

Trend analysis of MODIS NDVI time series for detecting land degradation and regeneration in Mongolia



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ABSTRACT

This study examines whether MODIS NDVI satellite data time series can be used to detect land degradation and regeneration areas in Mongolia. Time series analysis was applied to an 11-year MODIS NDVI satellite data record, based on the hypothesis that the resulting NDVI residual trend vectors would enable successful detection of changes in photosynthetically active vegetation. We performed regression analysis, derived regression slope values, and generated a map of significant trends. We also examined land cover development and meteorological data for the same period.

11-year time series of MODIS 16-day composite NDVI data proved sufficient for deriving statistically significant trend values for 50% of Mongolia's surface. MODIS land cover products proved suitable for identifying areas of vegetation cover change. Areas showing positive and negative NDVI trends mostly coincided with areas of land cover class change indicating an increase or a decrease in vegetation, respectively. Precipitation changes in the same time period seem to have had an influence on large NDVI trend areas. The NDVI time series trend analysis methodology applied successfully detected changes due to deforestation, forest fires, mining activities, urban expansion, and grassland regeneration. These findings demonstrate that NDVI time series trend analysis is suitable for detecting vegetation change areas and for identifying land degradation and regeneration.

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1. Introduction

According to the United Nations Convention to Combat Desertification (UNCCD), land degradation in arid, semi-arid, and dry sub-humid areas – also referred to as drylands – may result from various factors, including climatic variations and human activities (UNCCD, 1994; UNCCD, 2012). It includes diverse processes, ranging from changes in plant species composition to soil erosion, and reduces the land's productive potential (Hill et al., 1995; Reynolds, 2001; Reynolds et al., 2007). Land degradation may diminish the land's resilience, making it more vulnerable and reducing its capacity to recover from disturbances. Furthermore, land degradation can have negative effects on other resources, such as water, soil, flora, and fauna (Hennemann, 2001a, 2001b). Causes of land degradation can be natural or man-made. Natural causes

include periodic stress from extreme and persistent climatic events, aridity, and droughts. Man-made causes include unsustainable human land use – for example, overgrazing, deforestation, and over-cultivation – as well as indirect socio-economic drivers, such as unstable food market prices and political instability or changes (NPACD, 1997; UNCCD, 2004; WMO, 2006).

Ecosystems in Mongolia are particularly fragile due to the country's relatively high altitude and its continental climate. According to the fourth national report on biodiversity (UNCBD, 2009), about 71.8% of Mongolia's territory is affected by degradation or desertification. Degradation is generally severe, causing not only a decline in herbage yields but also an overall deterioration of the ecological environment. A combination of natural factors, such as climate change, and human activities, such as overgrazing of pastures, deforestation, intensified crop production on unsuitable land, and mining activities leads to severe soil and wind erosion, desertification, and an increased occurrence of sand storms (Batjargal, 1997; Foggin and Smith, 1996; Lai and Smith, 2003). The Mongolian government is well aware of these environmental problems. However, the country's size poses a major challenge. Mongolia covers an area of 1.564 million km² and spreads across latitudes between 41°35' and 52°06' North and longitudes between

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87°59' and 119°57' East. Detailed data on important indicators of land degradation and desertification – for example in the form of soil maps, geological maps, or spatial data on land cover, land use, and livestock distribution – are either non-existent, available only at a coarse resolution, or outdated. Moreover, precipitation and temperature recordings of several of the few existing weather stations were interrupted, and in some cases the measurement methodology changed over time, making the available meteorological data difficult to analyze.

Given Mongolia's vast territorial extent, any effort to assess and monitor the complex processes of land degradation, as well as its severity, extent, and spatial distribution throughout the country must make use of remotely sensed data in addition to field data. The Land Degradation Assessment in Drylands (LADA) project run by the Food and Agriculture Organization of the United Nations (FAO) and the United Nations Environment Programme (UNEP) offers proven methodologies and tools for local-level assessments based on field data (LADA, 2012). On a national or even continental scale, satellite remote sensing needs to be, and has widely been, used as means of detecting and classifying changes in the condition of the land surface over time (Coppin et al., 2004; Lu et al., 2004). Satellite sensors provide consistent and repeatable measurements at predefined spatial and temporal scales that are capable of capturing change, including natural and anthropogenic disturbances (Jin and Sander, 2005).

Several studies attempting to assess and monitor the complex processes of land degradation and desertification made use of remote sensing methodologies to model some of the indicators that describe one or more aspects of desertification. By relating these indicators to other climatic variables, such as rainfall, air temperature, land cover, and land use, they tried to reveal geo- and biophysical causes of observed changes in vegetation greenness or net primary production (NPP) (Fensholt et al., 2009; Herrmann et al., 2005; Hickler et al., 2005; Xiao and Moody, 2005). On a continental scale, Symeonakis and Drake (2003), for example, proposed a desertification monitoring system for sub-Saharan Africa that uses remotely sensed data to model vegetation cover and rain-use efficiency, while surface run-off and soil erosion were modeled based on spatial data from other sources. When combined, these indicators can serve to identify areas that are particularly susceptible to degradation. This method has potential for near-real-time monitoring. On a national scale, Omuto et al. (2011) developed a method for identifying the rate and extent of land degradation in Somalia. Interpolated precipitation data were combined with corresponding Advanced Very High Resolution Radiometer (AVHRR) Normalized Difference Vegetation Index (NDVI) time series, land cover and land use data, and a digital elevation model (DEM). The trend in the relationship between NDVI and precipitation was then combined with a coarse degradation map generated on the basis of expert knowledge.

On a regional scale, in 2004 the European Space Agency (ESA) established the DesertWatch project to develop an information system based on remote sensing technology for monitoring land degradation trends over time (extension, 2012). At the outset, this project focused on the Mediterranean countries of Portugal, Italy, and Turkey, where detailed data on several indicators are available. Later the approach was adapted for use in Mozambique and Brazil in order to demonstrate that it can be transferred to other areas, including areas where data might not be as readily available, and that it can be applied globally (extension, 2012). The methodology produces a land degradation index by integrating land use and land cover data with a desertification susceptibility indicator consisting of NDVI, soil brightness, and a meteorological parameter derived from long-term precipitation observations.

The studies mentioned, as well as other studies, have explored ways of detecting changes in vegetation from local to global scales, mostly by including and monitoring the NDVI and relating the amount of red and near-infrared reflected energy to the amount of vegetation present on the ground (Colwell, 1974; Huete et al., 1997). Reflected red energy decreases with plant development due to chlorophyll absorption in actively photosynthetic leaves (Huete et al., 1999). The NDVI is a normalized transformation of the near-infrared (NIR) to red (RED) reflectance ratio ($\rho_{\text{NIR}}/\rho_{\text{RED}}$), designed to standardize vegetation index values so they are between -1 and $+1$, with 0 standing for “no vegetation” and negative values for “non-vegetated surfaces” such as water or snow (Silleos et al., 2006). Vegetation indices are robust, empirical measures of vegetation activity at the land surface. They are designed to enhance the vegetation signal from measured spectral responses by combining two (or more) different wavebands, often the red ($0.6\text{--}0.7\text{ }\mu\text{m}$) and near-infrared wavelengths ($0.7\text{--}1.1\text{ }\mu\text{m}$). They provide consistent spatial and temporal comparisons of global vegetation conditions; these can be used to monitor the Earth's terrestrial photosynthetic vegetation activity, thus enabling phenological change detection and biophysical interpretations (Solano et al., 2010).

Over the past three decades, researchers developed methods for analyzing time series and detecting trends, with a view to detecting changes and even separate different type of changes. More recently, Eastman et al. (2009) introduced a procedure for analyzing seasonal trends in time series of environmental data derived by remote sensing. This technique, called Seasonal Trend Analysis (STA), proved to be robust to short-term interannual variability. Accordingly, it is very effective for focusing on the general nature of longer-term trends in seasonality, enabling the derivation of both gradual and abrupt changes in land cover.

Considering the lack of up-to-date spatial data on land degradation and regeneration areas in Mongolia, and given the availability of 11 years of Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data as well as the newly developed methods for time series trend analysis, in the present study we sought to apply time series analysis to an 11-year MODIS NDVI satellite data record. We hypothesized that the derived NDVI residual trend vectors might successfully detect changes in photosynthetically active vegetation and thus serve as an indicator for land degradation and regeneration processes. The study design included calculating the significance of detected trends in the analyzed time series. In addition, we were interested in the relationships between land cover, land cover change, and the detected NDVI trends, as well as the question of whether a similar trend pattern can be observed in pointwise precipitation and temperature data.

2. Materials and methods

2.1. Satellite data

This study is based on an analysis of MODIS data recorded by two sensors on board of the NASA's Terra and Aqua platforms, which were launched in 1999 and 2002, respectively. The two satellites are in a sun-synchronous, near-polar orbit at 705 km altitude and cross the equator every day at 10:30 am local time (NASA, 2012). For this study, two products were downloaded and analyzed: MCD12Q1 Land Cover Type (Collection 5) and MOD13Q1 Vegetation Indices. MODIS products are provided in HDF-EOS format (Hierarchical Data Format for NASA's Earth Observing System). The standard projection system is sinusoidal grid projection; MODIS tiles measure 4800 by 4800 pixels, which corresponds to about 1200 by 1200 km. All MODIS products can be accessed and

downloaded free of charge from the Earth Observing System Data and Information System (EOSDIS) internet portal.

The MODIS Land Cover Type product contains multiple classification schemes describing land cover properties that are derived from observations spanning a year's input of Terra and Aqua data (NASA, 2012). For this study, the 17-class International Geosphere-Biosphere Programme (IGBP) classification scheme was used. We worked with the most recent Collection 5 MODIS Global Land Cover Type product, which was made available in 2010 and covers the years 2001–2009 at a spatial resolution of 500 m.

The MODIS 16-day composite vegetation indices product was analyzed for the years 2001–2011. It contains the enhanced vegetation index (EVI) and the normalized difference vegetation index (NDVI) at a spatial resolution of 250 m. It consists of the most reliable pixel values (Huete et al., 1999).

2.2. Meteorological data

Meteorological data in Mongolia are recorded at 69 registered weather stations by the National Agency for Meteorology, Hydrology and Environment Monitoring of Mongolia (NAMHEM). Unfortunately, NAMHEM were unable to provide the entire data record due to national policy restrictions. Therefore, the Climate Research Unit Time Series (CRU-TS) global long-term climate database was used as an alternative. It covers the period from 1901 to 2009, and data are globally gridded at a spatial resolution of 0.5° (updated from Mitchell and Jones, 2005). The grids are based on raw station data. Each monthly grid is an interpolation based on the set of stations available at that moment in time. Thus the highest accuracy can be expected at the locations of weather stations.

2.3. MODIS NDVI time series analysis

The analysis of raster data time series is based on a number of statistical techniques implemented in the statistical program R (R

Development Core Team, 2008). The different methodological working steps for the MODIS NDVI time series analysis as well as the analysis of meteorological data are illustrated in Fig. 1.

First the MODIS data stacks of 253 datasets covering 11 years of 16-day composite NDVI recordings were searched and corrected for missing and erroneous data by reviewing the quality assurance flags that were provided together with the data. Missing pixel data values were replaced with the corresponding 11-year mean of the specific time series vector. Negative values were replaced with a zero; they occurred only in the case of water bodies, which were among the land cover classes that were excluded from the analysis. In a next step, the time series vectors were filtered using the Savitzky–Golay filter, in order to smooth spikes and data outliers. This filter was chosen because it has been successfully applied in previous studies (Cowpertwait and Metcalfe, 2009; Fontana et al., 2008; Jönsson and Eklundh, 2004; R Development Core Team, 2008). After this, the seasonality pattern of every yearly seasonal time interval using the corresponding annual mean was calculated and excluded from the vector. On the remaining anomalies simple linear regression modeling was then applied to extract the regression parameters of every time series vector (De Jong et al., 2011). Time was defined as the independent variable and the NDVI values as the dependent variable. The 104 million resulting individual linear regressions consisting of correlation coefficient and regression slope values indicate the strength and magnitude of the calculated trends (Fensholt and Proud, 2012).

The precision of trend estimates is strongly influenced by the variability and autocorrelation of the underlying noise process (Tiao et al., 1990; Weatherhead et al., 1998). Thus, the time needed to detect any future trends can be calculated by deriving these two statistical parameters from the existing time series vectors. According to Weatherhead et al. (1998), the number of years needed to give the trend significance can be approximated by:

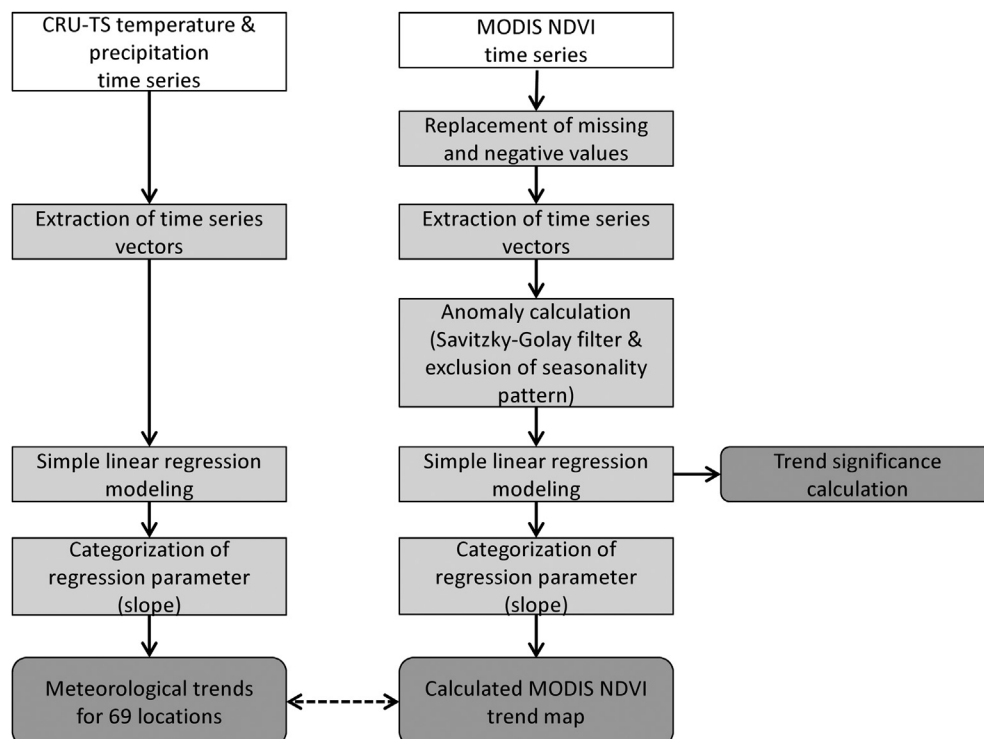


Fig. 1. Diagram of the methodological workflow.

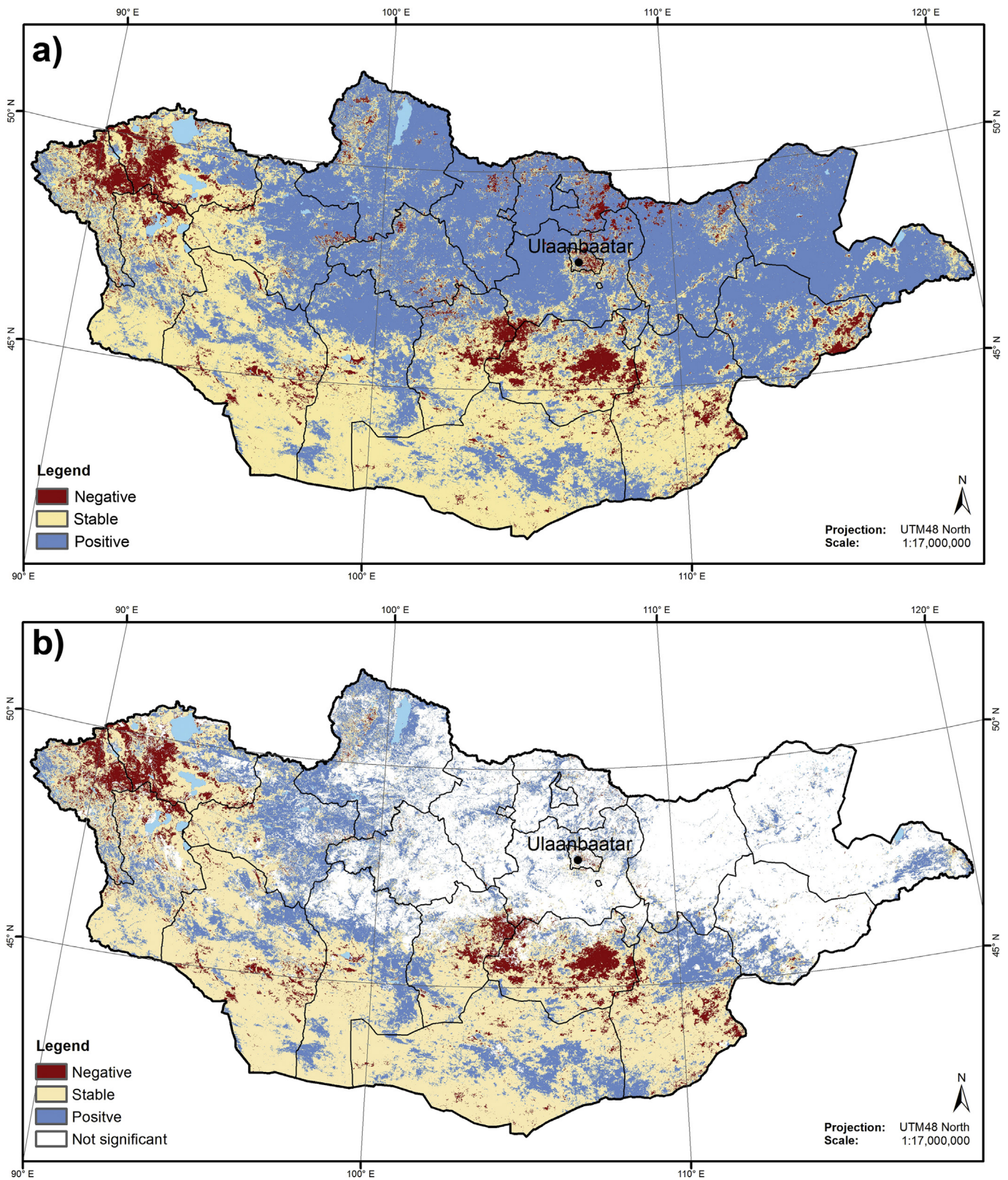


Fig. 2. a) Linear regression slope values for trends derived from MODIS 16-day composite NDVI observations from 2001 to 2011. b) Significant linear regression slope values for trends derived from MODIS 16-day composite NDVI observations from 2001 to 2011. A trend threshold value of 0.5 was defined, corresponding to an NDVI change of 0.0126 per 16-day interval.

$$n = \left[\frac{3.3\sigma_N}{\omega_0} \sqrt{\frac{1+\phi}{1-\phi}} \right]^{2/3}$$

Where σ is the variability or standard deviation, ϕ is the autocorrelation, and ω_0 is the expected trend of the data (Weatherhead et al., 1998). For ω_0 a trend threshold value of 0.5 was defined, corresponding to an NDVI change of 0.0126 per 16-day interval. This was done based on the theory and results presented by Weatherhead et al. (1998, 2002). The regression slopes of all pixel locations were thus categorized into “negative”, “positive”, “no trend”, and “not significant” categories and then mapped accordingly.

2.4. Land cover change analysis

The MODIS land cover type product was used a) to obtain first insights regarding possible reasons for observed trends; b) to identify areas of potential change; and c) to exclude water bodies and urban areas. We adapted the 17 land cover classes defined by IGBP, reducing them to eight classes according to the existing land cover in Mongolia. Thus, the permanent wetlands and water classes, all forest classes, open and closed shrubland, as well as woody savannas and savannas were merged; all other existing land cover classes remained as defined by IGBP. The final land cover class scheme used in this study is shown in Fig. 3. Then we analyzed the number of times each pixel had changed its land cover class between 2001 and 2009, as well as the related source and destination classes. On this basis, pixels were categorized in one of the following categories: class change indicating vegetation regeneration, hereafter referred to as “positive” class change (includes changes from grassland or shrubland to forest, and from barren or

sparsely vegetated land to grassland or shrubland); class change indicating vegetation degradation, hereafter referred to “negative” class change (includes changes from forest to grassland, shrubland, or barren and sparsely vegetated land, and from grassland and shrubland to barren and sparsely vegetated land); and no change or multiple class changes (including changes between similar land cover classes, e.g. from grassland to shrubland and vice versa, as well as multiple class changes indicating areas in transition).

2.5. Meteorological data time series analysis

First, the time series vectors of precipitation and temperature at the geographic locations of the 69 weather stations in Mongolia were extracted from the CRU-TS database. This was done for the period of 2000–2009, in accordance with the time span covered by the MODIS satellite data products used. Then simple linear regression modeling was performed. The resulting 69 regression slopes were categorized into the three trend categories as it had been done for the MODIS NDVI data analysis. The derived MODIS NDVI trend pattern and the pointwise precipitation and temperature trend pattern were visually compared. In addition to calculation of trends, the precipitation and temperature time series vectors were plotted and the temporal pattern was visually analyzed to enhance interpretation of the MODIS NDVI trend map and the meteorological trend data points.

3. Results and discussion

3.1. MODIS NDVI linear trends from 2001 to 2011

Fig. 2a illustrates the trends derived from MODIS NDVI time series from 2001 to 2011. Areas showing positive trends are most widespread in the center of Mongolia and towards the north and

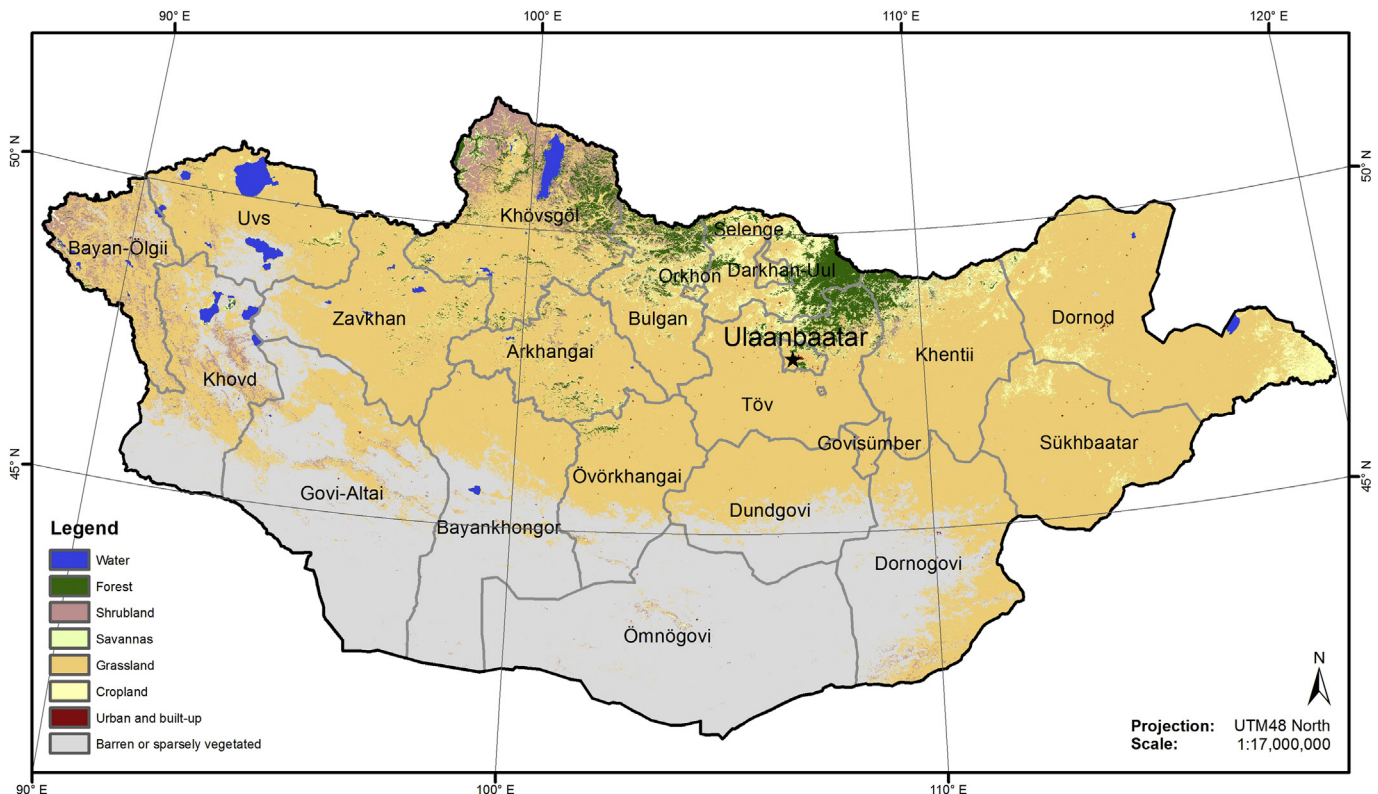


Fig. 3. Land cover in Mongolia in 2009, according to the latest MODIS land cover product (IGBP classification scheme).

northeast of the country. Areas showing negative trends, besides being interspersed between areas with positive trends in the center of Mongolia, occur above all in the far west, around the country's capital, Ulaanbaatar, and in the forest areas in the north and east. In the northwestern and southern parts of the country, where the land is largely barren and sparsely vegetated (Fig. 3), only few slight trends were observed; mostly, these areas showed trends within the threshold values of ± 0.5 and can thus be considered stable. In terms of land cover classes, positive and negative trends occur in barren and sparsely vegetated areas, grassland areas, and forest areas. Negative trends are additionally present in open shrublands. A closer look at small patches of land degradation and regeneration will be taken in Section 3.4 on the validation of results.

In order to determine the significance of trends, we analyzed their variability and autocorrelation. Fig. 2b depicts only trends with significant linear regression slope values. The figure shows that some of the identified larger trend areas as well as most areas in northern Mongolia have to be excluded from further analysis if only significant trend vectors are considered. Nonetheless, the trends derived from the analyzed time series vectors are significant for more than 50% of the country. In order to provide significant trends for 95.5% of Mongolia's surface, another four years of MODIS NDVI data would need to be included in the analysis. For the remaining 4.5% of Mongolia, it would take over 15 more years of MODIS data for trends to become significant. The spatial distribution of these findings is shown in Fig. 4.

3.2. Land cover change from 2001 to 2009

In order to find out which land cover classes show trends and thus may be affected by change, we analyzed MODIS land cover classification products from 2001 to 2009 and compared them with the generated MODIS NDVI trends. It should be noted that such

comparison is only valid where “positive” or “negative” land cover class changes correspond with an increase or decrease respectively in NDVI value, which is the case for the defined “positive” and “negative” land cover class changes. It is not valid for the “no change or areas in transition” category, where shrubland may show higher NDVI values than grassland depending on the season. Thus, Fig. 5 illustrates only areas for which permanent land cover class changes were detected. A comparison of Fig. 5 with Fig. 2 reveals that areas of positive and negative land cover class changes coincide with some of the larger areas for which positive and negative NDVI trends were detected, respectively. By contrast, small areas showing NDVI trends only coincide with a change in land cover class if the latter clearly shows in the MODIS spectral bands and, consequently, in the NDVI product. This is the case, for example, for newly constructed buildings near Ulaanbaatar as well as in the south of Mongolia, which led to both a negative NDVI trend and a switch from another land cover class to “Urban and built-up”. Slight changes in land cover or changes affecting only very small areas (e.g. an urban development site or a new mining site) may not be detected by the MODIS land cover classification product, as they do not cause a clear enough spectral change in the MODIS satellite data.

In general, changes occurred mainly at the boundaries between grassland and barren and sparsely vegetated land, as well as between shrubland and grassland. This indicates that such transition areas might be highly sensitive to natural or anthropogenic impacts. But a change in land cover class over a nine-year observation period may have other reasons as well: a) such transition areas might be highly sensitive to interannual variability in precipitation and temperature; b) they might be highly sensitive to the classification algorithm; or c) the change might have resulted from difficulties in clearly defining the land cover class, for example due to the similarity of open shrubland, grassland, and barren and

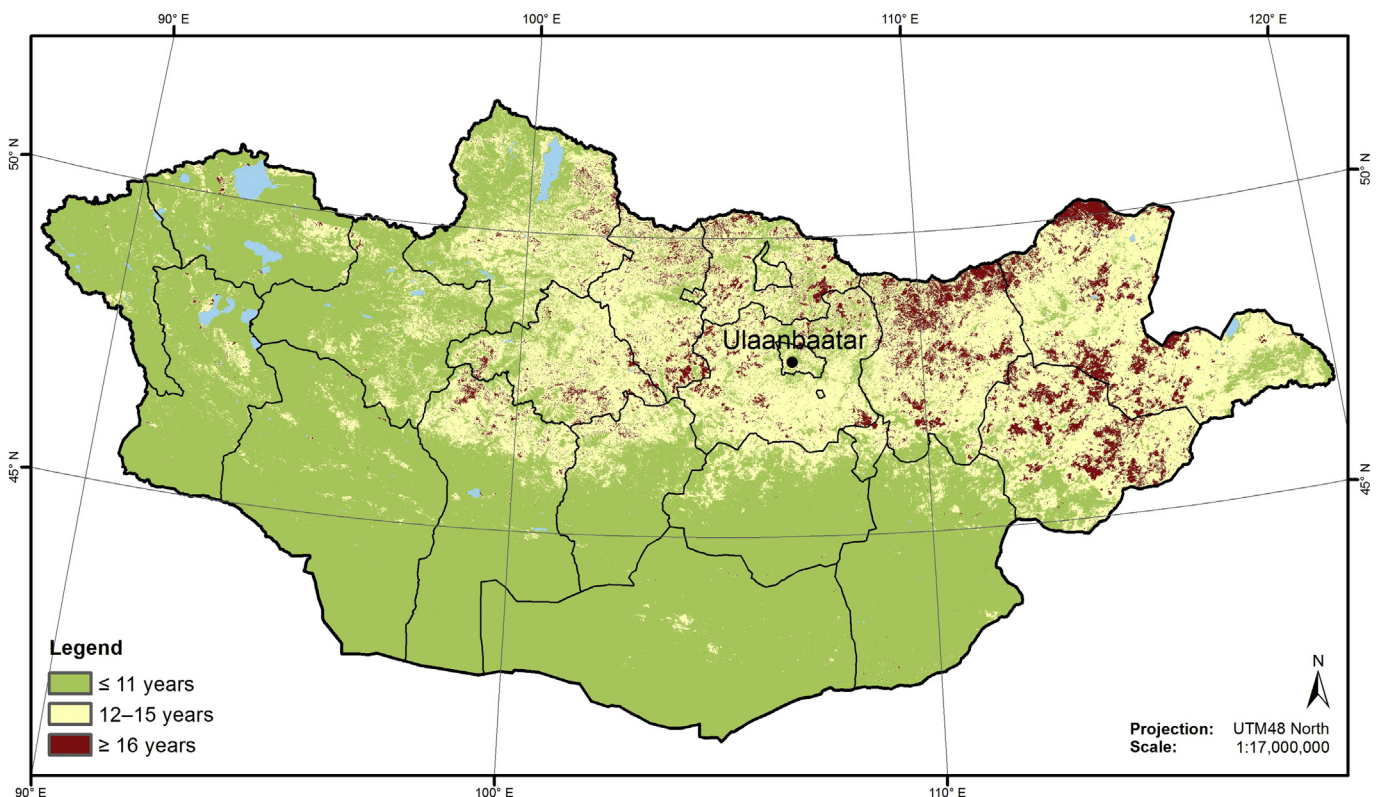


Fig. 4. Years of data records required to detect an NDVI trend of 0.0126 (corresponding to the trend threshold value $\omega_0 = 0.5$) for the studied area and time series vectors.

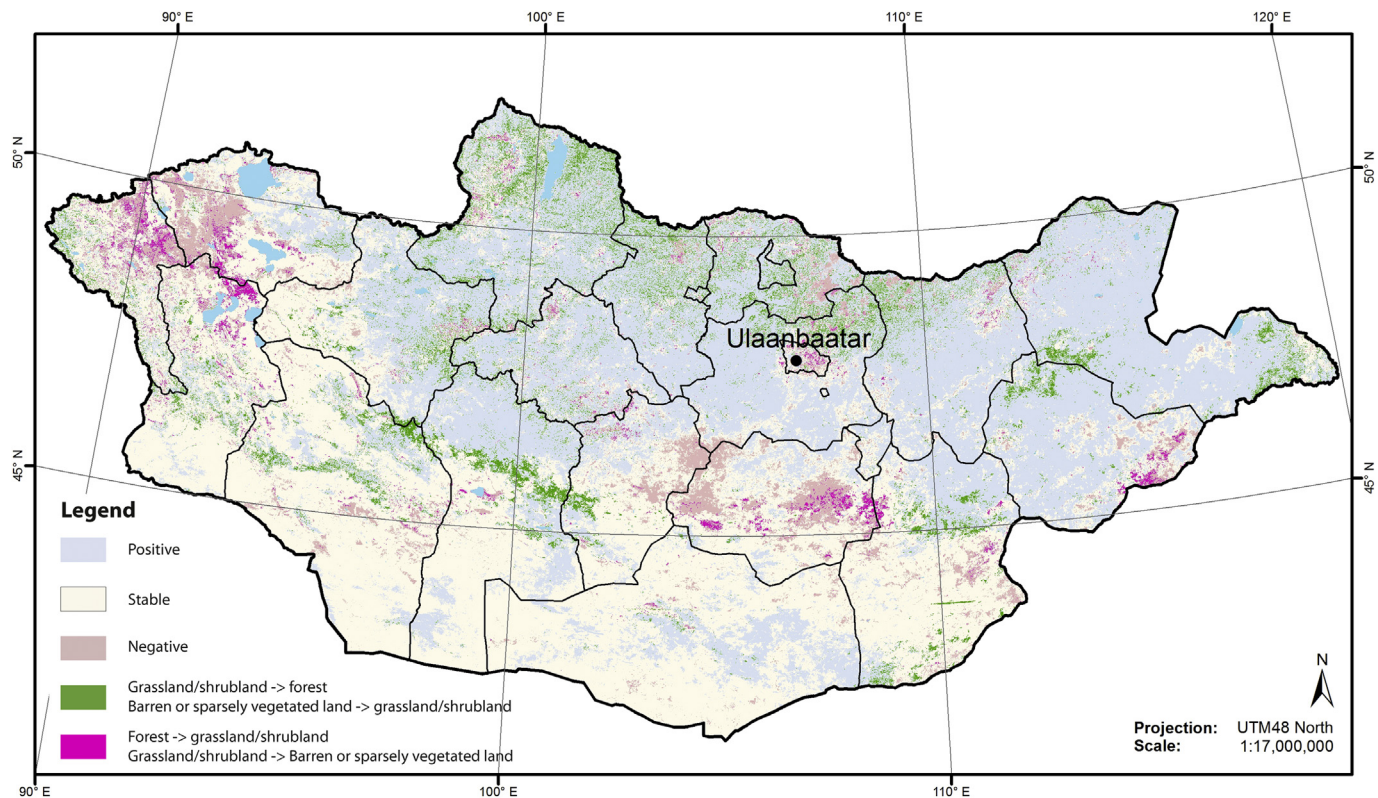


Fig. 5. Visual comparison of NDVI trends and land cover class change trends.

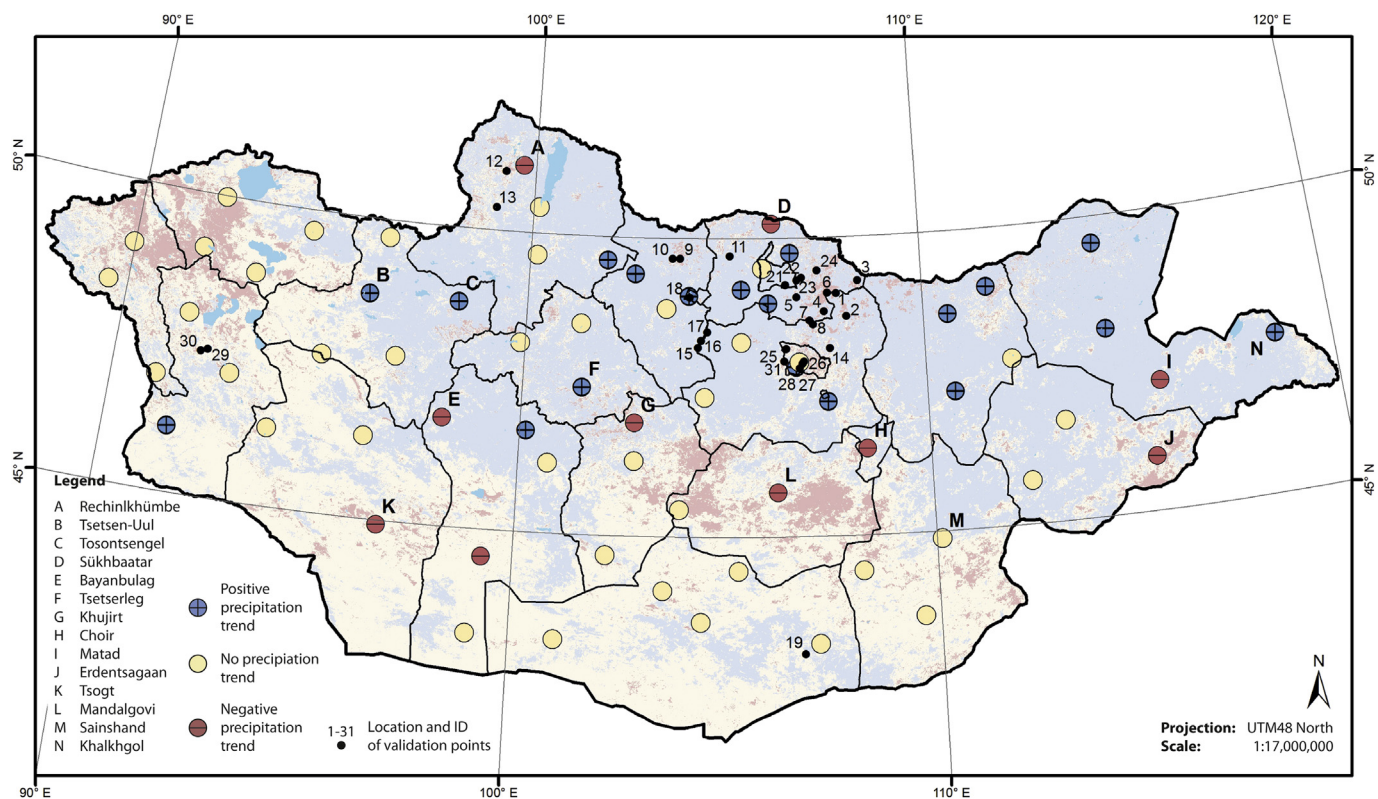
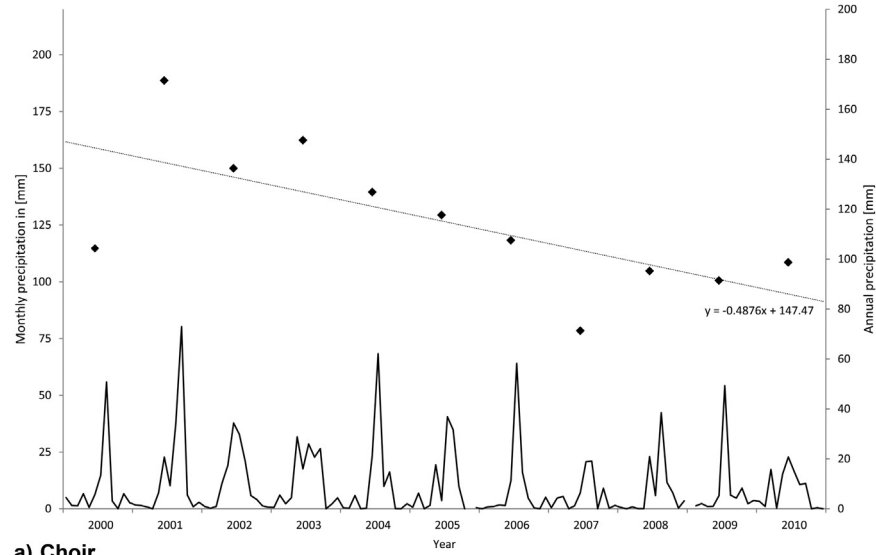
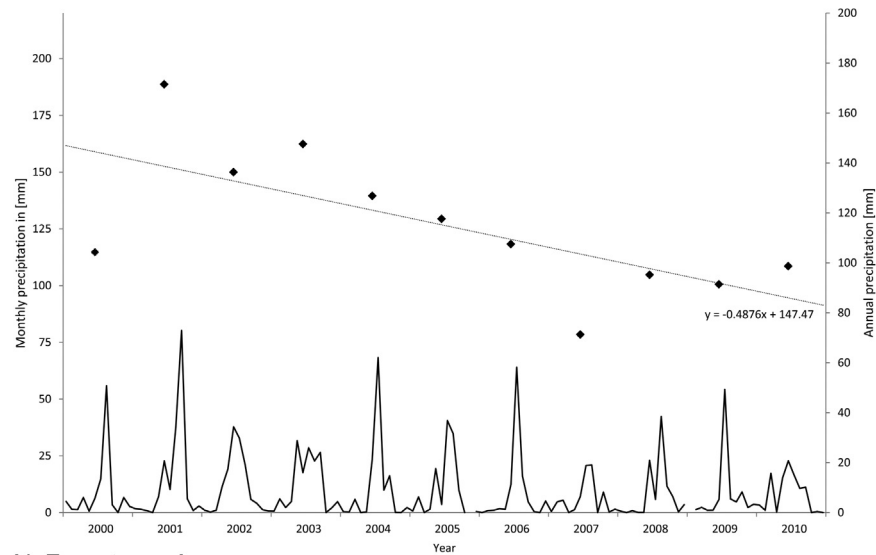


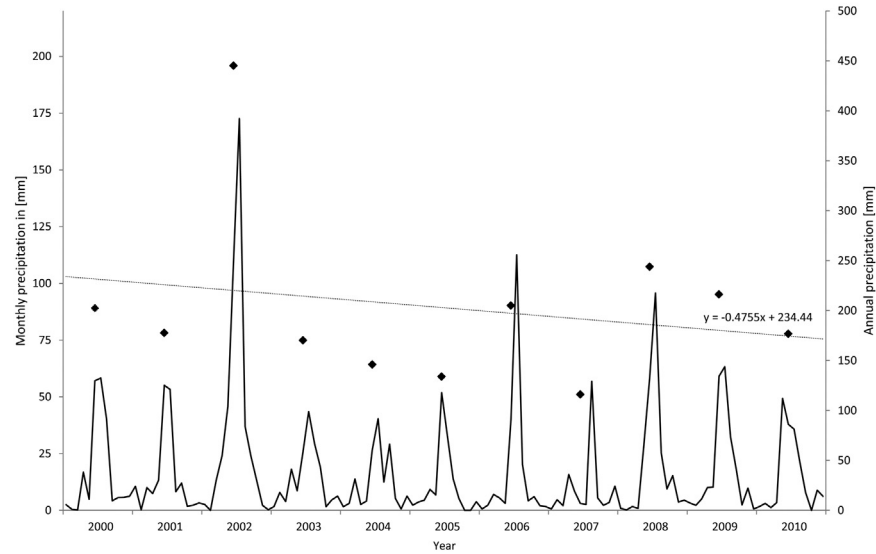
Fig. 6. Linear regression slope values for trends derived from MODIS 16-day composite NDVI observations from 2001 to 2011, overlaid with annual precipitation trends calculated based on 10 years of measured precipitation data. Numbered circles indicate the locations of the validation points.



a) Choir



b) Tosontsengel



c) Matad

Fig. 7. Monthly and annual precipitation values for a) Choir, b) Tosontsengel, and c) Matad. Gaps indicate months for which no precipitation data were recorded. The regression line was calculated for annual precipitation values. Choir is an example of decreasing yearly precipitation sums, Tosontsengel is an example of increasing annual precipitation values and Matad represents an example of high variability in annual precipitation values.

sparsely vegetated land. Examples of known classification errors are found in eastern Dornod and in southern Dornogovi. In Dornod, large areas were misclassified as agricultural areas, and in Dornogovi a large area was misclassified as grassland; in both cases this resulted in erroneous land cover class changes.

3.3. The temporal behavior of precipitation and temperature measurements

In order to understand the impact of meteorological parameters on NDVI trends, the derived MODIS NDVI trend pattern and the pointwise precipitation and temperature data as well as their trend pattern were visually compared. The analysis shows that temperature remained stable for all 69 locations considered; temperature maximum and minimum values as well as the monthly means did not vary much since 2000. By contrast, annual precipitation values display regression trends over the observed 10-year period. Regression slopes were calculated for annual precipitation over the 10 years considered. The 69 locations were classified as “stable” when trends ranged within ± 0.25 . Slope values >0.25 indicate a positive trend, slope values <0.25 a negative trend. As shown in Fig. 6, locations showing positive and negative annual precipitation trends mostly coincide with large NDVI trend areas. Annual precipitation values in Mandalgovi, Choir, and Khujirt — all situated near large negative NDVI trend areas — have shown a decreasing trend since 2000. The same is true for Erdenetsagaan and Tsogt, which are also both situated in areas where a simultaneous negative NDVI trend was observed. Conversely, several locations in areas where we had detected a positive NDVI trend had recorded increasing annual precipitation values since 2000: this was the case in Khalkhgol in the east of the country, in Tosontsengel and Tsetsen-Uul in the northwest, and in most parts of northern Mongolia. However, there are also areas where annual precipitation and NDVI exhibited opposite trends. This was the case, for example, in Madat in the east, Sükhbaatar and Renchinlkhumbe in the north, and Bayanbulag in the middle west. Although these precipitation trends observed between 2000 and 2009 may be temporary phenomena, they might still partially explain the large clusters of NDVI trend areas that we detected. Some locations showed no clear trends; but interannual variation in annual precipitation is high in some areas, indicating that there are both extremely dry and extremely wet years. This is also illustrated in Fig. 7, which shows annual precipitation measurements for three selected locations. The consequences that such extremes may have for the vegetation cover in the long term are still unknown. A longer reliable precipitation measurement record is needed to draw any conclusions regarding existing rainfall trends. This finding is also confirmed by Wesche and Treiber (2012).

3.4. Validation using in-situ observations and multi-temporal high-resolution satellite data

The spatial extent of the study area, the multi-temporal nature of degradation and regeneration processes, as well as the many interrelated natural and human influences on land degradation and regeneration make validating the NDVI time series trend map a challenging task. By analyzing land cover, land cover change, and meteorological data, we tried to explain the larger clusters (i.e. regional) of NDVI trend areas identified. Identifying local NDVI trends and land cover changes, however, requires information of a higher spatial resolution. Moreover, it would also be useful to know how the land was used and managed over the last decades. But such detailed spatial information does not exist. Therefore, we combined multi-temporal high-resolution datasets acquired in 2000 and 2010 with in-situ observations confirming a selection of

Table 1

In-situ and multi-temporal Landsat 5 TM data points used to validate and explain positive and negative trends derived from time series vectors.

- Multi-temporal landsat TM 5 data - In situ observations	ID	Type of land cover change	Reference point		Regression slope
			Latitude	Longitude	
LT5_131026_2001267	1	Deforestation	49.067	107.822	−3.17
LT5_131026_2011263	2	Deforestation	48.674	108.056	−11.06
	3	Deforestation	49.261	108.375	−15.90
	4	Forest Fire	48.765	107.493	−8.18
	5	Forest Fire	49.011	106.809	−5.46
	6	Forest Fire	49.077	107.588	−17.15
	7	Forest Fire	49.620	107.126	−0.49
	8	Forest Fire	48.551	107.212	−10.53
LT5_133026_2000263	9	Forest Fire	49.661	103.842	−2.90
LT5_133026_2010242	10	Forest Fire	49.664	103.654	−2.28
LT5_131027_2001251	11	Forest Fire	49.710	105.119	−1.79
LT5_131027_2011247					
LT5_137025_2000259	12	Grassland	50.993	99.210	−1.14
LT5_137025_2011273	13	Grassland	50.385	99.0241	−1.46
LT5_131026_2001263	14	Grassland	48.151	107.618	−1.48
LT5_131026_2011263					
LT5_133026_2000263	15	Mining	48.191	104.315	−2.25
LT5_133026_2010242	16	Mining	48.299	104.408	−7.95
	17	Mining	48.436	104.545	−6.27
	18	Mining	49.022	104.137	−5.70
LT5_130030_2000256	1929	Mining	43.035	106.839	−0.61
LT5_130030_2010235					
LT5_131026_2001263	20	Mining	48.744	106.168	−3.09
LT5_131026_2011263	21	Mining	49.229	106.458	−7.42
	22	Mining	49.279	106.815	−3.17
	23	Mining	49.346	106.923	−1.15
	24	Mining	49.479	107.373	−6.40
LT5_131027_2001251	25	Settlement	47.898	106.926	−4.73
LT5_131027_2011247	26	Settlement	47.935	106.963	−1.59
Photography	27	Forest Fire	47.822	106.872	−0.95
Photography	28	Forest Fire	48.152	106.525	−7.79
Photography	29	Grassland	47.458	92.226	2.25
Photography	30	Grassland	47.407	92.062	1.11
Photography	31	Infrastructure	47.941	106.473	−0.27

degradation types, as well as with auxiliary data such as a geo-spatial national forest fire monitoring dataset and a national mining activity dataset. We classified 31 validation points into six degradation classes. For each validation point, the corresponding trend line slope and intercept value were derived and visually documented using multi-temporal Landsat 5 TM data or, where available, photographs. All validation points are listed in Table 1. Their distribution is shown in Fig. 6.

Six validation examples are presented in Figs. 7 and 8. Fig. 8 illustrates two examples where newly introduced sustainable grassland management measures have led to an increase in vegetation cover and the recovery of a degraded patch of grassland (ID 29 and ID 30). Both of these increases in vegetation represent gradual, small changes over a fairly long period in time; nonetheless, both were detected by the trend analysis methodology. The two patches are rather small in size. Another example of a change occurring over a fairly long time period is the result of a lack in the planning and management of road networks in very remote areas of Mongolia, which led to the development of multiple parallel dirt tracks, causing land and soil degradation (ID 31). This trend analysis methodology correctly recognized some of the newer tracks as a negative change. ID 28 shows a small area where a rapid change occurred in a single event during the observed time frame: a forest fire. The patch was clearly detected in the time series analysis. In Fig. 9, ID 15 and ID 1 confirm two examples of change using multi-temporal Landsat TM data acquired in 2000 and 2010. ID 15 illustrates the Zaamar gold mine. The expanded, new mining areas are clearly recognized as a strong negative trend in the time series analysis. ID 1 shows a large forest fire that was clearly recognized as well.

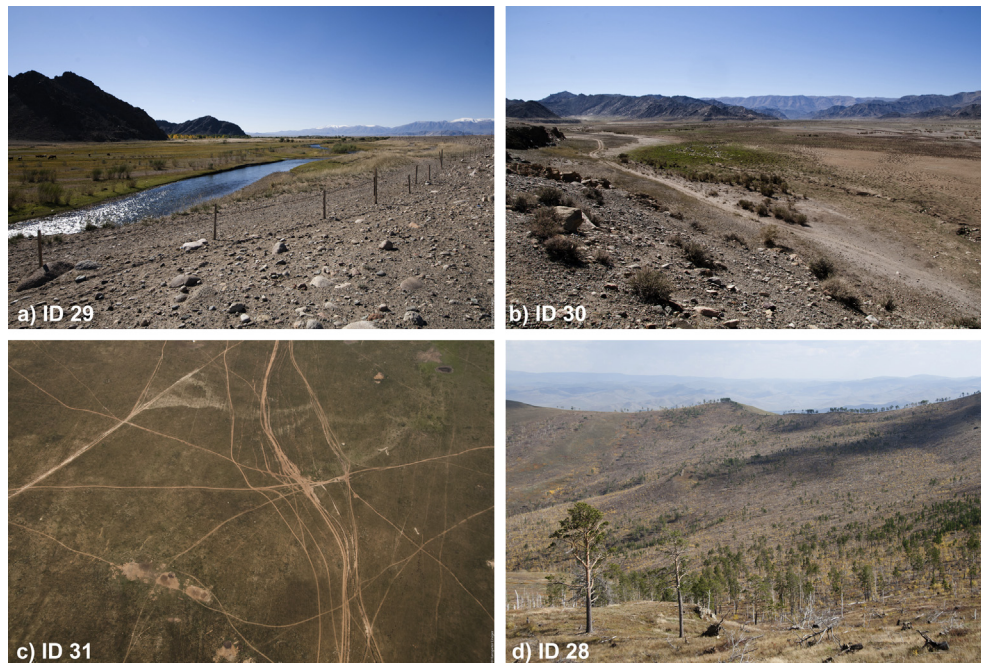


Fig. 8. Four selected validation points documented by photographs. a) A patch of grassland that has improved substantially since it is being managed sustainably; b) a patch of grassland that was fenced for regeneration and protection from grazing; c) changing dirt tracks have caused this land to degrade since 2000; d) forest destroyed by a fire a few years ago.

Given the country's vastness, the enormous amount of small patches showing distinct trends, and the many possible reasons for change and trends in NDVI, it is impossible to validate every patch showing a trend. However, with the help of higher-resolution multi-temporal satellite data analysis and, where available, photographs taken during field data collection, we were able to explain a selection of trends indicating changes caused by land degradation, land regeneration, deforestation, and mining activities. These examples included both abrupt and gradual changes affecting both large and small areas.

3.5. Limitations

Deriving significant trends from NDVI time series requires a fairly long record of NDVI datasets. This is particularly true for areas with a high seasonal variability in NDVI. For this study, MODIS NDVI data from 2001 to 2011 were available. But with both MODIS sensors, Terra and Aqua, still being in orbit and acquiring data, there is a good chance that sufficiently long NDVI data records can be collected for most sparsely vegetated dryland and grassland steppe areas in the world that are affected by land degradation and regeneration. However, the causes of land degradation and regeneration can only be understood based on detailed and accurate ancillary information on land cover, land use, land management, and livestock rates, as well as reliable long-term meteorological data and other similar parameters. For Mongolia, this information was only partially available. Accordingly, information on land cover had to be derived from a global land cover product available for the years 2001–2009 that contained no information regarding its accuracy for Mongolia; other data on land use and land management were not available. Reliable meteorological data records were available only as of 2000 and also until 2009, and livestock statistics could only be obtained at the *aimag* (province) level, which is too coarse for a spatial analysis. The data situation may be similar in many other areas of the world that are affected by land degradation and desertification.

Although the analyzed datasets vary by one or two years in their length and the years they cover, it is unlikely that these differences should have affected the resulting trends. The same is true with regard to the datasets' varying spatial resolution.

Validation of the derived NDVI trend map indicating land degradation and regeneration areas requires either cloud-free multi-temporal high-resolution satellite data or a well-documented database on land cover or land use change. Both do not always exist.

Seasonal Trend Analysis (STA) is robust to interannual variability and is a very effective procedure for focusing on the general nature of longer-term trends in seasonality. However, the method does not enable clear identification of, and differentiation between, a) seasonal changes, driven by annual temperature and precipitation interactions impacting plant phenology and proportional cover of land cover types with different plant phenology; b) abrupt changes, caused by disturbances such as deforestation, urbanization, floods, and fires; and – most importantly – c) gradual changes due to interannual climate variability, gradual changes in land management, or land degradation (Verbesselt et al., 2010).

4. Conclusion

This study explored 11 years of MODIS 16-day composite NDVI time series to detect land cover change – in particular land degradation and regeneration areas – in Mongolia. Time series vectors were analyzed for trends using regression analysis. Regression slope values were derived, and a trend map was generated that takes account of each time series vector's significance. In order to gain a better understanding of the derived trend areas, we also examined land cover development from 2001 to 2009, as well as trends in meteorological data from 2000 to 2009. High resolution satellite data and field photographs were used to validate small, local NDVI trends. The following conclusions can be drawn from this research:

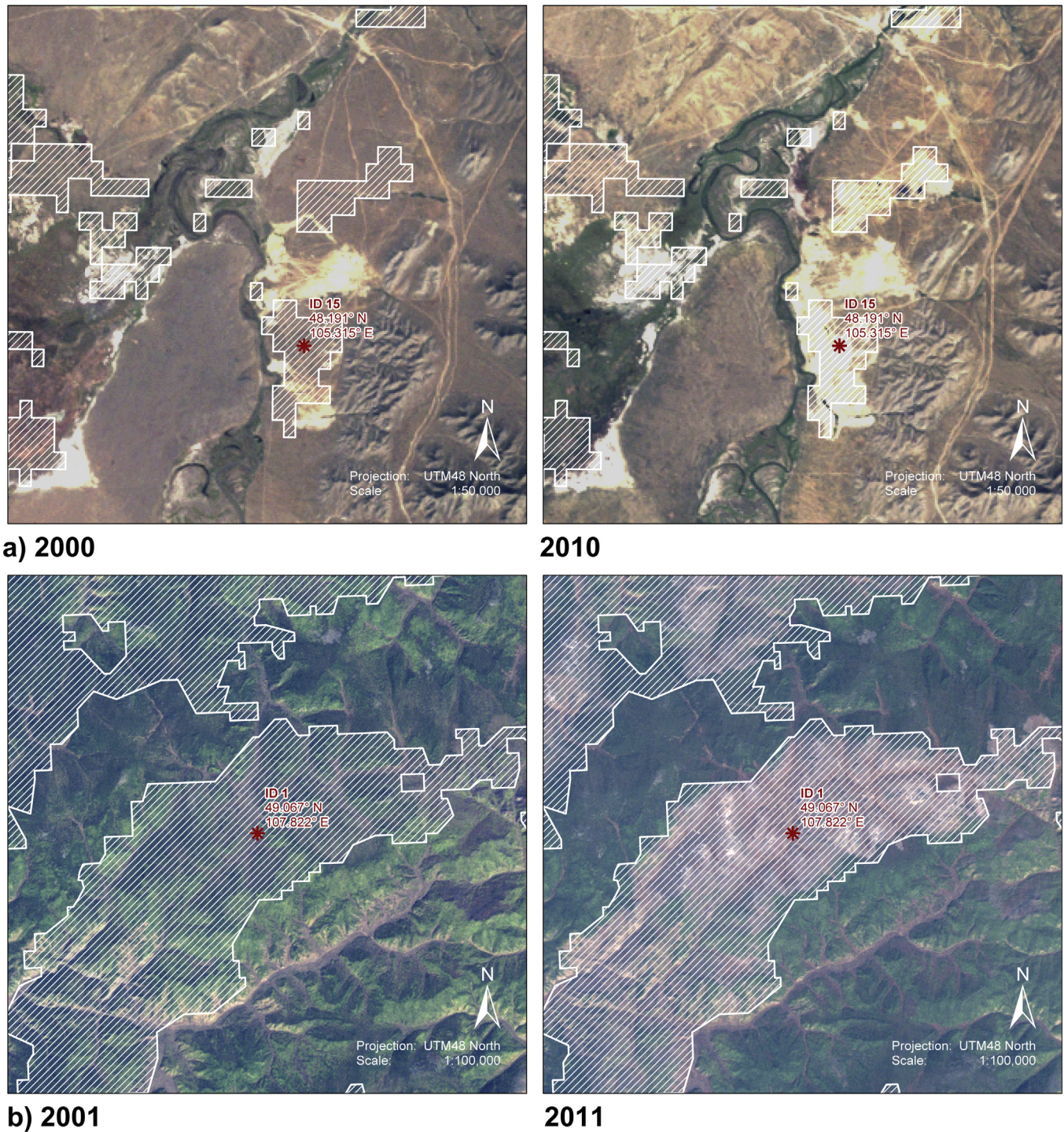


Fig. 9. Two selected validation points confirmed by two Landsat TM 5 scenes acquired in 2000 and 2011. a) Expansion of mining activities at the Zaamar gold mine (ID 15). b) Area deforested due to a forest fire (ID 1). Both examples are overlaid with the negative trend layer, which clearly indicates the resulting land cover change.

- Areas showing positive trends are most widespread towards the north and northeast of Mongolia, as well as in the Gobi desert in central and southern Mongolia. Negative trends are less frequent overall; they are interspersed between areas showing positive trends in the center of Mongolia, and slightly more widespread in the far west, around the country's capital city, Ulaanbaatar, and in the forest areas in the north and the east of the country.
- Eleven-year time series of MODIS 16-day composite NDVI data provided a sufficient basis for deriving statistically significant trend values for 50% of Mongolia's surface. In order to derive significant trends for 95.5% of the country, another four years of MODIS NDVI data is required. To date, the majority of positive and negative trends detected in the more densely vegetated north and northeast of Mongolia are not statistically significant.

- The MODIS land cover product proved suitable for identifying areas where the vegetation cover had increased or decreased, as well as areas where the vegetation cover had not changed much since 2001. Moreover, the product enabled the identification of transition zones where the land cover class had repeatedly changed back and forth. We were also able to detect erroneously classified areas.
- Indicated areas of positive and negative land cover class change mostly coincided with areas showing positive and negative NDVI trends, respectively.
- Linear regression trends of the 10-year annual precipitation data coincide well with the detected larger NDVI trend areas. This indicates that changes in precipitation might have an influence on large NDVI trend areas. No trends were observed for temperature.
- The validation of smaller, more localized NDVI trends with the help of multi-temporal high-resolution satellite data as well as field photography was successful. Changes due to deforestation, forest fires, mining activities, urban expansion, and grassland regeneration were successfully detected by the applied NDVI time series trend analysis methodology.

Using a selection of validation points to explain some of the trend areas, we demonstrated that MODIS NDVI time series analysis is suitable for detecting both large-scale and small-scale vegetation change areas and, hence, for identifying land degradation and regeneration in Mongolia. In cases where these changes occurred rapidly or abruptly, causality is often given and the causes are easy to determine. In some cases, it might be enough to acquire and analyze a pre-event and a post-event satellite dataset with a high or very high resolution. However, in cases where changes occur gradually over a fairly long period of time, as is often the case with land degradation or regeneration, understanding the processes and causes involved might be more difficult. Furthermore, it is not known whether the change will be permanent or whether it is only the expression of a short-term variability. For these reasons, our next research steps will focus on implementing the improved Breaks For Additive Season And Trend (BFASST) methodology, developed by Verbesselt et al. (2010). This method iteratively estimates the time and number of changes, and characterizes change by its magnitude and direction. Time series are decomposed into multi-year trend, seasonal variation, and a remainder component.

In addition, detailed spatial information – for example on historical and currently applied land management practices, livestock rates, topography, and long-term precipitation and temperature developments, to name only a few – need to be collected to understand and explain gradual changes in land cover and identify reasons for the emergence of larger clusters of NDVI trend areas. Validation of the derived NDVI trend dataset will be continued using high-resolution satellite data and field visits; the focus will be on areas that have experienced either land degradation, natural regeneration or restoration activities, in order to further develop the methodology's applicability. Furthermore, its transferability will be tested by applying it in other countries.

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