Assessment of desertification risk in Central Asia and Kazakhstan using NOAA AVHRR NDVI and precipitation data

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The primary objective of this study was to assess dry land degradation in Kazakhstan and Middle Asia based on time series of rainfall data and normalized difference vegetation index (NDVI) from NOAA AVHRR for the period 1981-1998. Normalized Difference Vegetation Index (NDVI) is generally recognized as a good indicator of terrestrial vegetation productivity. In arid, semi-arid and sub-humid regions rainfall is proved to have a dominant role in determining vegetation growth and in predicting trends in vegetation activity over time. Therefore, changes in vegetation cover imposed by human influences are difficult to identify. A new analytic methodology for the detection of areas undergoing degradation process driven by different reasons, climatic or anthropogenic, was developed and checked out in this project. The conceptual framework for the analysis is the combine use of time-series of Normalized Difference Vegetation Index (NDVI) and precipitation over the 20-year period. Linear regression was used to determine trends in NDVI and precipitation for each pixel. Changes in vegetation activity imposed by climate change were identified and pixels whose negative trends in NDVI are associated with downwards trends in precipitation considered to indicate climate-induced desertification. Areas with negative trends in NDVI which were not explained by trends in precipitation were considered to experience human-induced degradation. Results were validated by test of statistical significance and by comparison with the data from the remote sensing systems of fine resolution and trips to some field sites. According to our results, about 5 % of all territory is threatened by climatic desertification and only 1.2 % by anthropogenic. These modelling results were then combined with land-cover information to provide an assessment of desertification status.

Модель оценки опасности опустынивания в Средней Азии и Казахстане по данным NOAA AVRR NDVI и осадков

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Целью данного исследования было выявление райнов, подверженных антропогенному опустыниванию в Средней Азии и Казахстане. Оценка деградации земель базировалась на мониторинге двух индикаторов опустынивания: состояние растительного покрова и климата. Мерой состояния растительного покрова являлся нормализованный дифференциальный вегетационный индекс NDVI, получаемый спутником NOAA AVRR, климатическим индикатором служила сумма подекадных значений осадков за год. Известно, что для сухих регионов взаимосвязь между динамикой NDVI и осадками прямо пропорциональна и очень тесна. Поэтому тренды NDVI должны быть обусловлены трендами осадков. Мы предположили, что любой тренд NDVI, не соответствующий динамике осадков, может служить индикатором антропогенного влияния. Для выявления таких трендов были рассчитаны регрессионные модели для каждого пикселя между временными рядами NDVI и осадков за период с 1981 по 2000 годы. По результатам регрессионного анализа были выявлены площади климатического опустынивания , в которых отрицательный тренд NDVI обусловлен уменьшением осадков за расчетный период, и площади антропогенного опустынивания,, в которых уменьшение значений NDVI не подтверждается отрицательным трендом осадков. Согласно нашим расчетам 5 % всей территории подвержены климатическому опустыниванию, и лишь около 1.2 % антропогенному. Результаты нашего исследования уточняют оценку опустынивания в Средней Азии и Казахстане и служат улучшению землепользования.

Introduction

Desertification refers to land degradation at arid, semi-arid and dry sub-humid areas and has been seen as one of the major environmental problems in large parts of the land surface. Desertification is considered the result of a series of complex natural, mainly climatic, and anthropogenic processes that leads to gradual environmental degradation or loss of the lands biological and economical productivity. Common approaches to assess desertification demand for measurements of different indicators which usually describe one or more aspects of desertification and provide data on threshold levels, status and evolution of relevant processes.

Degradation of vegetation cover is one of the most important desertification indicators and can be monitored using satellite imagery. Satellite derived Normalized Difference Vegetation Index (NDVI) has successfully served as a vegetation indicator in many studies on desertification and land degradation [1, 2]. However, in many cases, the only use of NDVI for desertification monitoring can be problematical, because vegetation cover performance is strongly predicated on macro- and micro-climatic factors, such as temperature and rainfall distribution change, local topography characteristics etc. [3, 4, 5, and 6]. Therefore, discrimination between different causes of change in vegetation cover, climate and human activity, is rather difficult. The neglecting of this aspect can lead to mistakes by evaluation of land conditions. For example, the contemporary greening patterns in the Sahel are proved to be driving by an increasing trend in rainfall [7, 8]. A few recent studies have developed methods for application of discrimination by use of satellite data time-series and time-series of climatic variables [9, 10]. These methods have been based on identification of climate signal in inter-annual dynamic of vegetation activity. Once the climate signal is identified, it can be removed from the trends in vegetation activity. The remaining vegetation changes are attributed to human influence and these areas considered experiencing a human-induced degradation/rehabilitation of vegetation cover.

The objective of this study is to assess the area of degradation of vegetation cover in the former soviet republics of Central Asia. The assessment is based on synchronous monitoring of two indicators: vegetation and climate. The study utilized remotely sensed derived greenness index (NDVI) and precipitation data obtained from a global climate dataset. For the study, we examined trends in vegetation activity and precipitation over 1981-2000 and modelled interrelationships between these variables. The developed monitoring system enabled us to discriminate between two major causes of degradation: climatic or anthropogenic. Degraded areas were measured and mapped.

Data used in the study

NOAA AVHRR NDVI

Global Inventory Monitoring and Modelling System (GIMMS) NDVI dataset is a derivate from the NOAA AVHRR data and is freely available in Internet. We used GIMMS NDVI for the entire study region and for the period of 1981-2000. The GIMMS dataset was already pre-processed for radiometric and atmospheric corrections, calibration for sensor differences and orbital drift. The data, at 8-km spatial resolution, are originally processed as 15-day composites using the maximum value procedure to minimize effects of cloud contamination [11]. These original data were averaged to generate mean growing-season NDVI, mean summer NDVI and mean spring-summer NDVI for each year.

Precipitation dataset

A global data set of precipitation was used. This grid raster data are interpolated from climate station records and have a spatial resolution of 0.5°. The data are available from the Climatic Research Unit (CRU), School of Environmental Sciences, University of East Anglia (http://www.cru.uea.ac.uk/). The monthly precipitation data were resized to 8-km resolution to match the 8-km NDVI dataset.

Methods

We generated time series of mean growing season NDVI and time-series of total precipitation over the growing season (April-October) comprising every year from the period 1981-2000. Previous studies have shown a strong relationship between inter-annual changes in vegetation activity and precipitation in different dry regions [3, 4, 5]. Precipitation has a substantial control on NDVI through annual precipitation also in Central Asia (Figure 1). This control, however, should be predictable in every point of the study area where the relationship between NDVI and precipitation are statistically significant. Identification and quantification of climate signal may help to discriminate between two major factors of desertification, climatic and anthropogenic.

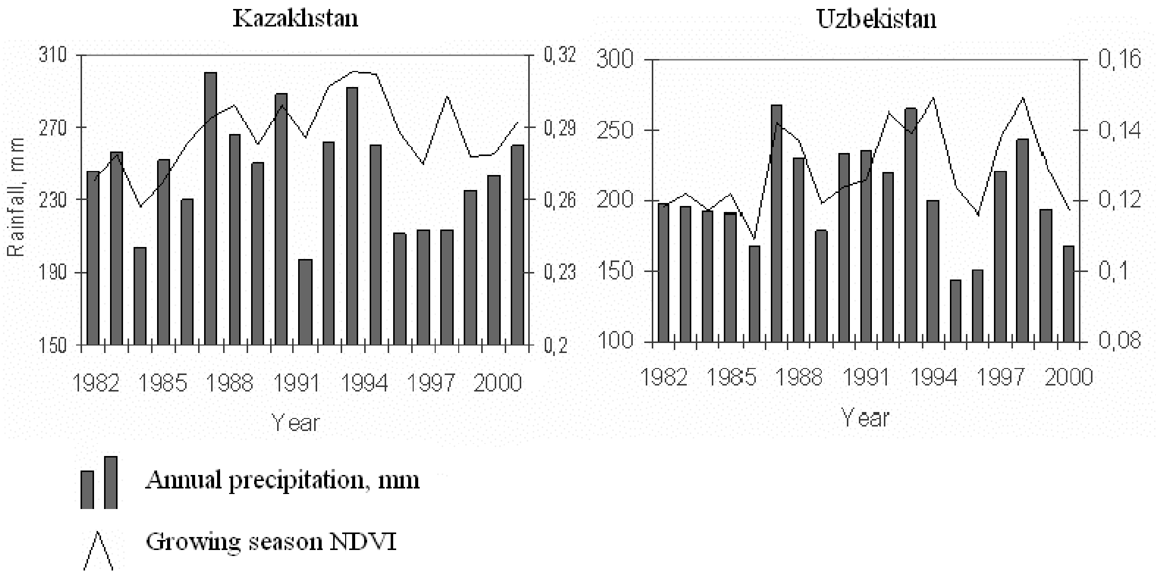


Figure 1. Time-series of annual precipitation and growing season NDVI over Kazakshtan and Uzbekistan during the period 1982-2000

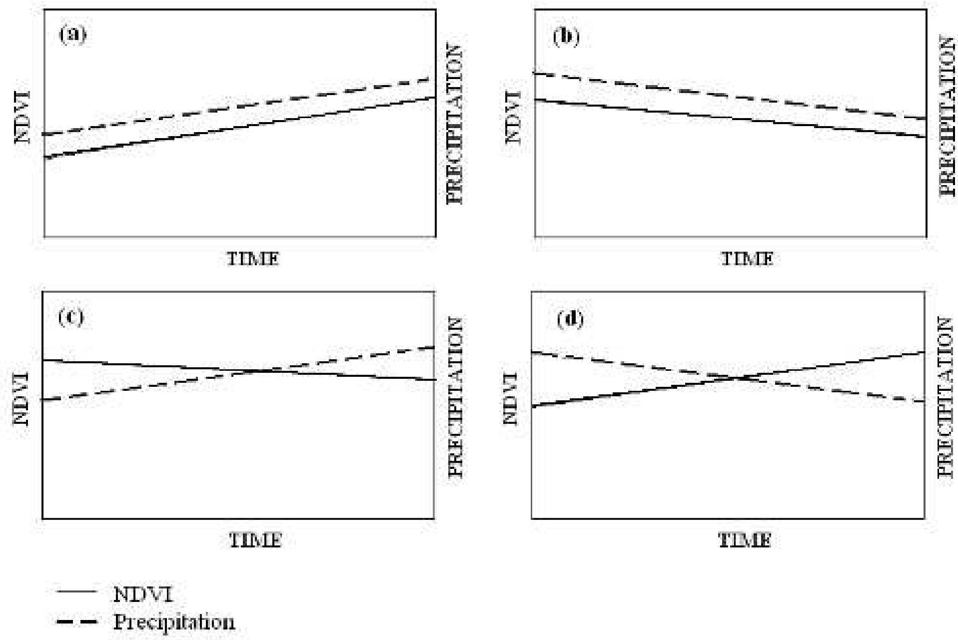


Figure 2. Scenarios illustrating how the combine use of NDVI and precipitation time-series may help to detect a vegetation cover being improved or degraded. Panel (a) displays improving vegetation cover caused by increase in precipitation; (b) vegetation degradation due to climate change; (c) recovering vegetation cover; (d) degradation of vegetation cover caused by human impact

Concept of synchrony/asynchrony between long-time trends in precipitation and NDVI

A simple and effective system of discrimination between climate and human driving forces in vegetation change has been developed in this study. This system is based on the concept of synchrony/asynchrony of time-trends in vegetation and climate factors. This concept is explained on an example framework (Figure 2). In panel (a), the upward trends in NDVI and precipitation are synchronous. Obviously, here we observe improving vegetation cover due to increasing precipitation amounts. In panel (b), the downward trends in NDVI and precipitation are also synchronous. In this case, decreasing NDVI is driven by a decrease of precipitation and human impact is not evident in the vegetation trend. In (c), the trends are asynchronous. NDVI increases even as precipitation decreases. This would indicate a case when vegetation cover is recovering due to diminishing human impact. In (d), the trends are once more asynchronous, but an increase of precipitation did not cause an improving of vegetation cover. On the contrary, the NDVI trend is negative. Here, we can suppose human-induced degradation of the vegetation cover.

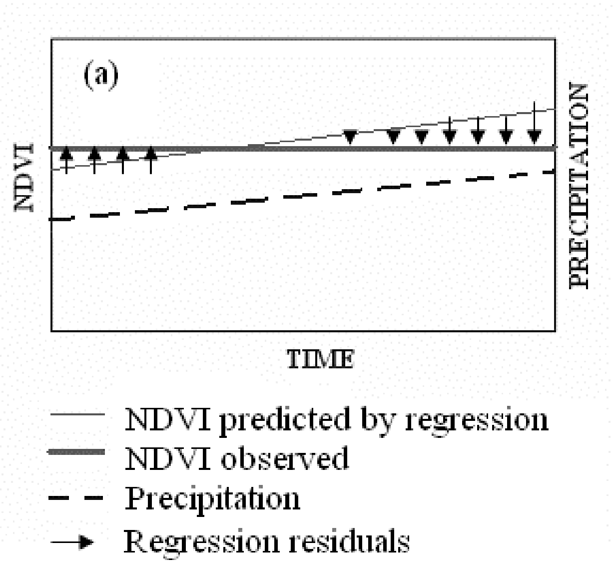
Identification of climate signal in vegetation change

The monitoring system based on synchrony/asynchrony concept would work only in areas where relationship between trends in vegetation and trends in climate factors are statistically significant and enough strong. We supposed that strong relationship between NDVI and precipitation in these areas would indicate a strong control of vegetation changes by changes in precipitation. For example, if an area reveals statistically significant correlation with precipitation and NDVI increases throughout the study period, it considers to indicate a climate (precipitation) driven improvement in vegetation cover (Figure 2, a). If a trend in NDVI is negative and an area reveals strong relationship with precipitation, it considers indicating degradation of vegetation cover due to decrease in precipitation (Figure 2, b).

Identification of anthropogenic signal in vegetation change

Detection of areas of human-induced changes in vegetation cover was more difficult. Figure 2 (c, d) presents examples of these cases. In both cases the trends in NDVI are opposite to trends in precipitation. This means a change of response of vegetation to precipitation during the study period. In general, vegetation cover reacts very sensitively on changes of precipitation particularly in dry regions [4, 7, 10]. If the response of vegetation to precipitation remains constant, increase/decrease of vegetation activity should exactly reflect changes in precipitation. That is the rule for undisturbed vegetation cover. However, the strength of vegetation response to climate factors will be significantly altered by external forces such as human impact. Disturbance of vegetation cover can be seen in change of its response to climate [9, 10]. Generally, a worse response of vegetation to climate means a degradation of vegetation cover caused by non-climatic factors (human impact) while a better response means an improvement of vegetation conditions. Thus, Figure 2 (c) demonstrates that a vegetation response to precipitation is getting worse. This would indicate a case of human-induced degradation of vegetation cover. An opposite case is shown in Figure 2 (d). Here, vegetation cover demonstrates increasing response to precipitation.

A successful detection of human-induced change in vegetation cover can be done through a detection of areas showing a change in vegetation response to precipitation. If this change is positive, one may speak about improvement of vegetation cover. If this change is negative, in that case vegetation cover is degrading due to human influence. To detect such areas, we analysed linear regression between NDVI and rainfall time-series over the period 1981-2000. For a given value of rainfall, a value of NDVI predicted by the regression, abbreviated as $NDVI_{pred}$, was obtained for every pixel and for each year, this value was considered to reveal the climatic component. The observed NDVI, abbreviated as $NDVI_{obs}$, may show deviations from the regression line. Positive deviations indicate a better response of vegetation to precipitation while negative deviations indicate a worse response. Deviations in $NDVI_{obs}$ from $NDVI_{pred}$ expressed in the regression residuals were computed at pixel-by-pixel basis for every year. On this way, we derived the response strength for every year and every pixel. In order to detect change in response strength, we looked into time-series of regression residuals. We suggested that any trend through time presented in the residuals would indicate changes in NDVI response not due to the climatic variable. A negative trend would mean diminishing response of vegetation cover to climate. This reduce can be caused either by a decrease of vegetation cover or by a change in plant species composition. According to this suggestion, this negative trend, if it is statistically significant, would indicate an area experiencing human induced degradation. Figure 3 demonstrates how decrease in vegetation response is reflected in a negative trend of regression residuals over the study period. An opposite case would indicate a positive trend in residuals.



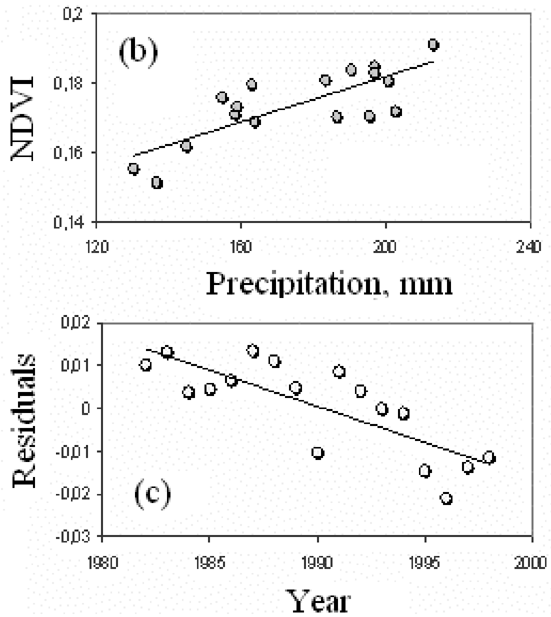


Figure 3. Example illustrating how the trends of regression residuals reflect changes in vegetation response to precipitation. Panel (a) shows steady decrease of deviation of $NDVI_{obs}$ from $NDVI_{pred}$ over the time. The deviation value turned from positive into negative during the observation period. That means a decreasing response of vegetation cover to precipitation. Even though precipitation amount rose, NDVI value remained at the same level. Panel (b) shows a regression between NDVI and precipitation for an area with like situation and panel (c) shows residuals from the regression arranged in a time-sequence

Results

Identification and quantification of precipitation signal in inter-annual dynamics of NDVI

Several previous studies have demonstrated a strong positive relationship between NDVI and rainfall in dry regions throughout the world [3, 4, 5, 6]. Numerous studies have suggested a linear relationship between NDVI and climate predictors. In the precipitation-dependent areas such as Central Asia, changes in NDVI are assumed to be affected by the occurrence of precipitation and NDVI can be considered as climatic recorder, mainly as a rainfall recorder. This assumption was used in various drought watching and drought early warning systems [12, 13]. However, the response of vegetation to precipitation varies between geographical regions and vegetation types [6, 10, 14]. From this view-point, it seems to be important to test several different analysis periods in order to find an optimum correlation between NDVI and precipitation. It is also apparent that over an area of about 5 million km² dryland is unlikely that a single analysis period will provide the best correlation. Instead, we would expect the optimum correlation period to vary with different vegetation communities, with soil properties, with morphological characteristics [3, 5, 6, 10]. Hence, correlations are calculated for many different combinations of precipitation and NDVI, allowing identification of its distinct optimum correlation (growing season, summer, spring-summer etc.). We also tried to generate time series of precipitation accumulated over two and more years and calculate correlation between them and time series of NDVI.

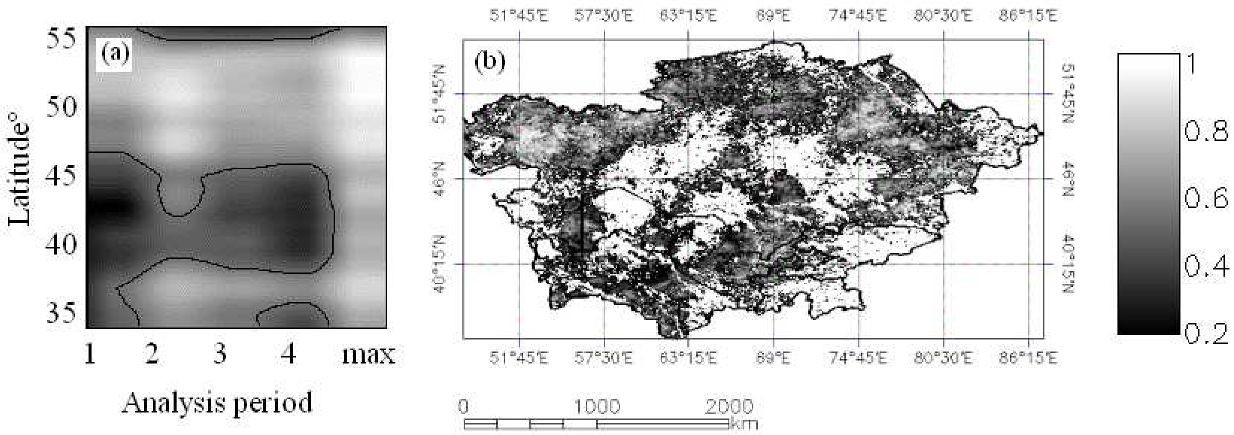


Figure 4. (a) Dependence of correlation strength on analysis period used for calculations. The numbers indicate: 1- summer rainfall/summer NDVI; 2- growing season rainfall/growing season NDVI; 3- growing season rainfall accumulated over 2 years/growing season NDVI; 4- growing season rainfall accumulated over 3 years/growing season NDVI; max- maximum correlation derived. The line shows the border of significance ($p < 0.05$) for correlation coefficient. (b) Spatial distribution of statistically significant maximum correlation coefficient ($p < 0.05$) between inter-annual NDVI and precipitation

In Figure 4 (a) demonstrates a matrix of correlation coefficients produced using different combinations between NDVI and precipitation. Strong correlations are derived by the combination of growing season precipitation and NDVI in all latitudes with an exception of the space between 40°- 45° N. Here, the correlation coefficients are low for all analysis periods.

Figure 4 (b) shows the results of correlation calculations at the per-pixel level. The map demonstrates the best correlation coefficient calculated for every pixel using different analysis periods. Our calculations revealed the borders of the precipitation-dependent areas in Central Asia and Kazakhstan. According to the results, about 75% of all vegetated pixels exhibited a statistically significant correlation with precipitation over the 1981-2000. The value of the correlation coefficient ranges from 0.47 to 0.92 indicating existence of a strong relationship between NDVI and rainfall. In these areas, the precipitation time series contain the climatic signal, and removing this precipitation signal from NDVI time series should expose trends in vegetation activity that are not influenced by the climate factor.

Long-time trends in NDVI and their explanation by precipitation

Spatial distribution of trends in growing season NDVI from 1981 to 2000 over Central Asia and Kazakhstan is shown in Figure 5 (a). Over the entire study region, about 25% of all vegetated pixels exhibited statistically significant upward trends of the growing season NDVI throughout the study period, while 9.72% of all pixels exhibited significant downward trends.

In order to identify trends in NDVI driven by precipitation factor, we compared the areas which exhibited significant correlation between NDVI and precipitation with the areas of significant trends in

NDVI. Intersection of these both maps helps us to detect pixels with NDVI trends caused by climate change. The results of this intersection are shown in Figure 5 (b). The map displays two categories of the climate-induced NDVI trends: positive trends which are considered to represent an improvement of the vegetation cover, and negative trends which are believed to indicate degradation of the vegetation cover. The entire area of precipitation driven trends is considerably less than that of all significant trends. About 15 % of all vegetated area is proved to exhibit upward trends in NDVI driven by precipitation change. More than a half (4.7 % of the entire vegetated area) of all significant downwards trends in NDVI showed a strong correlation with precipitation.

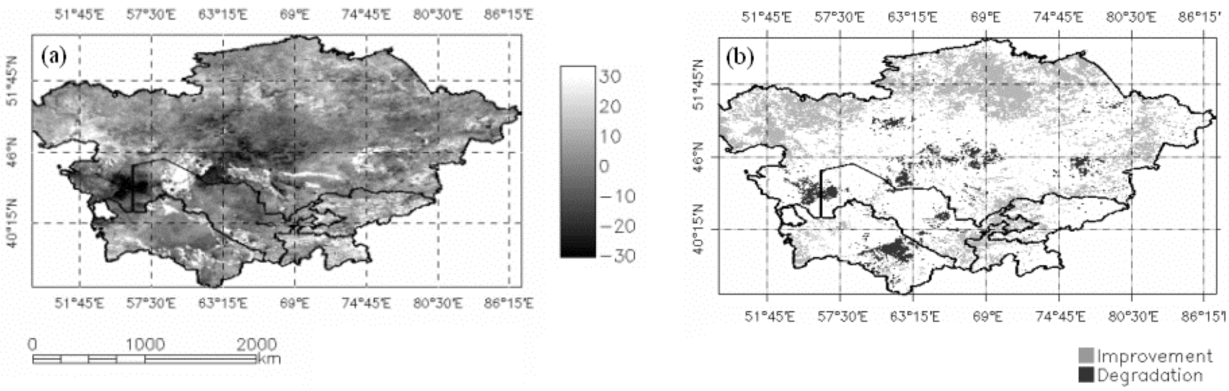


Figure 5. (a) Distribution of inter-annual changes in mean growing season NDVI over the period 1981-2000. The map show linear trends in % from the beginning of the period. (b) Inter-annual changes in NDVI explained by precipitation

Detection of areas of human-induced NDVI change

The detection of change of the vegetation response was made through observation of the deviations from the regression between the time-series of NDVI and precipitation. The regression line was understood as the climatic signal. Deviation of the observed NDVI value from the value predicted by the regression was understood as an indicator for the vegetation response to climate. Thus, any positive deviation indicates better response while any negative deviation indicates worse response. Having calculated these deviations for every year we derived time-series of annual vegetation response for every pixel. These time-series contained important information about evolution of the vegetation response to precipitation. Extraction and interpretation of this information helped us to identify areas of vegetation change that was caused by human impact. We supposed that any time-trend in vegetation response would indicate a change of characteristics of the vegetation cover. A positive trend would represent an enlargement of the vegetation response to precipitation. It means that the vegetation improves its effectiveness of rain use. A consequence of that is an increase of vegetation primary production per rainfall unit. It leads to a general increase of above-ground biomass. A negative trend would represent an opposite development.

The map of human-induced change in vegetation cover and results of area calculations are presented in Figure 6. Generally, human impact has a weak influence on the inter-annual trends of NDVI. As a whole, only about 5.5 % of all vegetated territory is considered to undergo a human-induced change of vegetation cover. Areas of human-induced improvement of vegetation cover (4.54 % of all vegetated pixels) are mostly distributed in the northern part of Kazakhstan. These territories are associated with a rapid diminishing of human impact after the collapse of the Soviet Union. The grasslands of these areas were extensively used for crop production and pasture during the Soviet era. Most of them were reported to be threatened by different types of land degradation or were considered to be already degraded [15]. After the disintegration of the Soviet Union during the period 1991-2000 Kazakhstan and other states in Central Asia experienced a strong economical crisis which massively reduced all agricultural and industrial productions. A great part of agricultural land was abandoned. The diminishing of human impact caused a rapid rehabilitation of vegetation cover throughout the pasture and crop lands particularly in the northern Kazakhstan. This rehabilitation reflected itself in the improvement of vegetation response to precipitation. Example of an abandoned agricultural area is presented in Figure 7.

This area is characterized by a positive trend of vegetation response to precipitation and can be evaluated as area with improving vegetation cover caused (Figure 8).

Negative trends of regression residuals associated with human-induced degradation of vegetation cover occur in about 1.2 % of all vegetated pixels and are distributed in the southern part of the region. We suggested that these pixels can be associated with areas of strong human influence which was not reduced during the years after the collapse of the Soviet Union. In order to prove this suggestion we tested a number of sites exhibiting negative trends of regression residuals. Most of the test sites revealed traces of human activities that led to degradation of vegetation cover. We present in the paper an example. This test site is located in the southern part of the Moyunkum Sands in the south-east of Kazakhstan. Originally, the area was covered by woody and grass vegetation, the *Haloxylon*-forest extends from south-west to north-east as a broad stripe with a width from 10 to 25 km (Figure 9, a). On the Landsat image from 1990, many light areas, especially in the western part, occurred within the contour of *Haloxylon's* stripe (Figure 9, b). On the third Landsat image shouted in year 2000, the light areas widespread over the significant part of the image associated with *Haloxylon* occurrence (Figure 9, c). Field surveys in this region in 2004 and 2005 as well as reports from local officials verified a clear signs of massive destruction of vegetation cover caused by intensive wood felling. Wide areas of the *Haloxylon*-forest are already completely cut out; at many places the wood cutting continues intensive at the present time. The destruction of vegetation cover, a decrease of biomass and higher rates of soil loss in this region resulted in a drastic decrease of vegetation response to precipitation over the period 1981-2000. That caused a negative trend of regression residuals.

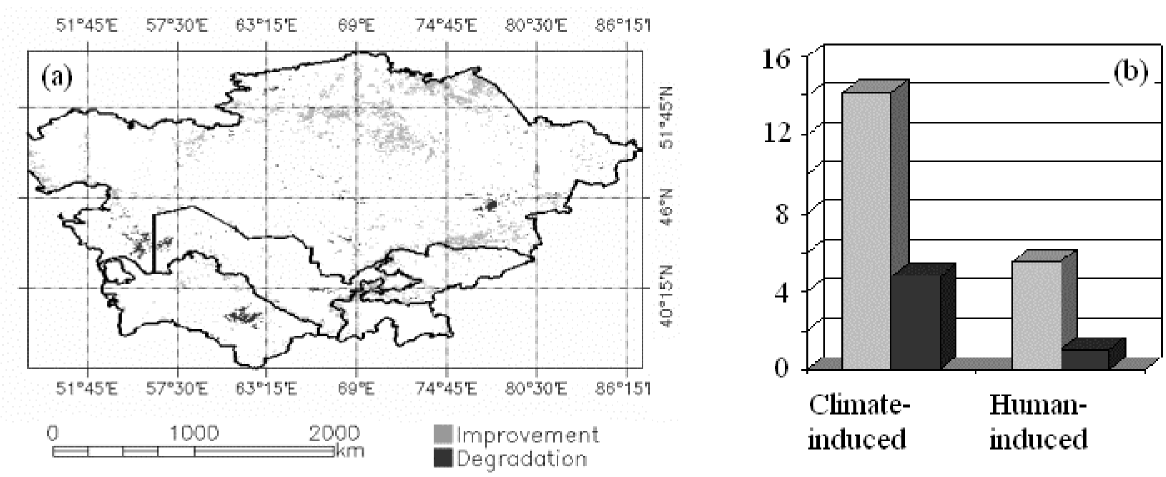


Figure 6. (a) Distribution of vegetation change induced by human impact. The map shows areas of improvement and degradation of vegetation cover derived by the analysis of regression residuals. (b) Measurements results for climate-induced and human-induced vegetation change in Central Asia and Kazakhstan

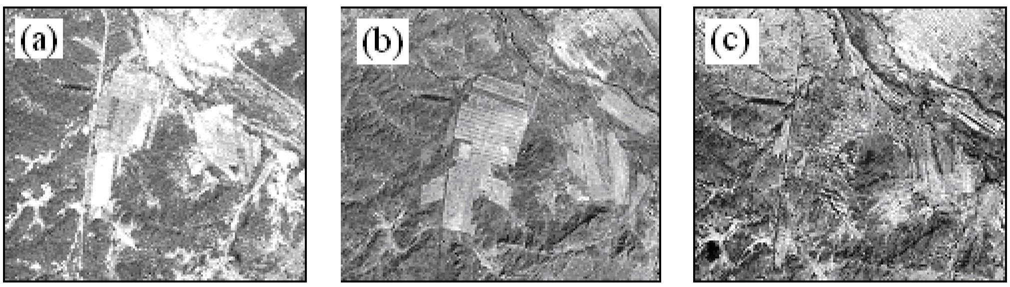


Figure 7. Traces of land-use change in satellite data. The Figure displays abandonment of a crop field in the northern Kazakshtan: (a) Landsat MSS image from 1975, (b) Landsat TM image from 1992, (c) Landsat ETM+ image from 2001. The corresponding regression between NDVI and precipitation and time-series of residuals are displayed in Figure 8

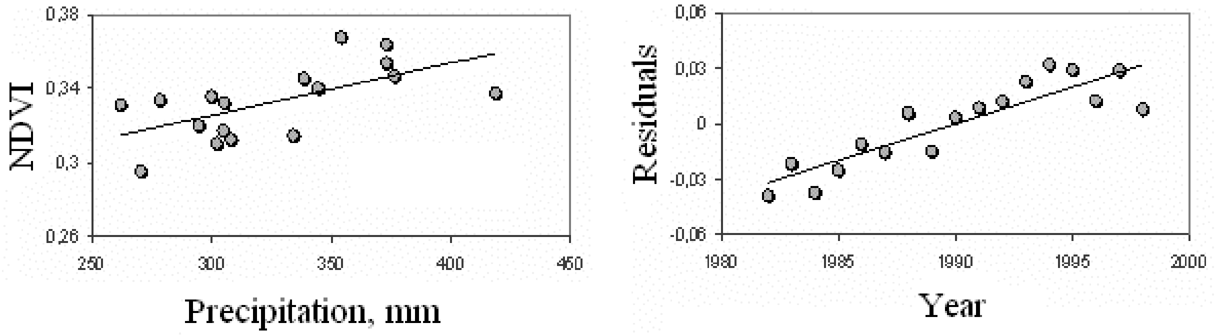


Figure 8. (a) Regression between mean growing season NDVI and precipitation for a site showed in Figure 7. (b) Time-series of regression residuals

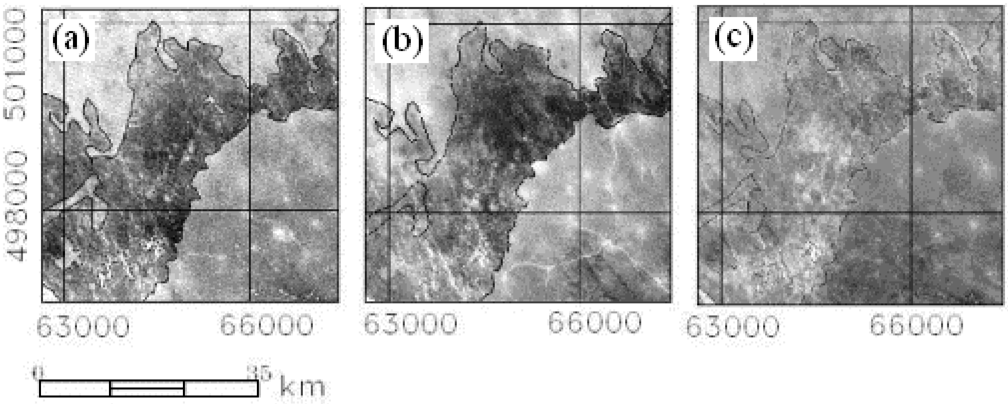


Figure 9. Time series of Landsat subsets (band 1) illustrating land cover change due to intensive degradation of vegetation cover in an area originally occupied by wood vegetation (Haloxylon aphylum) and short grasses. The reason for this desertification is intensive wood felling. The dark stripe in the first and the second images represents Halloxylon-forest that disappears in the third image. Images were acquired on June 1979, July 1991 and June 2000

Conclusion

The study demonstrates the importance of taking into account precipitation when trying to analyse performance of vegetation cover in drylands with high inter-annual rainfall variability. In precipitation-dependent regions such as Central Asia the inter-annual change of vegetation cover is significantly predicted by the inter-annual rainfall dynamics. The signal of precipitation is strongly presented in the time-series of the satellite derived Normalized Difference Vegetation Index and could be used to discriminate between the climate-induced vegetation change and the vegetation change triggered by other factors, mainly by human impact. The study used linear regression models between NDVI and precipitation fitted for every pixel in order to establish the boundary of the precipitation-dependent areas in Central Asia and to quantify the signal of precipitation in the inter-annual dynamics of vegetation cover.

We found that 74.71% of all vegetated pixels revealed a strong signal of precipitation in NDVI time-series. Being quantified the rainfall signal has been used to detect pixels with change in vegetation response to precipitation. The response of vegetation to climate has been understood as an effective indicator for human-induced change. Mathematically, this response is impressed in deviations of observed NDVI values from the NDVI values predicted by the regression models. These deviations were computed for every year and each pixel. Any statistically significant trend of deviations of a defined pixel over the study period reflects a change in vegetation response and considered to be a representative sing for human-induced change of vegetation cover. Computed trends of regression deviations helps to detect areas with diminishing or increasing vegetation response to rainfall. These areas were mapped as areas of human-induced improvement or degradation of vegetation cover. Results of the modelling were validated by test of statistical significance and by comparison with the data from the remote sensing systems of fine resolution and trips to key field sites.

The technique allows the monitoring of trends in vegetation cover driven by influences of other than climate. By doing so, it gives valuable hints to potential areas submitted to human-induced changes of vegetation cover. Once identified, they can be examined in more details with focus on their vegetation cover status, the forces driving biomass production and the most suitable rehabilitation measurements.

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