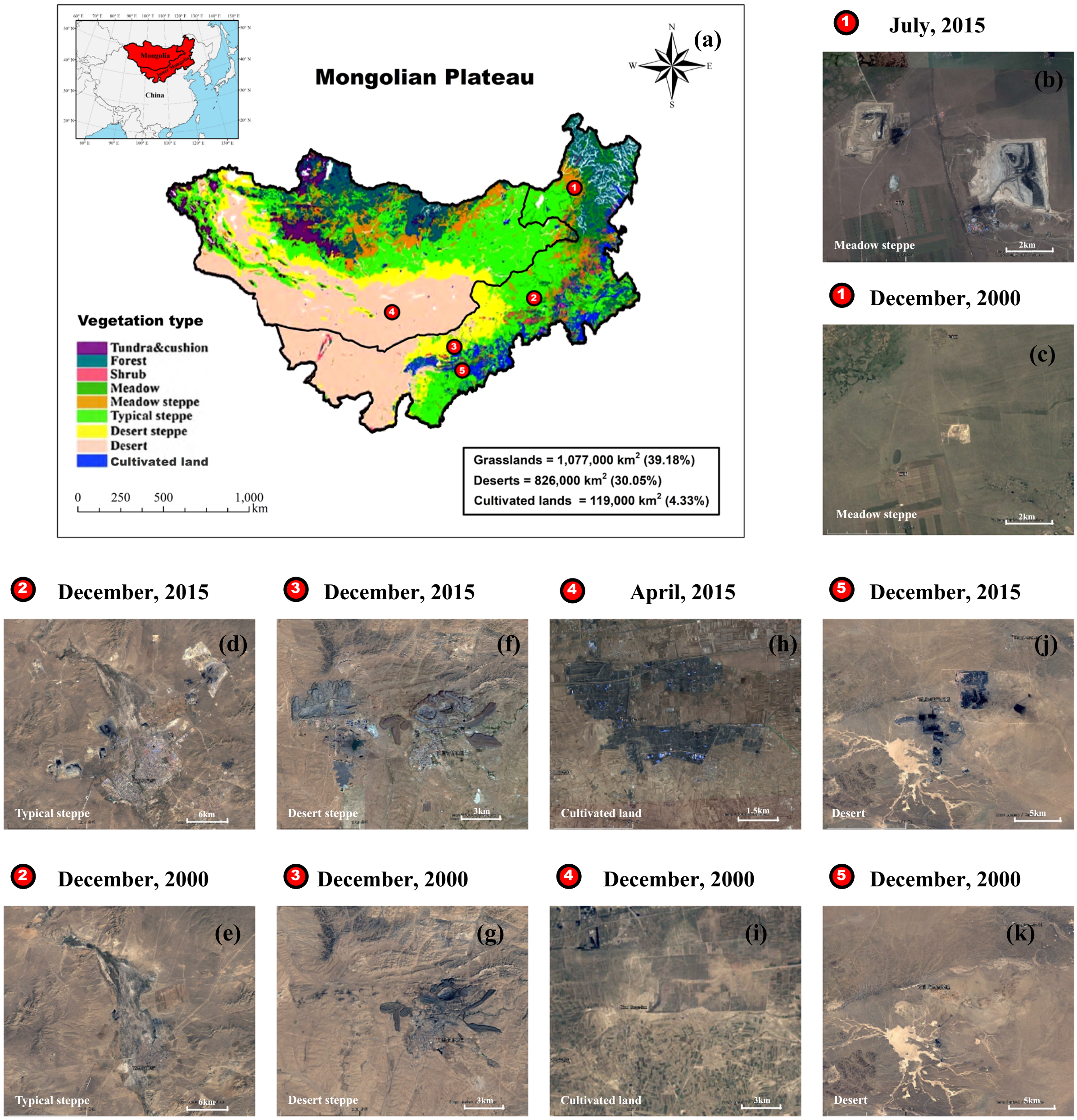

Fig. 2 Locational map of the five selected surface coal mining sites in the Mongolian Plateau (**a**) and their corresponding Google Earth images in 2015 (**b**, **d**, **f**, **h**, **j**) and 2000 (**c**, **e**, **g**, **i**, **k**). The surface coal mining sites from 1 to 5 were, respectively, located in meadow steppes (**b**, **c**), typical steppes (**d**, **e**), desert steppes (**f**, **g**), cultivated lands (**h**, **i**), and deserts (**j**, **k**). The vegetation map (**a**) was from Zhao et al. (2015)

Implementing VDI

Before calculating the VDI, we preprocessed the MODIS 16-day 250-m EVI data and precipitation data. The annual maximum EVI data (2000–2015) for the Mongolian Plateau were generated by Band Math in ENVI 5.0. Then we removed pixels with maximum EVI values less than 0.025 because these pixels were mainly associated with water bodies and snow/ice (Mildrexler et al. 2007). Daily precipitation data for Inner Mongolia at a spatial resolution of 250 m × 250 m were obtained by Ordinary Kriging interpolation, and monthly precipitation data (TRMM_3B43) for Mongolia were resampled to the pixel size of 250 m by a nearest neighbor resampling algorithm. Next, we acquired the annual cumulative precipitation data during the growing season for the Mongolian Plateau. After that, the EVI_{max} data and the $Precip_{cumulative}$ data from 2000 to 2015 were projected onto an Albers conical equal area projection, and the VDI was calculated by dividing the ratio of EVI_{max} to $Precip_{cumulative}$ for the year of 2015 by the ratio of $\overline{\mathrm{EVI}}_{\mathrm{max}}$ to $\overline{\mathrm{Precip}}_{\mathrm{cumulative}}$ for the period of 2000-2014. The results showed that the values of VDI for all pixels (except water bodies and snow/ice) in the Mongolian Plateau ranged from 0 to 5, with the mean value of 0.97 and the standard deviation of $\pm$ 0.34.

Identifying vegetation disturbances by surface coal mining

SCM can result in vegetation degradation. Thus, to identify vegetation disturbances by SCM, we should first determine the range of natural variability and detect the disturbances with the VDI values below the range. Two methods were generally used to define the range of natural variability. The first one was to use the values of a disturbance index that were within one standard deviation of the mean value for the entire study area as the range of natural variability (Mildrexler et al. 2007; Coops et al. 2009). Any values that were one or more standard deviations above or below the mean value coincided with disturbances. The second one was to set specific thresholds, such as 45%, 65%, and 75% increases or decreases from the multi-year mean of a disturbance index, as the range of natural variability (Mildrexler et al. 2009).

Referring to the two methods, we first set four different ranges with the VDI values of 0.6–1.4, 0.7–1.3, 0.8–1.2, and 0.9–1.1, which were within about one standard deviation ($\pm$ 0.34) of the mean VDI value (0.97), and then compared them for determining a proper range of natural variability. We found that the range of 0.8–1.2 performed best in detecting vegetation disturbances by SCM in the study areas (Fig. 3p–t). The regions outside this range not only accurately detected the locations of SCM areas (including coal-extracting areas, stripped areas, and dumping areas), but also exhibited their negative impacts on the surrounding land covers (Fig. 3p–t). By contrast, the ranges of 0.6–1.4 and 0.7–1.3 underestimated vegetation disturbances by SCM in reference to the actual spatial information obtained from Google Earth images (Fig. 3a–o). For example, the range of 0.6-1.4 obviously missed some coal-extracting areas (e.g., some areas in black circles) (Fig. 3f–j); in comparison, the range of 0.7–1.3 better quantified the spatial patterns of coal-extracting areas as well as stripping areas and dumping areas, but omitted their impacts on the surrounding land covers (e.g., some areas in black rectangles) (Fig. 3k–o). The range of 0.9–1.1 clearly overestimated vegetation disturbances, with most of natural variability falsely classified as disturbances-induced vegetation degradation (e.g., Fig. 3v, y). Thus, we selected the VDI values of 0.8–1.2 as the range of natural variability, and detected the areas of vegetation degraded by all disturbances during 2000–2015 using the threshold *VDI* value of 0.8 (i.e., pixels with the *VDI* values of < 0.8 were deemed to be negatively affected by disturbances).

To further quantify the spatial extents of vegetation disturbances by SCM, we assumed that the impacts of SCM on vegetation would decrease with distance away from coal-extracting areas, and the average vegetation disturbance distance of large mining sites would be greater than that of small ones. A national survey across China indicated that the distance of environmental impacts from a mining site ranged from a few hundred meters to 10 km (CMEP/CMLR 2014). In this study, we first divided SCM sites into small (with the coal-extracting area of $< 100{,}000$ m^2) and large (with the coal-extracting area of $\geq 100{,}000$ m^2) sites, and then compared different buffers to choose proper distances to cover the impacts of SCM with different sizes on vegetation. The proper distances were determined when the buffers at the specified distances not only covered all coal-extracting areas, stripped areas, and dumping areas in space, but also contained most of vegetation degradation regions around the mining areas without involving other kinds of human-disturbed land uses, such as built-up areas (Fig. 4a) or cultivated lands (Fig. 4b). Finally, we selected 1 km for the small sites and 5 km for the large sites as the distances of vegetation disturbances due to SCM (shown in black dashed lines) (Fig. 4). Thus, it is a conservative and robust first approximation of the extents of SCM damage to vegetation in the Mongolian Plateau.

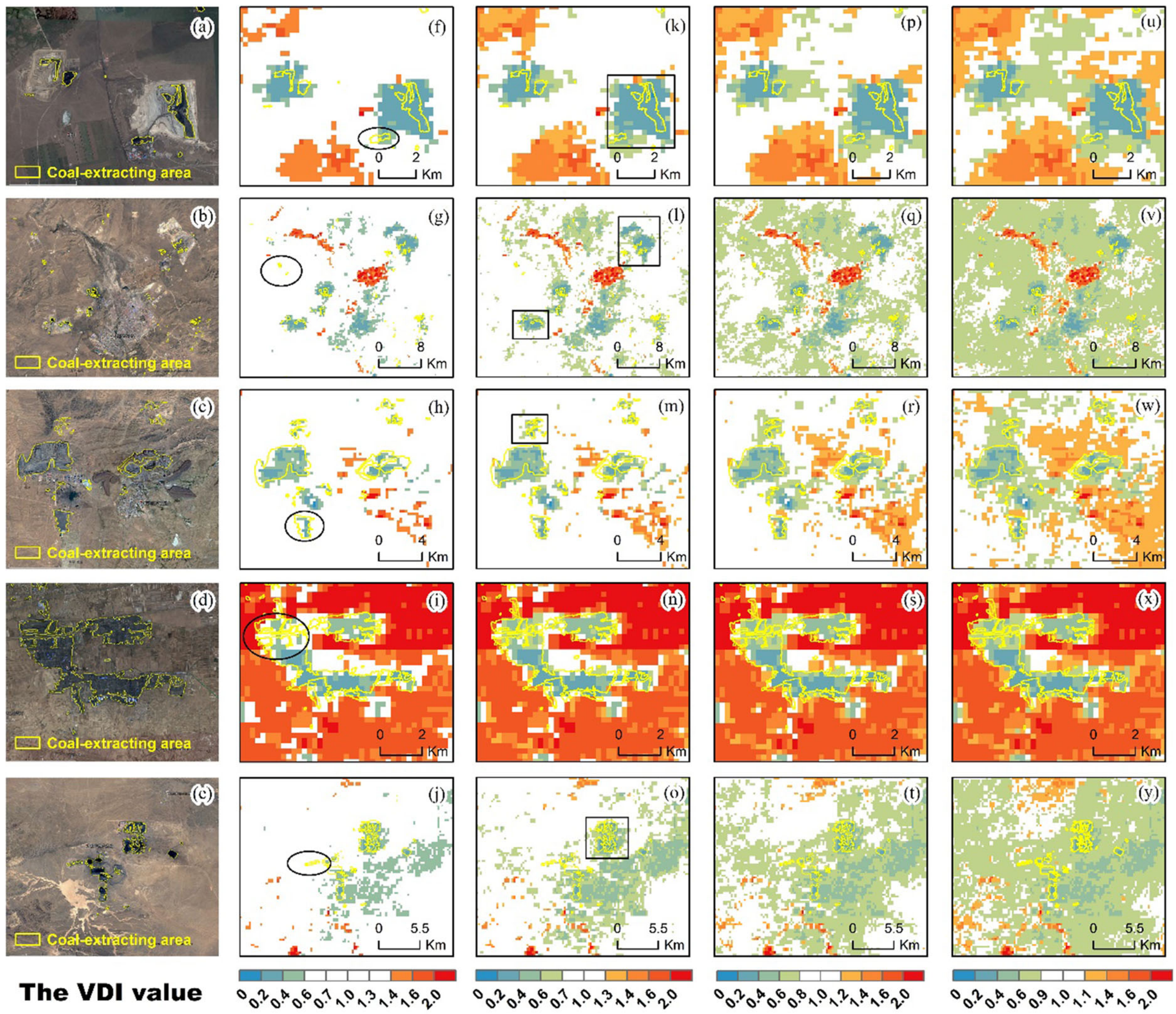

Fig. 3 Spatial distributions of coal-extracting areas obtained through the visual interpretation of Google Earth images in 2015 for the selected five surface coal mining sites (**a**–**e**) and their corresponding VDI patterns, with the VDI values between 0.6–1.4 (**f**–**j**), 0.7–1.3 (**k**–**o**), 0.8–1.2 (**p**–**t**), and 0.9–1.1 (**u**–**y**)

Based on procedures mentioned above, we obtained spatial distributions of vegetation disturbances caused by SCM during 2000–2015 for the five selected sites (shown in red polygons) (Fig. 5).

Accuracy assessment

Google Earth images and NPP data were used to assess the accuracy of our results. First, the locations and magnitudes of vegetation disturbances by SCM corresponded well with the characteristics shown in the corresponding Google Earth images (Fig. 5a–j). On the one hand, vegetation disturbances by SCM accurately captured the locations of SCM areas (e.g., Fig. 5a, f). On the other hand, vegetation disturbances with different VDI values effectively reflected the magnitudes of negative impacts of SCM on vegetation: the lower the values, the more serious the damage to vegetation. The values in coal-extracting/stripped/dumping areas were obviously lower than those in the surrounding regions (Fig. 5f–j).

Second, the spatial extents of vegetation disturbances by SCM also corresponded well with the characteristics of NPP data except for the second site (Fig. 5l–o). From 2000 to 2015, the decreases in NPP in the SCM-disturbed regions were obviously larger

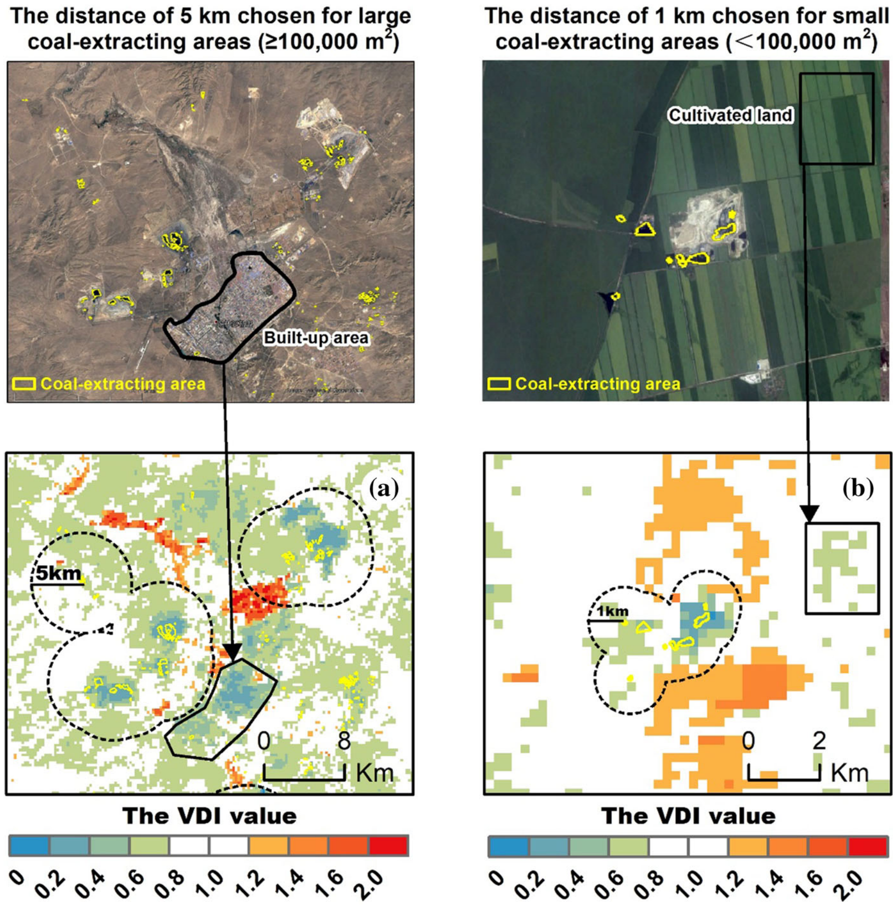

Fig. 4 A schematic illustration of buffers around the centers of coal-extracting areas to two specific distances of vegetation disturbances by surface coal mining with 5 km for large coal-extracting areas (**a**) and 1 km for small coal-extracting areas (**b**)

than those in the surrounding regions (Fig. 5k, m, n), which further proved the reliability of our results.

Discussion

Our results show that the VDI is an effective and simple index for detecting vegetation disturbances by SCM in arid and semiarid regions because the ratio of EVI to precipitation offsets the effects of precipitation fluctuations on vegetation (Fig. 5). For example, although precipitation surplus anomalies in the second SCM site during 2000–2015 masked the negative impacts of SCM on vegetation to some extent (Fig. 5l, q), the VDI was still able to identify the SCM-induced vegetation disturbances (Fig. 5g).

The VDI can not only capture the locations and spatial extents of vegetation disturbances by SCM, but also characterize the magnitudes of the SCM's negative impacts on vegetation from the core area of a SCM site outward (Fig. 5f–j). In general, a SCM area consists of three zones: coal-extracting zone, stripped zone, and dumping zone (Zeng et al. 2018). Vegetation damages within these three zones are most serious because SCM directly destroyed most or all vegetation. But negative impacts of SCM on vegetation go beyond the boundaries of SCM areas into the surrounding regions through exhausting surface and ground water and polluting soil, water, and air. With increasing distance from a SCM area, the damage to vegetation usually declines. These changes in disturbance severity were reflected in the values of VDI (Fig. 5f–j).

The VDI can also help detect vegetation disturbances with positive effects on vegetation (e.g., irrigation). For example, from 2000 to 2015, although there were no large precipitation variations in the fourth SCM site (surrounded by cultivated lands) (Fig. 5s), the vegetation productivity still improved substantially probably due to irrigation or

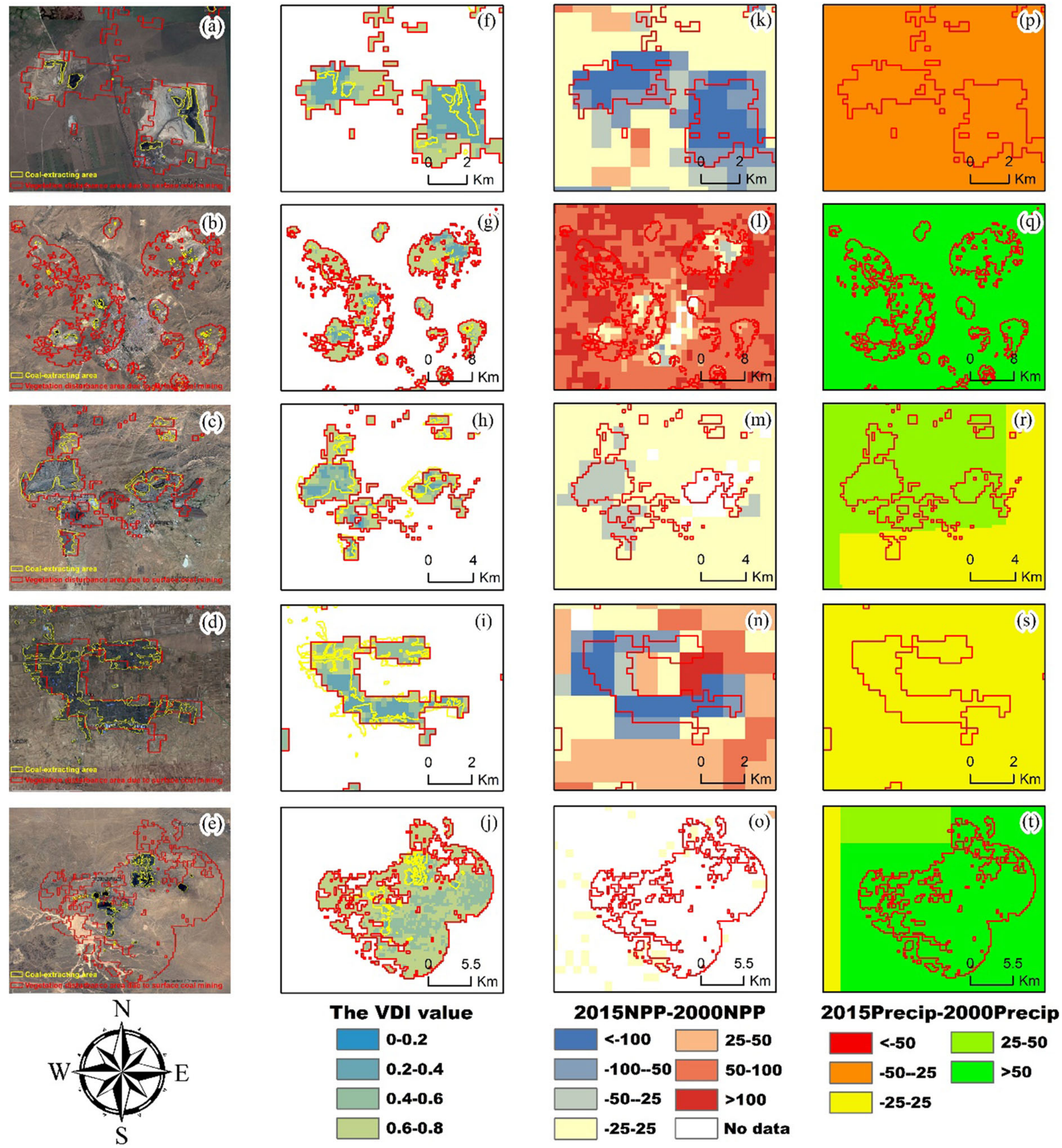

Fig. 5 Spatial distributions of vegetation disturbances by surface coal mining (shown in red polygons) for the five selected sites based on the VDI value (**f–j**) and their accuracy assessment in reference to differences in annual NPP (Units: gC·m^{-2}·year^{-1}) (**k–o**) as well as the cumulative precipitation during the growing season (Units: mm) (**p–t**) between 2015 and 2000. The disturbances with positive impacts on vegetation as well as natural variability were shown in white color (**f–j**). Several land cover types (e.g., deserts and water bodies) had no corresponding NPP data, thus shown in white color (**k–o**)

fertilization (Qiao et al. 2018). The VDI can accurately capture the spatial extents of vegetation disturbances by agricultural management practices with the VDI value of larger than 1.2 (Fig. 3s). Thus, the VDI provides an effective tool to distinguish both negative and positive vegetation disturbances from climate-driven vegetation changes in arid and semiarid regions.

In addition, the VDI is intuitive and simple to implement. On the one hand, the basic data for calculating this index can be easily obtained: the time-series MODIS EVI data and precipitation data can be directly obtained from websites for free. On the other hand, the algorithm of the index can be easily applied on a pixel-by-pixel basis. Thus, the VDI can serve as an efficient and automatic algorithm to detect vegetation disturbances in arid and semiarid regions for global application.

The VDI is developed on the premise that there is a significantly positive relationship between vegetation production and precipitation in arid and semiarid regions. However, it should be noted that the relationship shows spatial heterogeneity at different spatial extents (Li et al. 2012) and there are legacy effects of previous-year precipitation on vegetation production (Sala et al. 2012). In the case of the weak production-precipitation relationship, the VDI may not accurately detect vegetation disturbances because its basic premise is violated and the effects of precipitation fluctuations are difficult to be removed. A spatially explicit and pixel-based approach (Li et al. 2012) may be necessary to deal with this problem. To do it, we can first choose pixels with significant relationship between EVI and precipitation for the application of VDI. For the remaining pixels, other indices, e.g., the MGDI (Mildrexler et al. 2009) which combines MODIS EVI with LST, can be used to detect disturbances. Considering that the VDI and the MGDI are suitable for different ecosystems (i.e., the VDI for herbaceous plants and the MGDI for woody ecosystems), we can use the two indices together for better detecting disturbances at the global scale.

More detailed investigations using field surveys or finer spatial resolution images are needed to test our method (e.g., the selection of the distance of environmental impacts from a SCM site or the range of natural variability). In the future, researchers can make some attempts to further refine our method. For example, statistical tests (e.g., *T* test or Z-test) at the pixel level may help better identify the locations of vegetation disturbances by SCM based on the time-series EVI data before and after SCM; and the shape of a SCM area can be considered for better determining the spatial extent of SCM damage to vegetation. In addition, future studies should further assess the impacts of the identified vegetation disturbances on terrestrial ecosystems using different methods (e.g., Integrated Valuation of Ecosystem Services and Trade-offs model) for sustainable management of natural resources.

Conclusions

We have developed a new vegetation disturbance index, which combines MODIS EVI data with precipitation data, for quantifying the landscape-scale vegetation disturbances by SCM. Our results indicate that this new index is a simple but effective index for quantifying the locations, spatial extents, and severity of vegetation degradation due to SCM in arid and semiarid regions.

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