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ASSESSMENT AND MONITORING OF DESERTIFICATION PROCESSES IN MONGOLIA USING GEOGRAPHIC INFORMATION SYSTEM

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Executive Summary

Desertification has been defined as land degradation processes in arid, semi-arid, and dry sub-humid zones caused by various factors, including climatic variation and human activities. The land degradation that comprises the major processes of desertification occurs in drylands, i.e. where the aridity index is less than 0.65. Since up to 90% of Mongolia's territory belongs to hyper-arid, arid, and semi-arid areas, most of the country is vulnerable to desertification. The majority of the country is pastureland, and estimates about the amounts that are degraded vary.

The overall aim of the proposed research is to assess the dynamics of vegetation degradation in the drylands of Mongolia by using remote sensing and geography information system methods. Special attention was given to the following processes/phenomena: (1) Comparison of satellite derived drought indices by using change vector analysis technique based on long-term time series of satellite products in the reflective and thermal regions of the electromagnetic spectrum; (2) Examining the use of the vegetation health index over Mongolia in different geo-botanical zones of Mongolia, namely – taiga, high mountains, forest steppe, steppe, desert steppe, and desert; (3) Studing the 60-years vegetation degradation along the railway that crosses Mongolia from north to south in three geo-botanical zones - steppe, desert steppe, and desert using satellite imagery; and (4) Assessing land-use and land-cover change in the Bulgan Soum, Mongolia, by satellite imagery.
Research Objectives

Desertification has been defined by the UN Convention on Combat Desertification as land degradation processes in arid, semi-arid, and dry sub-humid zones caused by various factors, including climatic variation and human activities. In Mongolia, different types of desertification due to frequent droughts, degradation of vegetation cover, loss of soil nutrients and fertility in arable lands, and increase of deforested and denuded land. In addition to the frequent droughts, increasing grazing pressure on the pasture areas threatens the fragile environment of Mongolia thus that some areas have already exceeded the conditions for sustainable development and therefore experienced desertification. In recent years desertification and degradation of natural vegetation have become an important issue all over the world and particularly in Mongolia. Since the country's territory is large and its economy is a rather poor, remote sensing techniques could be used for assessing drought events, detecting and mapping categories or types of land use and land cover changes (LULCC), estimating vegetation degradation, assessing anthropogenic impacts on grassland plants, as well as distinguishing between the relative contribution of climatic- and human-impacts on the vegetation changes in intensively grazed areas. Since remote sensing technique can improve understanding of desertification and land degradation it could be supportive to the national activities of combat desertification. The general objective of this project is to explore different remote sensing tools for assessing desertification processes (particularly vegetation degradation) in Mongolia. The research was dealing with areas of (1) drought monitoring, (2) climate- and human-induced changes of land use and land cover, and (3) change detection analysis.

Complementary study, but with other partners in Mongolia was conducted in framework of EU-INCO project – Gobi Desertification (ICA CT 2000 10022), during the years 2000 – 2003.
Methods and Results

Part A – Drought Monitoring

A1. Introduction

Drought is a recurrent climate process occurs with uneven temporal and spatial characteristics over a broad area and over an extended period of time. Therefore, detecting drought onsets and ends and assessing its severity using satellite-derived information are becoming popular in disaster, desertification, and climate change studies. In the last decades, observations show that the frequency and intensity of droughts have increased in some parts of the world (Hulme and Kelly, 1993; McCarthy et al., 2001) including the Mongolian Gobi (Adyasuren, 1998). According to Natsagdorj (2000), regional climate warming in southern Mongolia has increased by 0.1 to 3.7°C during last sixty years. In this region, there is also evidence that spring precipitation has decreased by 17%, while summer precipitation has increased by 11%. It is likely that these changes in temperature and precipitation can intensify the occurrences of drought, especially during the vegetation green-up onset time. Moreover, it was reported that the frequency of drought in the spring and summer has increased from 1-2 to 3-4 times every five years in the Gobi region (Bolortsetseg et al., 2000). Drought has a disturbing effect not only on agricultural productivity and hydrological resources but also on the natural vegetation, and hence it may accelerate desertification processes when associated with destructive human activities (i.e., overgrazing) in semi-arid pastureland areas of Mongolian.

Traditionally, information on drought-affected-areas (DAA) for a certain year at a local administrative level (Soum) is derived from summertime weather observation in terms of agro-meteorological parameters (such as pasture yield, air temperature, and precipitation). Weather was categorized as favorable conditions, semi-drought, and drought, in connection with suitability for livestock grazing. Such descriptive information has been archived only in tabular, rather than cartographic, form at the Meteorological Institute of...
Mongolia. The DAA indicates if a drought event was observed but it does not provide any information on vegetation phenology or drought intensity on spatial and temporal domains.

Although drought is a complex phenomenon, it has been defined specifically by the meteorological community as a period of abnormally dry weather, which results in a change in vegetation cover (Tucker and Choudhury, 1987; Heim, 2002). With regard to this definition, changes in vegetation cover detected by remote sensing in the temporal and spatial domains have been using as indicator of droughts. As integrated pressure of a deficiency of precipitation over a certain period and other climatic factors such as high temperature, high wind, and low relative humidity in particular area, droughts have a stressing effects on vegetation cover. Even though drought has a specific duration (e.g., weeks, months, years) and have decreasing results in soil moisture and vegetation growth, it can end whenever a region receives the necessary amount of precipitation. When drought stops, land cover changes as well as reduced vegetation cover caused by the drought might be recovered (Nicholson et al., 1998; Prince et al., 1998) although this process occurs over time (Diouf and Lambin, 2001). In this context, the aim of the remote sensing change detection is to measure the degree or cumulative impact of drought-related changes on the vegetation cover over time.

Although a variety of change detection techniques, using remotely sensed data, have been formulated and frequently reviewed in the literature (e.g., Singh, 1989; Lunetta and Elvidge, 1998), selection of the best or most appropriate method for studying vegetation cover changes caused by drought events is challenging. This is because different types of changes due to droughts can occur concurrently and may be interpreted in different ways. Nevertheless, Change Vector Analysis (CVA) is becoming one of the powerful change detection algorithms (Cohen and Fiorella, 1998) and can be used to detect vegetation cover changes with respect to droughts in long-term data analysis. Degree and duration of accumulated drought events can be characterized by CVA as variations in magnitude and direction of the vector of
vegetation cover over successive periods (Lambin and Strahler, 1994a, b; Lambin and Ehrlich, 1997).

Among other applications related to vegetation studies, numerous researchers investigated the possibility of assessing and monitoring droughts in semi-arid environments (e.g., McVicar and Jupp, 1998) using either reflective or combined responses of reflective and thermal data derived from the Advanced Very High Resolution Radiometer (AVHRR) onboard the National Oceanic and Atmospheric Administration (NOAA) satellites. The NOAA-AVHRR is the most widely applied spaceborne sensor for investigating droughts. The sensor has been orbiting the globe since the late 70s with five spectral channels, one in the visible, one in the near infrared, one in the mid-infrared, and two in the thermal range. The sensor’s data (1981-2001) is archived, maintained, and distributed by NASA (WWW1). Its land products, Normalized Difference Vegetation Index (NDVI) and brightness temperatures, are widely used. The NDVI (Table A1) is based on the difference between the maximum absorption of radiation in the red spectral region (due to the chlorophyll pigments) and the maximum reflectance in the near infrared spectral region (due to the leaf cellular structure), and the fact that soil spectra, lacking these mechanisms, typically do not show such dramatic spectral difference (Tucker, 1979). Many studies show that NDVI can be a useful index for studying vegetation and ecosystems in semi-arid environments where vegetation cover is less than 30% (Huete and Tucker, 1991; Karnieli et al., 1996). Significant relationships between time series of NDVI and various vegetation indicators including green Leaf Area Index (LAI), green biomass production, as well as rainfall or soil moisture in semi-arid environments have been reported (Tucker et al., 1985; Hielkema et al., 1986; Maselli et al., 1993; Nicholson and Farrar, 1994; Peters and Eve, 1995; Richard and Poccard, 1998; Schmidt and Karnieli, 2000). Consequently, NOAA-AVHRR derived NDVI and other related indices (e.g., NDVI anomaly, integrated or standardized NDVI, Global Vegetation Index, Vegetation Condition Index, etc.) have been successfully used to identify and monitor areas affected by drought at regional and local scales (Malingreau, 1986; Tucker and Choudhury, 1987; Tucker, 1989; Peters

Tucker and Choudhury (1987) found that NDVI could be used as a response variable to identify and quantify drought disturbance in semi-arid and arid lands since its low values correspond to stressed vegetation. Recently, Ji and Peters (2003) found that NDVI is an effective indicator of vegetation response to drought in the Great Planes of the USA, based on the relationships between the NDVI and meteorological-drought index. Since NDVI has proven that it timely represents vegetation responses to climate variability as a normalized ratio, the Vegetation Condition Index (VCI, Table A1), which is NDVI normalization for each pixel based on minimum and maximum NDVI values over time, was developed by Kogan (1990, 1995) in order to relatively assess changes in the NDVI signal through time by reducing the influence of local ecosystem variables. Anyamba et al. (2001) used NDVI anomaly (NDVIA, Table A1), which is a departure of NDVI from its long-term average during a specific month, in order to indicate drought conditions as compared to the average on a range of time scales. More recently, historical drought events induced by El Nino Southern Oscillation, coincided with the NDVIA when it was standardized based on its standard deviation (Liu and Negron-Juarez, 2001). In addition, the probability of the standardized NDVI anomaly, the Standardized Vegetation Index (SVI, Table A1), has been used to monitor areas affected by drought and vegetation conditions in terms of relative greenness at pixel level over time periods (Peters et al., 2002). The NDVIA and SVI have been successfully used to monitor drought conditions over Africa and America (Anyamba et al., 2001; Peters et al., 2002; WWW2; WWW3).

Kogan (1995) adapted the VCI normalization approach to brightness temperature in the NOAA-AVHRR channel 4 and developed the Temperature Condition Index (TCI, Table A1). Later Kogan (1997, 2000) developed a new index, the Vegetation Health Index (VH, Table A1), which is an additive combination of VCI and TCI, to monitor vegetation health, moisture, and
thermal conditions as well as to determine drought-affected areas. The VCI, TCI, and VH have been used as tools for drought detection and vegetation stress mostly in the context of agricultural productions in different parts of the world (Liu and Kogan, 1996; Kogan, 1995, 1997, 2000; Kogan et al., 2004; Seiler et al., 1998; Hayes and Decker, 1998). Land surface temperature (LST) is derived from the two NOAA-AVHRR thermal channels by applying different variants of split window algorithms (Price, 1984, Qin and Karnieli, 1999). Several authors used combined responses of reflected (e.g., NDVI, VCI) and thermal (e.g., LST, brightness temperature) products of the NOAA-AVHRR to provide a more ecological and physical interpretation of remotely sensed data for examining drought conditions (Gutman, 1990; Kogan, 1997, 2000; Kogan et al., 2004; McVicar and Jupp, 1998; Karnieli, 2000; Bayarjargal et al., 2000; Karnieli and Dall’Olmo, 2003). This approach is based on the strong negative correlation between NDVI and LST. It is hypothesized that the relationship between LST and NDVI is caused by an increase in evaporation with a decrease in soil moisture, which results in a decline of the vegetation cover (Nemani and Running, 1989; Lambin and Ehrlich, 1996). Gutman (1990) concluded that the thermal data from polar orbiters might be useful for detecting the inter-annual changes in surface moisture, when the change in the vegetation index fails to produce a significant signal. McVicar and Bierwith (2001) validated that the ratio of LST and NDVI (LST/NDVI, Table A1) provides a rapid means to assess drought conditions in cloudy environments. A new index - Drought Severity Index (DSI, Table A1) - was invented in framework of this study and compared to the other drought-indices. The DSI is calculated as subtraction of standardized LST and NDVI for a certain month, based on the normalization approach that was suggested by Bayarjargal et al. (2000) to bring different variables (e.g., NDVI and LST) into a same, comparable, scale in terms of their range.

Although a considerable number of drought-indices have been developed and used as a monitoring tool for drought or favorable conditions, no comprehensive study for evaluating the performance of these indices has been conducted. The frequent occurrence of droughts in semi-arid...
environments justifies the need to evaluate the effectiveness of different drought indices. The indices can be compared among themselves, but also with respect to meteorological-based drought index such as the Palmer DroughtSeverity Index (PDSI, Table A1) (Palmer, 1965). PDSI measures the accumulated effect of monthly rainfall deficit relative to the monthly rainfall (National Drought Mitigation Center, 2003). PDSI is based on the supply-and-demand concept of the water balance equation, taking into account precipitation and temperature data, as well as availability of the soil water content (Dai et al., 1998). PDSI has been widely used for a variety of applications related to drought monitoring especially in the United States (Woodhouse and Overpeck, 1998; Heim, 2002; National Drought Mitigation Center, 2003) as well as on a global scale (Dai et al., 1998; 2004). Recently the PDSI has been applied by the Mongolian Institute of Meteorology and Hydrology as a standard drought index.

Consequently, the prime objective of this paper is to compare the spatial occurrences of droughts, detected by remotely sensed drought-indices over the desert-steppe and desert geo-botanical zones of Mongolia. This objective was implemented by using the Change Vector Analysis technique applied to the NOAA-AVHRR dataset and meteorological-derived drought-indices from 1982 to 1999. In order to enhance the evaluation of drought occurrences, the growing season was divided into several sub-periods. In addition, ground-based observations of drought-affected areas for a Soum level are also incorporated in the comparison performance.

A2. Study area

The research was carried out in the Mongolia's desert and desert-steppe geo-botanical zones, which cover more than 40% of country (Fig. A1). The study area includes the Great Lakes Depression, the Valley of Lakes, the plateau of the eastern Gobi and Gobi-Altai Mountains, and the southern and southwestern parts of the Mongolian Gobi. Low grasses, semi-shrubs, and woody plants are dominant vegetation of the study area, and peak biomass occurs in late summer (Batima et al., 2000). The study area is an area of
extremely unique landscapes of changing forms including hills, hillocks, rolling heaths, and sand dunes. The continental climate of Mongolia is very harsh with sharply defined seasons, high annual and diurnal fluctuations in air temperature, and low precipitation. The mean annual air temperature is about 4°C. July is the warmest month with an average temperature of 25°C and maximum temperatures of 35-45°C (Natsagdorj, 2000). The total annual precipitation is about 100 mm for the whole study area. About 75-85% of the precipitation falls during the three summer months, from June to August (Shirevdamba, 1999). The air humidity in spring is 20-25% or less in both ecosystems and the velocity of spring winds often reaches 15 meters per second for more than 30-40 days.

Figure A1. Geo-botanical zones of Mongolia. Study area is restricted to the desert and desert-steppe zones.

A3. Materials and Dataset preparation

The Pathfinder AVHRR Land (PAL) Normalized Difference Vegetation Index (NDVI) and brightness temperatures in channel 4 (10.3–11.3 μm) and channel 5 (11.5–12.5 μm) were used in this study for calculating the drought-indices
Dataset were composed of monthly maximum values for vegetation growing season (from April to September) over the period of 1982-1999, reprojected from the Goode's equal-area projection to the Geographical projection with spatial resolution of 0.1 x 0.1 degrees in latitude and longitude. The PAL dataset was generated from the NOAA satellite 7, 9, 11, and 14 (Agbu and James, 1994) and was obtained from the Goddard Space Flight Center (GSFC) Distributed Active Archive Center (DAAC). Radiometric calibration, atmospheric correction for Rayleigh scattering, as well as solar zenith angle effects in PAL dataset were processed by the Pathfinder processing team (Defries et al., 2000).

Table A1. The NOAA-AVHRR images-derived and meteorological-measured drought-indices.

<table>
<thead>
<tr>
<th>Drought Indices</th>
<th>Formula*</th>
<th>Source and Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Normalized Difference Vegetation Index (NDVI)</td>
<td>$NDVI_{\mu} = \frac{(NIR_{\mu} - R_{\mu})}{(NIR_{\mu} + R_{\mu})}$</td>
<td>Tucker, 1979; Tucker and Choudhury, 1987; Ji and Peters, 2003</td>
</tr>
<tr>
<td>2. Anomaly of Normalized Difference Vegetation Index (NDVIA)</td>
<td>$NDVIA_{\mu} = \bar{NDVI}<em>{\mu} - NDVI</em>{\mu}$</td>
<td>Anyamba et al., 2001</td>
</tr>
<tr>
<td>3. Standardized Vegetation Index (SVI)</td>
<td>$SVI_{\mu} = \frac{(NDVI_{\mu} - \bar{NDVI}<em>{\mu})}{\sigma</em>{NDVI_{\mu}}}$</td>
<td>Liu and Negron Juarez, 2001; Peters et al., 2002</td>
</tr>
<tr>
<td>4. Vegetation Condition Index (VCI)</td>
<td>$VCI_{\mu} = \frac{(NDVI_{\mu} - NDVI_{\mu_{\text{min}}})}{(NDVI_{\mu_{\text{max}}} - NDVI_{\mu_{\text{min}}})}$</td>
<td>Kogan, 1990, 1995, 1997, 2000</td>
</tr>
<tr>
<td>5. Temperature Condition Index (TCI)</td>
<td>$TCI_{\mu} = \frac{(BT_{\mu_{\text{max}}} - BT_{\mu})}{(BT_{\mu_{\text{max}}} - BT_{\mu_{\text{min}}})}$</td>
<td>Kogan, 1995, 1997, 2000</td>
</tr>
<tr>
<td>6. Vegetation Health Index (VH)</td>
<td>$VH_{\mu} = 0.5<em>VCI_{\mu} + 0.5</em>TCI_{\mu}$</td>
<td>Kogan, 1997, 2000, 2004</td>
</tr>
<tr>
<td>7. Ratio between LST and NDVI (LST/NDVI)</td>
<td>$LST_{\mu}/NDVI_{\mu}$</td>
<td>Lambin and Ehrlich, 1996; McVicar and Bierwith, 2001; Karnieli and Dall'Olmo, 2003</td>
</tr>
<tr>
<td>8. Drought Severity Index (DSI)</td>
<td>$DSI_{\mu} = \Delta LST_{\mu}/\Delta NDVI_{\mu}$; $\Delta LST_{\mu} = (LST_{\mu} - LST_{\mu})/\sigma LST_{\mu}$; $\Delta NDVI_{\mu} = (NDVI_{\mu} - NDVI_{\mu})/\sigma NDVI_{\mu}$</td>
<td>Bayarjargal et al., 2000</td>
</tr>
</tbody>
</table>
Land surface temperature (LST) was computed from the brightness temperatures in the thermal channels by a split-window algorithm (Price, 1984) of the form:

\[
LST = T_4 + A(T_5 - T_4) + B(\varepsilon)
\]  

(A1)

where \(T_4\) and \(T_5\) are brightness temperatures measured by the AVHRR channels 4 and 5, respectively, \(A\) is a coefficient related to the atmospheric transmittances, being dependent on the atmosphere type, and \(B(\varepsilon)\) is the emissivity effect, which depends on both the channel surface emissivities \((\varepsilon_4\) and \(\varepsilon_5\)) and atmosphere type. Price (1984) assumed that the emissivity of most of the land surface and vegetation cover is equal to 0.96, thus this value was used in the current research.

Palmer Drought Severity Index (PDSI), which was calculated over the 56 meteorological stations from 1982 to 1999 for the vegetation growing months (April-September) was obtained from the Meteorological Institute of Mongolia.
Monthly PDSI data in a tabular form was interpolated into the raster image format with the same projection and resolution of the PAL dataset. This was performed by using the ArcMap spline-technique of ArcGIS 9.0.

A4. Analysis

The analysis consists of comparison among eight different drought-indices derived from the NOAA-AVHRR and one meteorological-based drought-index (Table A1). Only the warm-summer season is relevant for vegetation monitoring in Mongolia (Tserenjav and Janchivdorj, 1999). Consequently, all data processing in this study was performed for a vegetation-growing period (VGP) that lasts for 6 months from April to September in the study area. Furthermore, the VGP was divided into three different sub-parts: the beginning – April and May; the middle – June and July; and the end – August and September.

The change detection technique – Change Vector Analysis (CVA) – that was adapted to multi-temporal concept by Lambin and Strahler (1994a, 1994b) from the original multi-spectral idea (Malila, 1980; Vigar and Colwell, 1987) was used in this study for successive sub-parts of the VGP from 1982 to 1999. The remote sensing CVA of temporal term has advantages in the consecutive data analysis and time-series data compression over other change detection methods (e.g., differencing or principal component analysis) since it can uniquely be characterized by its two variables – magnitude and direction.

A pixel value of each drought index, $I$, for a given year, $Y$, creates a $n$-dimensional temporal vector, $v_{I,Y}$, for that given pixel:

$$v_{I,Y} = \begin{bmatrix} I_{1,1} \\ I_{1,2} \\ \vdots \\ I_{1,n} \end{bmatrix}$$  \hspace{1cm} (A2)
where \( t \) is the time dimension, ranges from \( t_1 \) to \( t_n \), and \( n \) equals to 6 — the relevant VGP months from April to September. Difference between the temporal vectors, \( v_{I,Y} \), and the reference year (subscript \( \text{REF} \)), is called a temporal change vector, \( c_{I,Y} \):

\[
c_{I,Y} = v_{I,\text{REF}} - v_{I,Y}
\]  (A3)

The temporal change vector is characterized by a magnitude and direction. The absolute magnitude of the change vector of the index \( I \), \( |c_{I,Y}| \), can measure the intensity of the change in vegetation cover caused by drought and is calculated as the Euclidean distance between the index value of the reference and a selected year:

\[
|c_{I,Y}| = \sqrt{\sum_{t=1}^{n} (l_{\text{REF}} - l_{Y})^2_t}
\]  (A4)

The direction of the change vector, \( s_{I,Y} \), is measured by the sign between time \( t_n \) and \( t_{n+1} \) caused by subtracting the index value for the reference and selected years for each index \( I \):

\[
s_{I,Y} = \pm \{ (l_{\text{REF}} - l_{Y})_{t_n+1} \text{ between } (l_{\text{REF}} - l_{Y})_{t_n} \} \]
\]  (A5)

\( s_{I,Y} \) indicates the nature of the change in vegetation cover.

The CVA algorithm was coded into a graphical modeling script within the ERDAS image-processing package (ERDAS, 1997) and applied to the nine different drought indices. The algorithm produces two images for each drought-index, for each year. One image represents the change magnitude (drought intensity) and the other the change direction (drought status). In this research drought status means the onsets or ends of droughts at any sub-part of the vegetation phenology. The change vector directions were coded from 1 to 8 (referred hereinafter as drought categories) according to the sub-parts of the VGP. These categories are: (1) non drought or favorable condition; (2)
drought at the end (August & September); (3) at the middle (June & July); (4) at the middle and end (June to September); (5) at the beginning (April & May); (6) at the beginning and at the end (April & May and August & September); (7) at the beginning and at the middle (April to July) of the VGP; and (8) the entire season of VGP (April to September). It is assumed that a negative value of change vector direction of all the indices between the reference and examined years would be indicated as decreases of vegetation cover that were caused by the integration of harmful weather variables such as low precipitation and high temperature. Likewise, a positive sign would be assumed for reverse phenomenon. For that reason, it was considered that LST/NDVI and NDVIA would respond to drought when those have positive values in the images of change vector directions according to theirs calculation ways, while the other indices would response with negative values. However, direction images of all the drought-indices were coded into same categorical ranges of drought as given above for a comparison purpose.

In the CVA, other two items were considered. One was the concept of a "reference image" that is a reference against which derived change information can be compared (Cohen and Fiorella, 1998). Information of a change can be comparable to a reference, which is a long-term average, median, or minimum profile, and can correspond to the optimum conditions (Lambin and Ehrlich, 1994b). In the current study, the monthly multi-year medians of the indices were considered as a reference year in our multi-temporal CVA performance. The second critical element in CVA was deciding where to place the threshold boundaries between "change" and "non-change" pixels displayed in the histogram of the change image. Thresholds are typically set to a standard deviation value from the mean of the change value histogram of the change image (Lunetta, 1998; Singh, 1989). In this study, one standard deviation above the mean value of change magnitude image's histogram for each index was applied as a threshold boundary for every pixel. Here it is assumed that values above the threshold were resulted due to severe drought conditions.
In order to compare spatial similarity of drought-indices over the growing season, a drought-occurred-area (DOA) map was created for each of nine drought-indices – eight of those were derived from NOAA-AVHRR dataset and one was calculated from the meteorological measurement. The DOA map for every index was developed based on a combination of the change direction and magnitude images. Pixel values that were higher than a certain threshold (e.g., one standard deviation above the mean of histogram) in the change magnitude image were sliced and then coded into the drought-categories (Table A2) according to the change direction image. The DOA map for every index indicates occurrences and accumulations of drought events during the VGP for every year in relation to the reference year. The DOA maps of eight satellite-based and one meteorological-derived drought-indices were compared to each other within and between the examined years, and also compared to the traditional drought information observed at the local administration level.

To identify spatial relationships among the drought-indices, pixel-to-pixel paired correlation coefficients were computed between the change magnitude images of the indices for each study year. Since the dynamic ranges of the change vector magnitude images for nine different drought indices are different, a normalization approach was applied to all nine indices before the correlation analysis:

\[
|c_{i,Y}^{\text{normalized}}| = \frac{|c_{i,Y}| - |c_{i,\Sigma Y}|_{\text{mean}}}{|c_{i,\Sigma Y}|_{\text{Stdev}}}
\]  

(A6)

where \( |c_{i,Y}^{\text{normalized}} | \) is the normalized-change-magnitude, with mean value equals to 0 and standard deviation equals to 1, for study year \( Y \) for each drought index \( i \), \( |c_{i,Y}| \) is the change magnitude value created by Equation 4, and \( |c_{i,\Sigma Y}|_{\text{mean}} \) and \( |c_{i,\Sigma Y}|_{\text{Stdev}} \) are the respective multi-year mean and standard deviation. Values that are located above the one standard deviation from the mean of the change magnitude’s histogram and would be equal to the drought-categories from 2 to 8 were considered in the normalization.
(Table A2). When, either the change direction was equal to the drought category 1 (favorable condition in Table A2) or there were no significant changes, no vegetation stress was assumed.

**Table A2.** Coding drought categories of drought-indices in multi-temporal change vector analysis: Direction of change vectors of drought-indices between the reference and a given years in sub-parts of the vegetation growing period (VGP).

<table>
<thead>
<tr>
<th>Drought Category</th>
<th>Code description*</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Favorable condition</td>
</tr>
<tr>
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* indicates pixel value increase from the one part (e.g., beginning, both April and May) of vegetation growing period to the next part (e.g., middle, both June and July),
- indicates pixel value decrease from the one part of vegetation growing period to the next part.

The code description is for the drought-indices of NDVI, SVI, VCI, TCI, VH, DSI and PDSI. Reverse version of the sector code is valuable for the indices of LST/NDVI and NDVIA due to theirs formulas.

In addition to the spatial comparison of drought-indices, we evaluated drought occurrences at every sub-parts of VGP as combining all the satellite-derived indices into a single map. Droughts that were identified by the all indices would be added into a combined drought-affected-area (CDOA) map at every sub-parts of the VGP. Comparison of the combination of satellite-based drought-indices was conducted for the selected years as well as among the sub-parts of the VGP.

**A5. Results and discussion**

Several representative years were selected as a bases for the evaluation of the CVA results, these are: 1993 as a wet year, 1989 as a dry year, and 1998.
as a normal year (Fig. A2). For these years, Fig. A3 illustrates the total drought area identified by the different drought-indices disregards the sub-parts of the VGP. In 1993, the wet year, about 3.0-4.6% of the study area is identified as drought by the NDVI and NDVIA, while 0.3-0.8% is identified by the SVI, VCI, and LST/NDVI (Fig. A3a). In this year, the TCI, VH, and DSI detect relatively less drought (0.04-0.2%) while non-drought is identified by the meteorological-derived drought-index (Fig. A3a). In 1989, the drought year, about 15.6-16.4% of the study area is identified as total drought, except LST/NDVI (Fig. A3b). In this year about 17.4% of the study area is detected as drought by the meteorological-derived index, PDSI (Fig. A3b). Therefore, it should be note that there are good agreements among the satellite- and meteorological-derived drought-indices in the drought year in terms of sum of drought categories. In 1998, the normal year, about 6.6-9.9% of the area is identified as total drought by the NDVI, NDVIA, SVI, and VCI (Fig. A3c). 9.1% of the study area is marked as total drought by the LST/NDVI. These findings are similar to the meteorological-based PDSI. Remotely sensed drought-indices such as TCI, VH, and DSI show superior results; about 12-16.9% of the total study area is affected by drought.
Figure A2. Precipitation departure from the normal during the vegetation-growing season of the study area along the study years (1982 – 1999).

Drought occurred area (DOA) maps, resulted from the CVA, for the nine satellite- and meteorological-derived drought-indices along with the ground observations (DM) are shown in Figs. A4, A5, and A6. The drought categories are compatible with Table A2. The DOA maps of drought-indices are evaluated against the traditional drought affected area (DAA) maps for wet (1993) and drought (1989) years (see Figs. A4j and A5j), except for the normal year 1998 which lacked ground data. It should be noted that the traditional method, DOA map, does not distinguish between sub-parts of the VGP, as can be done with the image- and meteorological-derived drought-indices.
Figure A3. The total drought area identified by the different drought-indices by all drought categories occurred in sub-parts of the VGP, for each of eight different remotely sensed drought-indices and one meteorological drought-index in (a) wet, (b) drought, and (c) normal years.
Figure A4. Comparison of Change Vector Analysis based drought-occurred-area (DOA) maps of satellite- and meteorological-derived drought-indices over sub-parts of the vegetation growing period for 1993 in desert and desert-steppe zones of Mongolia. Ground observed drought-affected-areas (DAA) are also shown. Indices are according to Table A1 and drought categories are according to Table A2.
Figure A5. Comparison of Change Vector Analysis based drought-occurred-area (DOA) maps of satellite- and meteorological-derived drought-indices over sub-parts of the vegetation growing period for 1989 (dry year) in desert and desert-steppe zones of Mongolia. Ground observed drought-affected-areas (DAA) are also shown. Indices are according to Table A1 and drought categories are according to Table A2.
Figure A6. Comparison of Change Vector Analysis based drought-occurred-area (DOA) maps of satellite- and meteorological-derived drought-indices over sub-parts of the vegetation growing period for 1998 (normal year) in desert and desert-steppe zones of Mongolia. Ground observed drought-affected-areas (DAA) are also shown. Indices are according to Table A1 and drought categories are according to Table A2.
Fig. A4 illustrates the wet-year DOA maps for each of the nine different drought-indices. It can be noticed that the NDVI and NDVIA (Figs. A4a and A4b) identify relatively small areas as drought at the beginning (spring) of the growing season (category 5, Table A2) in the Great Lakes Depression and in the fringe of the Eastern Gobi Plateau. Only a few pixels were detected as drought by LST/NDVI in the southern-fringe and central parts of the Gobi Desert, (Fig. A4g). The PDSI did not show any indication to drought anywhere in the study area while the DAA map marks much larger areas as drought for this year (Fig. A4j), however these area do not match with the NDVI and NDVIA areas, partly match with the LST/NDVI area, and detect other areas which do not match any of the satellite-derived indices in the south-eastern part of the study area.

In contrast to the wet year and when precipitation was significantly below normal in 1989 (Fig. A2), drought events occurred over relatively large areas as shown by the DOA maps of the satellite- and meteorological-derived drought-indices (Figs. A5a-A5i) as well as in the DAA map (Fig. A5j). For the dry year, most drought events are identified as combinations of drought categories of the VGP (rather than a single category) by the NDVI-based indices such as NDVI itself, NDVIA, SVI, and VCI. The Depression of Great Lakes, the Valley of Lakes, bottom of the Gobi-Altai Mountains, and the Plateau of Eastern Gobi are identified as droughts occurred from the middle to the late of the VGP (i.e., summer-autumn drought that is a category 4, Table A2) or entirely occurred drought (i.e., category 8) by these indices (Figs. A5a-A5d). In drought year, the NDVI, NDVIA, SVI, and VCI exhibit almost similar results. The Valley of Lakes, lower parts of the Great Lakes Depression, the Gobi-Altai Mountain, south of the Plateau of Eastern Gobi and Gobi Desert areas in the southwest of the study area are identified as entirely occurred droughts by the TCI, VH, LST/NDVI, and DSI (Figs. A5e, A5f, A5g, and A5h). In addition, the LST/NDVI detects several areas in the middle (summer), end (autumn), and entire period of the VGP. Thus, these combined indices of reflected and thermal channels of the NOAA-AVHRR have similar meaning. The DOA maps of remotely sensed drought-indices only partially match the
PDSI map (Fig. A5i). The PDSI map (Fig. A5i) shows three drought-affected areas. The western one partially matches only to the TCI, the central area partially to the VH and DSI, and the eastern area partially to the NDVI-based indices. Entire-season droughts (i.e., drought category 8) are found by the PDSI in the Plateau of Eastern Gobi and western point of the study area. More surprising is the DAA map that almost systematically detects other areas than the satellite- and meteorological-derived indices (Fig. A5j).

A small area in the Depression of Great Lakes in the northwestern fringe, in the Plateau of Eastern Gobi, and in the eastern and central parts of the study area are identified as droughts at different sub-parts of the VGP in 1998 (normal year) by the DOA maps of NDVI, NDVIA, SVI, and VH (Figs. A6a, A6b, A6c, and A6d). Early droughts continued to the middle (summer) of the VGP (drought categories of 3, 5, and 7, Table A2) are found in these areas. Dissimilarly, relatively larger areas over the Gobi Desert in the south-central parts of the study area are identified as drought over the beginning-middle, the middle-end (i.e., drought category 4), and entirely season (i.e., drought category 8) of the VGP in the DOA of TCI, VH, LST/NDVI, and DSI (Figs. A6e, A6f, A6g, and A6h). Other than a few areas in the Plateau of Eastern Gobi in the east of the study area, spatial distributions of DOA maps of the indices derived from the satellite data and ground-observed drought-indices do not show similar results in sub-parts of the VGP in the year with normal precipitation. Beginning and beginning-middle (i.e., summer and summer-autumn) droughts in the Plateau of Eastern Gobi and entirely occurred droughts are found by the PDSI in the north of the Great Lakes Depression and west point of the Gobi (Fig. A6i). Consequently, the PDSI does not completely match to the satellite-derived drought-indices in this year.

The pixel-to-pixel paired correlation was applied to the normalized change-magnitude images for eight satellite based and one meteorological-derived drought-indices. Correlation matrix \( r \) among the indices is presented in Table A3, for selected years with different rainfall regimes and for the average of 18-year period from 1982 to 1999.
In the wet year Table A3a reveals relatively poor but mostly significant correlations among the indices except for the NDVI and NDVIA which are positively related each to others. In the normal and dry years) and also in the multi-year average, significant high correlations are found among NDVI, NDVIA, SVI, and VCI (Table A3b, A3c, and A3d) that are NDVI-based indices (Table A1).

Table A3. Correlation matrix (r) among the satellite- and meteorological-derived drought-indices for the years with different rainfall conditions, (a) wet year (1993), (b) dry year (1989), (c) normal year (1998), and (d) 18-year average. The number of pixels that is used for the correlation analysis for every index is shown in parentheses. Relative good correlations are marked in bold and significant values at the $p<0.05$ are shown as Italics.

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<th>VCI</th>
<th>TCI</th>
<th>VH</th>
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All other correlations, among the LST group and among these indices and the NDVI-based ones are rather poor, under all precipitation regimes, except for the correlation between DSI and VH for drought, normal years as well as for multi-year average. All correlations between the satellite-derived indices and the PDSI were also found to be very poor.

The combined drought-affected-area (CDOA) maps of satellite-derived drought indices in different drought categories for selected wet, dry, and normal years are displayed in Figs. A7, A8, and A9, respectively. The CDOA maps show that there are mostly short-term drought events in the wet year, such as drought at the beginning, middle, and end of the VGP (Figs. A7a and 7b). However, most droughts were detected at the middle and end of the sub-parts of VGP and along the entire season in the dry year (Figs. A8c, A8d, A8e, A8f, and A8g). In the year with normal rainfall, in addition to the short-term droughts during early, middle, and late sub-parts of the VGP (Figs. A9a, A9b, and A9c), longer droughts over two or more sub-parts of the VGP are mostly happened (Figs. A9e, A9f, and A9g). Generally, relatively wider areas were identified as droughts in sub-parts of the VGP when all drought categories are overlaid onto a single map - CDOA map, although rainfall was high or around normal (Figs. A7h and A9h). Also, as expected, droughts were detected during the whole season of the VGP over the study area by the summation of all drought categories of satellite indices in drought year (Fig. A8h). This summing of all drought categories of all drought-indices is much higher than the DOA map of meteorological-derived PDSI and traditional DAA maps for every years as showed previously in Figs. A4, A5, and A6. This might be explained by the difference in observation methods between the remote sensing and meteorological measurements. Also, a precision of ground measured DAA maps at the local level might not be enough to

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compare to the remotely sensed based indices even though spatial interpolation approach was applied to meteorological-derived drought-index.

**1993 - Wet Year**

(a) Drought at beginning of VGP  (e) Drought at begin. and middle of VGP  
(b) Drought at middle of VGP  (f) Drought at begin. and end of VGP  
(c) Drought at end of VGP  (g) Drought at middle and end of VGP  
(d) Drought for entire season of VGP  (h) Overlay of all drought categories

**Figure A7.** Comparison of the combination of DOA (CDOA) maps of all drought indices into the every sub-part of the vegetation-growing period (VGP) for 1993 with higher than normal precipitation over the study area. Droughts detected by all the satellite-derived drought-indices are separated into drought categories as droughts (a) at the beginning of the VGP; (b) at the beginning and the middle of the VGP; (c) at middle of the VGP; (d) at the beginning and
the end of the VGP; (e) at the middle and the end of the VGP; (f) at the end of the VGP; and (g) over the entire season of VGP. All droughts that are identified over sub-parts of the VGP in 1983 by the all indices are overlaid into a single map (h).
Figure A8. Comparison of the combination of DOA (CDOA) maps of all drought indices into the every sub-part of the vegetation-growing period (VGP) for 1989 (dry year) with higher than normal precipitation over the study area. Droughts detected by all the satellite-derived drought-indices are separated into drought categories as droughts (a) at the beginning of the VGP; (b) at the beginning and the middle of the VGP; (c) at middle of the VGP; (d) at the beginning and the end of the VGP; (e) at the middle and the end of the VGP; (f) at the end of the VGP; and (g) over the entire season of VGP. All droughts that are identified over sub-parts of the VGP in 1983 by the all indices are overlaid into a single map (h).
1998 - Normal Year

(a) Drought at beginning of VGP
(b) Drought at middle of VGP
(c) Drought at end of VGP
(d) Drought for entire season of VGP
(e) Drought at begin. and middle of VGP
(f) Drought at begin. and end of VGP
(g) Drought at middle and end of VGP
(h) Overlay of all drought categories

Figure A9. Comparison of the combination of DOA (CDOA) maps of all drought indices into the every sub-part of the vegetation-growing period (VGP) for 1998 (normal year) with higher than normal precipitation over the study area. Droughts detected by all the satellite-derived drought-indices are separated into drought categories as droughts (a) at the beginning of the VGP; (b) at the beginning and the middle of the VGP; (c) at middle of the VGP; (d) at the beginning and the end of the VGP; (e) at the middle and the end of the VGP; (f) at the end of the VGP; and (g) over the entire season of VGP. All droughts that are identified over sub-parts of the VGP in 1983 by the all indices are overlaid into a single map (h).
A5. Conclusions

Remote sensing Change Vector Analysis technique was used to compare the spatial distributions of drought-detection indices derived from the reflective and thermal channels of the NOAA-AVHRR sensor over the desert and desert-steppe geo-botanical zones of Mongolia. It can be concluded that:

- There is no consistent spatial overlapping among the satellite-derived drought-indices. Different indices identify different areas as drought in different parts of the vegetation growing period and under different precipitation regimes. Only the NDVI and NDVIA, due to their formulation, produce almost similar results.

- There is no agreement between the satellite-derived drought-indices and the drought index derived from the meteorological measurements and also between the traditional ground-observed drought-affected-areas maps. Wider areas are identified as droughts by overlaying all the satellite-derived drought-indices than by the meteorological-based one. This can reveal that the precision of meteorological measurements and ground observations at the local level is not sufficient to compare remotely sensed drought indices over wide regions, even though spatial interpolation approach was applied.

- Statistical results show that relatively higher correlations were found among the NDVI-based drought-indices than among the LST-based ones. Poor correlations are found between the satellite- and meteorological-derived drought-indices.

- Finally, the differences in the ability of the eight different drought-indices to detect the drought occurrences and status with respect to ground-observations emphasize the importance to study the evaluation performances of the indices for further utilization of this information.
Part B – Vegetation Health

B1. Evolution of the Vegetation Health Index

Spaceborne data have been widely used for estimating herbaceous biomass accumulation in grasslands and steppes. The first satellite application for assessing biomass was in northern Senegal in 1981-1983 (Tucker et al. 1983, 1985). Subsequently, other investigators expanded this work throughout the Sahelian zone and elsewhere, and reported similar results. Among the various available sensors, the Advanced Very High Resolution Radiometer (AVHRR), onboard National Oceanic and Atmospheric Administration (NOAA) satellites, has been the most suitable and applicative for this purpose. This instrument provides two major land products—the Normalized Difference Vegetation Index (NDVI) and the Land Surface Temperature (LST). The NDVI is the most frequently used vegetation index, and is based on the ratio between the maximum absorption of radiation in the red (R) spectral band and the maximum reflection of radiation in the near infrared (NIR) spectral band (Tucker 1979). Since the Earth's surface temperature influences vegetation growth (Running et al. 1995, White et al. 1997, Tucker et al. 2001, Badeck et al. 2004), LST values have been used as criteria, in addition to the NDVI, for evaluating the status and development of vegetation.

Using these AVHRR-derived products, various researchers have developed algorithms for time series analysis, or for relating a specific period of interest to a long-term statistic, e.g., the NDVI Anomaly Index (Liu and Negron-Juarez 2001) and the Standardized Vegetation Index (Anyamba et al. 2001; Peters et al. 2002). In this connection, Kogan (1995) has suggested the Vegetation Condition Index (VCI):

\[
VCI = \frac{(NDVI - NDVI_{\text{min}})}{(NDVI_{\text{max}} - NDVI_{\text{min}})}
\]  

(B1)

This equation relates the NDVI of the composite period of interest (which can be a week, dekad, month, or a year) to the long-term minimum NDVI (NDVI_{min}), normalized by the range of NDVI values calculated from the long-
term record of the same composite period. The VCI values range from 0 to 1, the low values representing stressed vegetation conditions, middle values—fair conditions, and high values—optimal or above-normal conditions.

On the presumption that the LST provides additional information about vegetation condition, Kogan (1995) adapted the VCI normalization approach to LST and developed the Temperature Condition Index (TCI):

\[ TCI = \frac{(B_{T_{\text{max}}} - BT)}{(B_{T_{\text{max}}} - B_{T_{\text{min}}})} \]  

where \( BT \) represents the brightness temperature derived from the AVHRR band 4. Note that, in order to apply the TCI for determining temperature-related vegetation stress, it was formulated in reverse ratio to the VCI, based on the hypothesis that the higher the temperature, the worse the conditions for vegetation. Consequently, low TCI values (close to 0) indicate harsh weather conditions (due to high temperatures), relative to the composite period, middle values reflect fair conditions, and high values (close to 1) reflect mostly favorable conditions.

Several authors have used the combined responses of reflected (e.g., NDVI, VCI) and thermal (e.g., LST, brightness temperature) products of the NOAA-AVHRR, to provide a more ecological and physical interpretation of remotely sensed data for examining vegetation conditions (e.g., Gutman 1990, McVicar and Jupp 1998, Karnieli 2003). This innovative approach assumes a strongly negative correlation between NDVI and LST, due to an increase in evaporation along with a decrease in soil moisture, caused by higher temperatures, resulting in a decline in the vegetation cover (Nemani and Running 1989, Lambin and Ehrlich 1996). For example, McVicar and Bierwith (2001) use the ratio of LST and NDVI (LST/NDVI) to provide a rapid means of assessing drought conditions.

Following the above-mentioned hypothesis, Kogan (1995) proposed a new index, the Vegetation Health (VH) index, which is an additive combination of VCI and TCI:
\[ VH = \alpha VCI + (1 - \alpha)TCI \]  
(B3)

where \( \alpha \) is the relative contribution of VCI and TCI in the VH. In most published analyses, \( \alpha \) has been assigned a value of 0.5, assuming an even contribution from both elements in the combined index, due to the lack of more accurate information (Kogan 2000). The VH has been applied for different applications, such as drought detection, drought severity and duration, early drought warning (Seiler et al. 1998), crop yield and production during the growing season (Unganai and Kogan 1998), vegetation density and biomass estimation (Gitelson et al. 1998), assessment of irrigated areas (Boken et al. 2004), and estimation of excessive wetness (in contrast to drought) (Unganai and Kogan 1998). These applications have been demonstrated in various scales—global (Kogan 1997, 2000), regional (Liu and Kogan 1996), and national (Seiler et al. 1998) in many parts of the world.

A recent publication of Kogan et al. (2004) deals with applying the VH for drought detection and derivation of pastoral biomass in Mongolia. The VCI, TCI, and VH were computed from the long-term NOAA Global Vegetation Index (GVI) dataset for the period 1985-2000, in 16x16 km resolution (Kidwell 1997). Due to lack of more accurate information on the influence of VCI and TCI on the VH in Mongolia, the \( \alpha \) coefficient of the VH equation was fixed at 0.5. Spatial results of the VH, for the three relevant years, from the Gobi desert in the south (41° N), to north of the Lake Baykal in Siberia (56° N), are presented.

The prime objective of the current letter is to investigate the VH-based hypothesis that increasing temperatures act negatively on vegetation vigor and consequently cause stress. The territory of Mongolia (about 1.5 million km\(^2\)) can serve as a good example for such a research, since this country is located in the cold desert belt of central-east Asia. Mongolia is characterized by mostly natural vegetation, without anthropogenic influences, such as urban heat islands, industry, agricultural crops etc. The north-south transect across the country is relatively short (ca. 1000 km), but covers six different ecosystems namely Taiga, High Mountains, Forest Steppe, Steppe, Desert...
Steppe, and Desert, from the north southwards (Fig. B1). Mean annual temperature increases gradually from -7°C in the north to 7°C in the south, while mean annual precipitation ranges from less than 75 mm in the south to more than 350 mm in the north.

![Map showing different ecosystems across the country](image)

**Figure B1.** Six different ecosystems across the country namely Taiga, High Mountains, Forest Steppe, Steppe, Desert Steppe, and Desert from the north southwards in a relatively short distance (ca. 1000 km).

### B2. Dataset and methodology

The Pathfinder AVHRR Land (PAL) Normalized Difference Vegetation Index (NDVI) and brightness temperatures, in bands 4 and 5, were used in this study. Data are composed of monthly maximum values, with an 8 km spatial resolution, in geographical (lat/long) projection, spanning a period from 1981 to 1999. The PAL dataset was generated from the NOAA satellites 7, 9, 11, and 14 (Agbu and James 1994) and was obtained from the Goddard Space Flight Center (GSFC) Distributed Active Archive Center (DAAC).

NDVI values were extracted directly from the PAL archive. LST values were computed from the brightness temperatures in the thermal bands, by a split-window algorithm (Price 1984) of the form:
\[ LST = BT_4 + A(BT_4 - BT_5) + B(e) \]  \hfill (B4)

where \( BT_4 \) and \( BT_5 \) are brightness temperatures in bands 4 and 5, respectively. \( A = 2.63 \) is a coefficient related to atmospheric transmittance, being dependent on the atmosphere type, and \( B(e) = 1.27 \) is the emissivity effect, which depends on both the channel surface emissivities (\( \epsilon_4 \) and \( \epsilon_5 \)) and atmosphere type. Price (1984) assumed that the emissivity of most of the land surface and vegetation cover is equal to 0.96, so this value was used in the current research.

**B3. Analysis, results, and discussion**

Scatterplots of the NDVI vs. the LST values are presented in Fig. B2. Linear regression analysis of the entire dataset reveals a significant (\( F < 0.001 \)) inverse relationship between NDVI and LST. This trend is well documented on regional and continental scales (e.g., Nemani et al. 1993). However, the regression results of the six separated distinct clusters, representing the six different ecosystems, disclose a different situation. Individual regression analysis results of these clusters reveal negative relationships between NDVI and LST for the southern ecosystems – Desert, Desert Steppe, and Steppe; a flat relationship for the Forest Steppe ecosystem; and positive relationships for the northern ecosystems – High Mountains, and Taiga. Note that the regressions of the Taiga, Steppe, and Desert Steppe were found to be statistically significant (\( F < 0.05 \)). Gradual transition from the most negative (Desert), to the most positive (Taiga), relationships can be observed.

A time series of NDVI and LST values for the Desert Steppe ecosystem, as representative of out-of-phase relationships, is presented in Fig. B3a. A mirror reflection of the two trends can be seen. By contrast, the two variables progress almost in-phase along the study period in the Taiga ecosystem (Fig. B3b). These results are consistent with previous observations showing a substantial change in the correlation slopes between NDVI and LST (e.g., Lambin and Ehrlich 1996, Tateishi and Ebata 2004). Low latitude regions of
the Northern Hemisphere are characterized by negative correlations, since water is the main limiting factor for vegetation growth.

![Figure B2. Scatterplots of the NDVI vs. the LST values. Note an overall significant negative relation between the two variables. When examining each ecosystem separately, the northern ecosystems are characterized by a positive trend.](image)

On the other hand, mid and high latitude regions, where energy is the major limiting factor for vegetation development, are characterized by a positive correlation, implying that rising temperatures favorably influence vegetation activity. Temperature is the main driver of many biological processes, namely chemical (enzyme-catalyzed) reactions, which usually increase plant maturation (Badeck et al. 2004). Mongolia, located in the cold desert belt of central-east Asia, exhibits along a relatively short distance, both precipitation-dependent ecosystems in the south, and temperature-dependent ecosystems in the north. Therefore, the VH cannot be applied to the entire territory.
Figure B3. Time series of NDVI and LST values for the (A) Desert Steppe ecosystem; and (B) Taiga ecosystem. Note out-of-phase and in-phase relationships in (A) and (B), respectively.
B4. Conclusions

This study was attempted to investigate the VH-based hypothesis that increasing temperatures act negatively on vegetation vigor and consequently cause stress. It is shown that analysis of spaceborne-derived vegetation indices, such as NDVI/LST and VH, which are based on the NDVI and LST, requires a good understanding of the relationships between these variables in different ecosystems. Since the role of the \( \alpha \) coefficient in the VH index is to determine the individual contributions of the NDVI and the LST to the vegetation condition, it is generally expected that \( \alpha \) correlates to the slope of the regression of these two factors. As was demonstrated, however, not only does the magnitude of the slope vary across different ecosystems, its direction can be reversed. Consequently, in its present form, the VH index can be successfully applied only in the low latitudes, mainly in arid, semi-arid, and sub-humid climatic regions, where water is the main limiting factor for vegetation growth. Another physiology mechanism exists in the tropics around the Equator and in the humid regions of the high latitudes, where vegetation development is primarily limited by energy. In these regions, higher temperatures speed up plant development and, therefore, using the VH index to assess vegetation state and condition, has to be undertaken with caution.

Further research has to be conducted to refine the existing VH formulation, in order to apply it to a wide range of ecosystems.
Part C – Vegetation Degradation

C1. Introduction

Grazing by domestic animals is a major form of land use practices on native vegetation in rangelands all over the world. According to the FAO (FAOSTAT data, 2005), permanent grasslands extend over ca. 26% of the land surface of the Earth. Therefore, range management and monitoring, especially over vast and remote areas, based on traditional field survey and measurement, might be problematic since it is an expensive, manpower demanding, and time-consuming process. Alternatively, satellite remote sensing, due to large surface cove and frequent routine observation, has been intensively used for a large number of vegetation applications in range regions. Recently the Enhanced Vegetation Index (EVI) was developed in order to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring while correcting for canopy background signals reducing atmosphere influences (Liu and Huete, 1995; Huete et al. 1997). The EVI is based on the NDVI, SAVI, and ARVI indices, and uses functionalities from each one of them in order to overcome the soil and the atmosphere interferences. EVI is formulated as:

\[
EVI = G \cdot \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + C1 \cdot \rho_{\text{red}} - C2 \cdot \rho_{\text{blue}} + L}
\]  

where \(\rho\) are atmospherically-corrected or partially corrected (Rayleigh and ozone absorption) surface reflectances in the respective spectral bands, \(L\) is the canopy background adjustment term, and \(C1, C2\) are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the EVI algorithm are, \(L=1, C1 = 6, C2 = 7.5,\) and \(G\) (gain factor) = 2.5.

Overgrazing is considered to be the key cause of rangeland degradation (Thomas and Middleton, 1994) while rangeland degradation is almost entirely a matter of vegetation degradation (Dregne and Chou, 1992). The latter is
directly related to reduction in biomass and/or decrease in species diversity (Eswaran et al., 2000). However these tendencies can be more complicated since vegetation degradation might be measured qualitatively rather than quantitatively. For instance, invasion or increase of undesirable brush species that may actually increase biomass production on degraded rangelands or loss of palatable pasture grasses and their replacement with unpalatable species (Dregne and Chou, 1992; Brown and Archer, 1999). From the remote sensing point of view, implementing the above-mentioned vegetation applications that are related to quantitative variables is a common task and wildly used in rangelands. Bastin et al. (1995), examined the potential of spaceborne systems for rangeland degradation mapping around Australian watering points, noted that there is no possibility to distinguish between different plants or change in species composition. However, only in recent years, tacking advantage of hyperspectral image spectroscopy technology, a few studies were aimed at mapping the distribution of some biological invaders (Lass et al. 2002, 2005; Underwood, 2003) and evaluating changes in canopy chemistry and other canopy characteristics caused by invasion (Asner and Vitousek, 2005).

In Mongolia, from historic times, animal husbandry has been the main branch of the economy. 99% of the Mongolian territory has been used as natural pastures. During the last 70 years, the population density in the Mongolian drylands has increased more than 3 times and the total domestic livestock (sheep, goats, cattle, horses, and camels) have increased over 2.3 times, reaching 30 million animals. Consequently, irrational anthropogenic activities, such as overgrazing, have accelerated, causing vegetation degradation to be the main type of rangeland degradation (Adyasuren 1998, Batjargal 1999). A few case studies, at plot-scale level, drew attention to sever decrease of vegetation cover due to overgrazing near settlements water sources. Yonghong and Jargalsaihan (1993) noted that the plant community abundance (composition and richness) decreased as grazing pressure increased and the native vegetation were replaced by exotic species in the northeast pastureland of the country. They found that succession series
along the grazing gradient were *Stipa grandis* + *Leymus chinensis* in the lightly grazed sites, *Stipa kreylovii* + *Artemisia frigida* + low grasses in the moderately grazed sites, and *Carex duriuscula* + *Artemisia scorparia* + annuals in the heavily grazed sites. Fernandez-Gimenez and Allen-Diaz (2000) found, based on ground observations over two years, that vegetation pattern (in species composition, biomass, etc.) changed along grazing-gradients from the watering points in response to increased grazing pressure in the Mountain-Steppe and Steppe zones of Mongolia, while no consistent changes due to grazing were observed in the Desert-Steppe. Also, it was noted that vegetation changes over degraded and eroded areas are significant and unpalatable plants or weeds fully occupied these areas. However, no shrub encroachment is associated with degradation of the Mongolia’s grassland (Tserenbaljid 2002, Fernandez-Gimenez and Allen-Diaz 2000).

Advantage was taking of a unique phenomenon in Mongolia. The railway across the country, more than 1000 km in length from the northern border with Russia to the southern border with China (Fig. C1) was established in the 1960s. Since then, it has been protected by fences all along for avoiding animals to cross the railway and therefore no grazing is allowed inside the fences while intensive grazing characterizes the surrounding area. Since the railway passes the steppe biome, it enables to investigate the anthropogenic-induced rangeland degradation. When the train is winding the length between the fences can be as wide as 4 km, enabling remote sensing research using high resolution imagery (Fig. C2). This paper attempts in exploring the ability of remote sensing technique to assess vegetation degradation in the range regions of Mongolia.

**C2. Study area**

Mongolia has a continental climate, characterized by cold and dry winters and warm and wet (rainy) summers. The current research is focused on the Mongolian steppe biome (excluding the desert steppe) (Fig. C1). The area
occupies ca. $4.5 \times 10^8$ hectares. Mean annual precipitation ranges between 150 to 300 mm and the mean annual temperature between -3 to +3 °C. The aridity index (ratio of precipitation to potential evapotranspiration) ranges between 0.2 to 0.5, indicating semi-arid environment. The southern part of the region is characterized by flat plains and rolling hills covered in feather grass and shrubs. Typical species of grass include *Stipa krylovii* and *Agropyron cristatum*, and unpalatable shrubs such as *Caragana spp.* and *Artemisia* species are abundant. Mountains that exist in the northern are characterized by coniferous forests on the northern slopes, while the southern slopes are covered by open steppe vegetation. The vegetation is therefore a combination of Siberian taiga forest and Mongolian steppe flora, including species such as pine (*Pinus sylvestris*), aspen (*Populus tremula*) and edelweiss (*Leontopodium ochroleucum*).

![Geo-botanical Zones of Mongolia](image)

**Figure C1.** Geo-botanical map of Mongolia, showing the study sites along the railway that crosses the country from the northern border with Russia to the southern border with China.
C3. Methodology

The research was conducted in six study-sites selected along the railway (Fig. C1). Three of them are located at the Mountain-Steppe zone (denoted hereafter as sites M1, M2, and M3) and the other three in the Steppe zone (S1, S2, and S3). Each site consists on pairs of study polygons – ungrazed (the fenced-off area) and heavily grazed (outside the fences). All sites are large enough in term of the spatial resolution of Landsat images, e.g., 30 x 30 meter and characterized by flat topography.

![Image: Example of a Landsat ETM+ image (RGB=4,3,2) showing a study site (M1). The area between the fence and the railway is the ungrazed side while intensive grazing characterized the surrounding area.]

Figure C2. Example of a Landsat ETM+ image (RGB=4,3,2) showing a study site (M1). The area between the fence and the railway is the ungrazed side while intensive grazing characterized the surrounding area.

Four Landsat-7 Enhanced Thematic Mapper Plus (ETM+) images, acquired in early 2000s were used. In order to reduce image-to-image variations that are related to sun angle, differences in atmospheric condition, and vegetation
phenology, all images were selected during the vegetation growing season, when the possibility to discriminate between vegetation and soil covers is the highest. In addition, cloud covers are minimal in all images. Digital number values were converted to radiance, and ground-leaving reflectances were created from the raddiances using the 6S algorithm (Vermote et al., 1997). Later, the four images were merged to create a continuous scene. The Enhanced Vegetation Index (EVI) (Eq. C1) was computed from the reflectance values. This index was selected in order to reduce the uncertainty in soil background and atmospheric effect along the entire study area. Approximately the same number of pixels was sampled in the grazed and the adjacent ungrazed polygons.

Ground-truth activities were conducted during two field-campaigns in the summers of 2002 and 2003 in framework of the Joint Russian-Mongolian Complex Biological Expedition in participation of the University of Moscow, Remote Sensing Laboratory (Blaustein Institute for Desert Research, Ben-Gurion University of the Negev), the Institute of Botany (Academy of Science of Mongolia), and the National Remote Sensing Center (Ministry for Nature and Environment of Mongolia). Biophysical variables of dominant and co-dominant plants species, including plant density (i.e., number of plants per unit area), composition, dry biomass, and percent of vegetation cover, were sampled and measured. The study polygons were precisely located by a Global Positioning System (GPS).

In conjunction with the above, spectral reflectance measurements were implemented with the FieldSpec-HandHeld Spectroradiometer (manufactured by Analytical Spectral Device (ASD, 2000) at wavelengths of 325-1075 nm with a spectral resolution of 2 nm. A High Intensity Contact Probe device with a fiber optic was attached to the spectroradiometer. This device has an independent light source (about two fold of the solar intensity) and made it feasible to measure under all-weather conditions. The contact probe was attached to clipped plants and soil samples. Measurements of a white reference panel (Spectralon plate, Labsphere Inc.) were taken immediately before each spectral measurement.
C4. Results and discussion

It was hypothesized that intensive grazing will reduce the plant density, biomass, and plant cover. It is further assumed that the EVI will have lower values outside the fences due to vegetation degradation. Table C1 summarized the results of the field campaigns and the image processing along with the descriptive statistics and significance. As expected, between 23 to 34 plants per unit area were measured inside the fence while 12 to 25 plants outside. As expected, Fig. C3a confirms that a higher plant density characterizes each ungrazed polygon than the adjacent grazed ones. Similarly, it is shown in Fig. C3b that inside the fences the average dry biomass is twice as much than outside. This ratio is higher in the Mountain Steppe polygons than in the Steppe ones. The same trend can also be observed in the plant cover (Fig. C3c). Higher cover observed in the ungrazed polygons than the ungrazed. However, a revised trend was revealed by analysis of the spaceborne data (Fig. C3d). Landsat-ETM+ derived EVI shows significant higher values outside the enclosures than inside. This phenomenon exists in each of the study sites as illustrated in Fig. C4. These unlikely results, i.e., negative correlation between the biophysical variables and the vegetation index, should lead for further discussion about the plant composition, phenology, and palatable characteristics of the plants.

Table C1. Biophysical variables at the study sites, in the grazed and ungrazed polygons, descriptive statistics, and significance.

<table>
<thead>
<tr>
<th>Polygon</th>
<th>Plant density</th>
<th>Biomass (g/m2)</th>
<th>Cover (%)</th>
<th>EVI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ungrazed</td>
<td>Grazed</td>
<td>Ungrazed</td>
<td>Grazed</td>
</tr>
<tr>
<td>M1</td>
<td>23</td>
<td>12</td>
<td>216.7</td>
<td>32.2</td>
</tr>
<tr>
<td>M2</td>
<td>29</td>
<td>25</td>
<td>126.4</td>
<td>81.2</td>
</tr>
<tr>
<td>M3</td>
<td>34</td>
<td>25</td>
<td>188.6</td>
<td>43.7</td>
</tr>
<tr>
<td>S1</td>
<td>30</td>
<td>12</td>
<td>53.6</td>
<td>19.2</td>
</tr>
<tr>
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<td>14</td>
<td>66.1</td>
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</tr>
<tr>
<td>S3</td>
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<td>20</td>
<td>122.8</td>
<td>114.6</td>
</tr>
<tr>
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<td>18.00</td>
<td>129.03</td>
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<tr>
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<td>6.16</td>
<td>64.70</td>
<td>35.00</td>
</tr>
<tr>
<td>t-test significance (one tail)</td>
<td>0.004</td>
<td>0.036</td>
<td>0.037</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Amon Karnieli
Figure C3. Values of the biophysical variables (density, biomass and cover) and the Enhanced Vegetation Index in the study sites, separated by the grazed and ungrazed polygons. Bars indicate one standard deviation from the mean.
Figure C4. EVI values along a cross section perpendicular to the railway fence in the study sites. Bars indicate one standard deviation from the mean.
Mountain-Steppe Zone

Different perennial grasses are dominated the ungrazed areas while mostly forbs with little contributions of grasses were dominated the grazed areas. The species composition of the ungrazed areas consists of *Stipa krylovii*, *Halerpestes salsuginosa*, *Leymus chinensis*, *Agropyron cristatum*, *Poa attenuata*, *Galium verum*, and *Agrostis mongolica*. These perennial native grasses have good palatable value for the animals during the summer, especially *S. krylovii* and *A. cristatum* are highly nutritious and very good digestible plants to all livestock throughout the year (Jigjidsuren and Johnson 2003). They bloom in early August and have seed matures in September. Also, communities such as *P. attenuata*, *L. chinensis*, and *A. mongolica* have very high palatability to all livestock especially to small animals (i.e., sheep and goats) during the whole season, and those are high-costly and main contributor plant for Mongolia’s pastureland (Tserenbaljid 2002) in addition to the other native Poaceae grasses. During the blooming period in August, main perennial grasses (e.g., *S. krylovii*, *L. chinensis* etc.) have bright-gray and brown-gray flowers with 1-1.5 cm wide at the top of spikes and very straight tall about 30-70 cm. Since these needle grasses grow relatively uniform and cover about 20-30% of the fenced-off areas in each study-site, the surface looks relatively brighter for the human eyes (Fig. C5a). In the false color composite of the Landsat image the ungrazed area looks dark and no indication for photosynthetic activity is observed (Fig. C2). In the grazed areas, *Artemisia frigida*, *Artemisia dracunculus*, *Potentilla acaulis*, *Glaux maritime*, *Bupleurum scorzonerifolium*, *Allium bidentatum*, *Agrostis mongolica*, *Caragana pygmaea*, *Leymus chinensis*, *Koeleria cristata*, *Gallium verum*, *Potentilla acaulis*, and *Iris bungei* are dominant. Livestock, especially sheep, can hardly graze these perennial forbs and sub-shrubs in summer while goats moderately grazed them in autumn. Because of indigestibility value during the mid summer of those unpalatable perennial forbs (e.g., *A. frigida* and *A. dracunculus*), weedy annuals (e.g., *P. acaulis*), and subshrubs (e.g., *C. pygmaea*), the areas under the control of these plants are shown relatively green (Fig. C5a). Nevertheless, these dense bunch-forming semi-shrubs are
very nutritious for livestock in early summer and late autumn when toxic values might be low (Mandakh Bayar, personal communication). Gunin et al. (1999) noted that several species such as Artemisia (A. scoparia, A. frigida) and Echinopsilon divaricatum are indicators for rangeland degradation and human-induced desertification processes.

Figure C5. General view of the research sites: (A) Mountain Steppe site (M1): association in the ungrazed area – Halerpestes saluginosa+Agrostis mongolica; grazed area – Glaux maritima+Agrostis mongolica. Note the darker tones in the grazed area are due to the wide spread of Iris bungei. (B) Steppe site (S1): association in the ungrazed area – Stipa krylovii+Bupleum scorzonerifolium+Clæstogenes squarrosa; grazed area – Carex
duriuscula + Artemisia adamsii. Note the brighter tones in the fenced-off area due to the S. krylovii.
**Steppe Zone**

In the three selected study-sites of the Steppe zone, communities of *Stipa krylovii*, *Allium senescens*, *Agropiron cristatum*, *Festuca sibirica*, *Stipa grandis*, *Cleistogenes squarrosa*, and *Buplerum scorzonerifolium* are dominant the ungrazed areas. All these perennial grasses have very high nutritious values, so they are invaluable forage plants (Jigjidsuren and Johnson 2003). In contrast, *Carex duriuscula*, *Artemisia adamsii*, *Artemisia frigida*, and *Potentilla acaulis* were dominant in the grazing allowed areas. As noted by Fernandez-Gimenez and Allen-Diaz (2000), these species response in different levels of degradation in the Steppe zone of Mongolia. Visually, ungrazed areas in the Steppe are shown as brighter than the grazed areas due to the wide spread of the *S. krylovii* (Fig. C5b).

Based on the above-mentioned hypotheses, one-tail t-test was performed for each of the variables (Table C1). It can be seen that there is a significant difference between the grazed and the ungrazed data series, and, indeed, grazing had the expected significant effect on the biophysical variable but the EVI.

Fig. C6 illustrates the spectral reflectance graphs of different species in the steppe biome of Mongolia. It can be seen that most of the dominant species in the fenced-off area, mostly good palatable plants such as *S. krylovii*, *B. scorzonerifolium*, *A. senescens*, and *A. mongolica* have lower reflectance levels in the NIR part of the electromagnetic spectrum. On the contrary, other unpalatable species, such as *G. maritime*, *L. chinensis*, *P. acaulis*, and *I. bungei* that occupy the grazing areas have higher reflectance levels in the NIR. Fig. C7 demonstrates these differences with two representatives. *S. krylovii* is a good palatable grass that represents the protected area. In the middle of the summer the grass turn yellow, therefore its cells losses water, the refractive index decrease, and hence reflectance in the NIR decrease. *I. bungei* represents the grazed area. This is a succulent plant and therefore it characterizes by high refractive index that produces high reflectance values.
Figure C6. Spectral reflectance graphs of different species in the Steppe biome of Mongolia. Note relative higher level of reflectance in the NIR for the unpalatable species.

Figure C7. Dominant species in the Mountain Steppe zone. (A) Iris bungei, a succulent plant characterized by high refractive index that produces high reflectance values; (B) Stipa krylovii, a good palatable grass representing the protected area. In the middle of the summer the grass turn yellow, therefore its cells losses water, the refractive index decrease, and hence reflectance in the NIR decrease.
C5. Conclusions

Ground observations along the Mongolian railway confirms previous range condition model of vegetation dynamics (e.g. Dyksterhuis 1949). The model predicts that as herbivore numbers increase, plant biomass and cover decline and species composition shifts from dominance by perennial grasses and forbs ('climax' species) towards dominance by unpalatable forbs and weedy annuals. When grazing is decreased or removed, biomass and cover are predicted to increase and species composition shifts back towards late-successional stages. Although the common remote sensing based vegetation indices models assumed higher index values as biomass and cover increase, the current observations show the opposite. The reason is the difference in leaf structure and phenological stage between the palatable species inside the fenced-off area and the unpalatable species outside the fences. The palatable species are mainly grasses that turn yellow in the mid summer, while the ruderal species can be succulent plants characterize by high refractive index that produces high reflectance values.
Part D – Land-Use and Land-Cover Change

D1. Introduction

The current part reports a practical application of remotely sensed data coupled with change detection technique to assess land-use and land-cover change (LULCC) for a 12-year period in Bulgan Soum\(^1\), South-Gobi Aimag\(^2\), Mongolia. The Bulgan Soum is geographically located in the northern edge of the Mongolia’s Gobi desert, in the desert-steppe environment. LULCC that exists within the Bulgan Soum are highly affected by natural factors as a consequence of seasonal and interannual fluctuations of precipitation, prolonged and frequent drought events, strong windstorms, etc. In addition, the area is also affected by pressure of human activities such as intensifying grazing by domestic livestock, overexploiting natural recourses (e.g., collection of firewood), developing irrigate agriculture, and unlimited use of the ground for off-road driving.

Methods for assessing LULCC range from a plot-level *in-situ* sampling to wide-ranging analysis of remotely sensed data. Although aerial photography can detect LULCC over relatively wide area at a reasonable cost, satellite imagery has proven as more cost-effective in terms of space and time. Enormous number of studies, utilizing remote sensing data, derived from various satellites with specific characteristics, over different ecosystems have been well documented during the past two-decades (e.g., Jensen 1986, Lunetta and Elvidge 1998). Moreover, a large variety of change detection techniques have been formulated, applied, and evaluated (Singh 1989, Lambin and Strahler 1994b, Collins and Woodcock 1996, Lunetta and Elvidge 1998, Sohl 1999). Multitemporal Landsat series data (Multispectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper Plus (ETM+)) in association with numerous change detection techniques have been demonstrated their usefulness for studying LULCC over semi-arid environments (e.g. Pilon et al. 1988, Ram and Kolarkar 1993, Chavez and

\(^1\) Soum (district) - a local administrative unit.
\(^2\) Aimag (province) is a largest administrative unite that has including several Soums.
MacKinnon 1994, Knick 1997, Lunetta et al. 1998, Abuelgasim et al. 1999, Elmore et al. 2000, Koch 2000, Rogan and Yool 2001, Helmschrot and Flugel 2002). The Landsat imagery that has high spatial resolution imagery of 30 m provides complementary information to the field survey in attempting to detect and evaluate LULCC. However, practical utilization of such data and technique is limited in Mongolia. Here, either coarse resolution images or ground measured information were used for assessing land cover change (Chuluun et al. 1999, Erdenetuya and Khudulmur 2002) and classification (Tateishi et al. 1997), for studying relationships between vegetation cover and vegetation indices (Purevdorj et al. 1998), and for monitoring vegetation state with respect drought events (Adyasuren and Bayarjargal 1995; Bayarjargal et al. 2000, Bayarjargal and Karnieli 2004).

Consequently, the objective of this study is to detect and quantify land cover changes over more than a decadal period (1990 – 2002) by using remote sensing change detection technique. The study intends to reply the following three questions: (1) were there changes of land cover? (2) which ground features had been affected? And (3) were the changes derived by human activity or natural phenomena?

D2. Study area and dataset

D2.1. Study area

The study area, Bulgan Soum of South-Gobi Aimag, is located between 43.75°-44.85°N and 102.85°-104.12°E (Fig. D1). The total area of Bulgan Soum is 747,907 ha and it belongs to the desert-steppe environment. In spit of that, a more arid-desert environment is found in the central west and eastern regions of the Soum while the southwestern- and western-edges are characterized as mountain steppe environment. A harsh seasonal climate and limiting resources of water and nutrients for domestic and wild herbivory dominate the study area.
Figure D1. Bulgan Soum. (a) Location map; (b) Landsat-5 TM, 1990; (c) Landsat-7 ETM+, 2002. Band combination: R,G,B = 7,4,1.
The desert-steppe part of the study area is characterized by relatively flat terrain with high-erodible light-chestnut and stony soils, and sparsely distributed perennial grasses along with semi-shrubs. The desert environment is characterized by sandy soil with eolian deposits and desert woody shrubs. The mountain steppe area is characterized by rocky terrain, rolling topography with broad ridges and sharply indented valleys, and higher plants, wheatgrass herbs joining in sage shrub. Elevations within the Bulgan Soum range from 1030-1700 m AMSL in the desert and desert-steppe plateau and up to 2600 m in the mountain steppe area. The climate of the Bulgan Soum is harsh; cold winter, and dry and hot summer. Precipitation, which is the most important climatologic factor for vegetation growth in this area, varies considerably from year to year and from month to month. Mean annual precipitation is 120 mm, varying from 54 to 195 mm during the 42-year long-term data from 1961 to 2002 (Fig. D2a). 82% of the total precipitation is mainly concentrated in the vegetation-growing season, from May to September, with a peak in July-August (Fig. D2b). Mean monthly temperature varies from -13°C in January to 22.3°C in July.

A major land-use practice in the Bulgan is domestic-livestock grazing that is still a natural-dependent and semi-nomadic. Five kinds of animals (sheep, goats, cattle, horses, and camels) have been herding all year-round, and an utilization rate of pasture capacity for the Soum was below fifty percent in 1990 when 63.7 thousand numbers of livestock had been grazed over some 728,100 ha area. Due to the collapse of state-owned support at the beginning of 1990s and herders' interest to increase the number of privatized livestock, the rate was doubled in 1999. The numbers of livestock, especially number of goats, in the Bulgan Soum has increased from 1990, and currently goats are 48% of the total animals. One reason for increasing the number of the animals can be related to migration of joblessness from the Soum and Aimag centers to the countryside. While less than 1,000 people were living in countryside in 1991, this number increased to 1671 in 2000. In addition to a direct influence of livestock grazing on the pastureland, land degradation processes were taken place around the watering points (e.g., natural spring, drilled wells, and lake), cattle-breeding camps (winter shelters, folds), and
local administrative centers. Irrigated agriculture that is potatoes and vegetable planting by the rural residents in a relatively small area became an intensive mainly in the rural centers during the last a few years. Also, few herders who are living in or near the settlements with a smallest-numbers of animals grew vegetables as supplementary for their income. In addition, considerable cover of disturbance and land degradation was caused by unlimited use of the ground for off-road driving.

![Graph](image_url)

**Figure D2.** (a) Inter-annual variation of accumulated precipitation during the vegetation-growing period over the study area. Solid line shows the long-term average precipitation; (b) Multi-year average of monthly precipitations for the years 1990 through 2002. Arrows mark acquisitions dates of the Landsat images.

Arnon Karnieli
D2.2. Dataset

The basic requirement for detecting LULCC by using remote sensing techniques is the availability of images for (at least) two dates on which a same area can be observed (Yuan et al. 1998). Since the geographic location of the Bulgan Soum is larger than a single Landsat scene (185X185 km), six scenes of the Landsat imagery, three of Landsat-5 TM (1990) and three of Landsat-7 ETM+ (2002), were acquired. In order to reduce scene-to-scene variations that are related to sun angle, differences in atmospheric condition, and vegetation phenology, all images were selected during the vegetation growing season, when the possibility to discriminate between vegetation and soil covers is the highest. The main specifications of the Landsat scenes are listed in Table D1. Also, cloud covers were minimal for these images. However, the study years have different precipitation regimes. 1990 was an extremely wet year with 195 mm of rainfall, higher than the long-term average (120 mm). 107 mm of rainfall occurred between July and September. Opposing, 2002 was a dry year with 79 mm of rainfall. 39 mm rainfall occurred in July and September (Fig. D2b).

Table D1. Specifications of the Landsat-5 TM and Landsat-7 ETM+ scenes used in this research.

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<th>Sun elevation (°)</th>
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</table>

D3. Methods

D3.1. Fieldwork

The objective of the fieldwork was to collect ground reference data that could be used for satellite data analysis. Although unbiased ground reference information at the time of each remote sensing data acquisition needs to be collected in order to aid satellite image interpretation, this is rarely possible when historical images have to be used. Hence, we collected ground
information for the most recent imagery, Landsat ETM+ in 2002. Fieldwork took place from late July to mid August in 2002. Ground information was collected at fifty-five sites. Sites were selected throughout the north-south and east-west extent of the Bulgan Soum based on an erratic network of major and minor roads. The locations of sites, which were considered enough homogenous or significantly heterogeneous, were recorded by using a Global Positioning System (GPS) and mapped directly onto the corresponding topographic map sheets with scale 1:100,000 and satellite images. A color printout image of the Landsat TM in 1990 was used during the fieldwork. Descriptive information, which includes identification of plant species, percentage cover of green vegetation, plant phenological stages and heights, and spreading of bare soil and sand dunes, was noted for each site. These records were compared to the soil type and vegetation maps and then used as reference and validation information for satellite image processing.

D3.2. Satellite image pre-processing

Prior to applying change detection analysis, pre-processing operations were performed on the remotely sensed data in order to improve image quality, adjust digital values for the difference of the atmospheric conditions, and bring images into registration with the same projection. The most important procedures in the performances of the pre-processing are radiometric calibration, atmospheric correction, and geometric rectification or registration. The thermal bands of the TM and ETM+ sensors were not included in the processing and further analyzing. All other six bands were individually subject to calibration and correction. This process included the conversions of digital number (DN) values to at-satellite radiance values (Landsat 7 Users Handbook, Markham and Barker 1987).

Atmospheric correction of the radiance values at satellite for each Landsat images were carried out using the Second Simulation of the Satellite Signal in the Solar Spectrum (6S) algorithm (Vermote et al. 1997a). The 6S computer program can correct satellite-derived solar radiation that was backscattered from the Earth-surface-atmosphere system. Due to the absence of in-situ or
ground measured information of the atmospheric condition at the time of satellite data acquisition, the Landsat TM images were corrected by using a default midlatitude-summer atmospheric model. In addition, because there was no correction model for Landsat-7 ETM+ in the 6S code (Vermote et al. 1997b), the program was upgraded for ETM+ during in framework of the current research. Data about the atmospheric condition such as aerosol contents and total precipitable water that are required for atmospheric correction during the images acquisition times were obtained from an automatic tracking sunphotometer (CIMEL), which is installed in Dalanzadgad, center of South-Gobi Aimag, about 60 km southeast of the study area (Fig. D1). Atmospheric correction procedure ended with surface reflectance values.

In order to obtain cartographic uniformity of the scenes, a geometric rectification to a unique geodetic system (UTM, Zone 48, Spheroid WGS 84) was applied to the Landsat-7 ETM+ images of 2002 based on 49 ground control points that had been collected by using GPS during the fieldwork in summer 2002. A polynomial second-order transformation with cubic convolution resampling method in ERDAS image-processing package was adopted in this study (ERDAS 1997). Mean root-mean square errors (RMSE) in geometric rectification approach were less than half pixel for each scene, and the images' pixels were carried out with 28.5-meter pixel size. After applying the geometric rectification, two merged images were created for 1990 and 2002 based on three-registered images (RMSEs were less than 0.3 pixel for every registration set) for each year. Two mosaic images in 1990 and 2002 were registered one to another with the RMSE of less than 0.2 pixels. The study area was subseted on the inter-registered images by using vector file of ARC-GIS. Thus, the ground reflectance values on the subseted images for 1990 and 2000 over the Bulgan Soum area (Fig. D1) are used simultaneously in the further change detection analysis.
D3.3 Change detection analysis

The change detection method, named vegetation index differencing (Lyon et al. 1998) was used. Main assumption was that LULCC could be detected in variation of vegetation index images on two different dates, 1990 and 2002. Vegetation indices are algorithms aimed at simplifying and reducing data from multiple reflectance bands to a single value correlated to physical vegetation parameters, such as biomass, productivity, leaf area index, or percent vegetation ground cover. The majority indices are based on intensive chlorophyll absorption in the visible red part of the electromagnetic spectrum used for photosynthesis and strong reflection in the near-infrared (NIR) part of the spectrum due to scattering caused by internal leaf structure (Tucker 1979). The most widely used and well-known vegetation index – the Normalized Difference Vegetation Index (NDVI; Rouse et al. 1974) is formulated as:

\[
NDVI = \frac{(\rho_{\text{NIR}} - \rho_{\text{Red}})}{(\rho_{\text{NIR}} + \rho_{\text{Red}})} \quad (D1)
\]

where \(\rho_{\text{NIR}}\) and \(\rho_{\text{Red}}\) are the reflectance in the near-infrared and red spectral bands, respectively. Thus, denser and/or healthier vegetation having higher NDVI values, while lower values response to sparse or stressed vegetation (Sellers 1985). Soil spectra typically do not show such dramatic spectral difference as vegetation. The ease in calculating NDVI from a variety of sensors and the success of the NDVI in detecting vegetation and vegetation change has made it a popular index. The NDVI was used as vegetation index differencing method in numerous studies for analyzing vegetation conditions and changes (Briggs and Nells 1991, Chilar et al. 1991, Lyon et al. 1998). This technique also been used to detect changes in canopy or vegetation biomass (Hayes and Sader 2001). Singh (1989) compared several methods of change detection and found that the NDVI ratio is one of the most accurate techniques. Lyon et al. (1998) found this method to be less affected by topographic features than other change detection techniques. Moreover, Yuan and Elvidge (1998) concluded that NDVI differencing do better than other tested change-detection techniques.
The vegetation index differencing method consists of three processing levels: vegetation index transformation, vegetation index differencing, and evaluation of change statistics (Lyon et al. 1998). The NDVI values calculated, individually for the 1990 and 2002 images, by using Eq. D1 from the surface reflectance values. The NDVI image of 1990 was subtracted from those of 2002 to create the NDVI change differenced image. In order to identify actual LULCC, it is necessary to determine a threshold value that can be used to distinguish between pixels that were not changed and those that were significantly changed. Once a histogram of changed pixels was established, pixels that their values were not changed are distributed around the mean, while pixels with significant change are locating on the tails of the histogram (Jensen 1986). A standard deviation from the mean of change is often selected as the threshold between “change” and “no change” pixels (Jensen 1986). Higher degrees of change can be located beyond higher levels of standard deviation. In this study, NDVI differenced image’s histogram was examined and the mean and standard deviation values were calculated.

Uncertainty of NDVI differencing method was accounted for a range of threshold values from one standard deviation (where 80% of the study area is assumed unchanged) up to three standard deviations where more than 99% of areas are probably unchanged. Through this study, we assumed that more than 80% of the study area has been unchanged during the monitoring period. In other words, we believed that there were no large-disturb effects for the study area; however, LULCC should be no larger than 20% of the study area if there were some disturbing impacts on land cover. Then, two standard deviations above and below the mean of the histogram of NDVI differenced image (mean±2 standard deviations) were selected as a threshold to determine the changes of land cover in differenced image of two NDVI images in 1990 and 2002. Therefore, area that is located within two standard deviations from the mean of NDVI differenced image’s histogram was considered to represent no-change (Fig. D3a). While, the area downward within two standard deviations (higher NDVI in 1990 and lower NDVI in 2002) represents negative change of land cover, and area upwards plus two standard deviations (higher NDVI values in 2002 and lower in 1990)
represents positive change of land cover. Moreover, to enhance and assess LULCC over the Bulgan Soum, NDVI differenced image was labeled from high decrease to high increase of NDVI changes during the 12-year period, with one standard deviation interval, as shown in Fig. D3b.

Figure D3. (a) Frequency histogram of NDVI change differencing image. Significant changes of NDVI values are highlighted in color ranges with interval of one standard deviation, no-changes are shown as gray tones within threshold of 2 standard deviations around the mean; (b) Changes of land cover from 1990 to 2002 for the Bulgan Soum obtained by the NDVI differencing change detection method. Change types are in color range from blue to red, and superimposed on the red band of the Landsat-5 TM in 1990.
D4. Results and discussion

Fig. D3b presents results of NDVI differencing change detection superimposed on surface reflectance values of Band 3 in 1990 as gray-levels. Brighter tones in the background indicate a higher surface reflectance values while darker tones indicate lower ones. Significant changed values of NDVI were bounded by two standard deviations from the mean of NDVI differenced image's histogram, and are highlighted in colors from red to blue. Positive changes are colored from green as low change to blue as high change through cyan as middle change of NDVI value. Negative changes are colored from yellow as low change to red as high through orange as middle change of NDVI. Positive and negative changes were subdivided in intervals of one standard deviation.

The quantified change information of NDVI between 2002 and 1990 is shown in Table D2. No-change of land cover or no difference of NDVI between the study years over the Bulgan Soum, within the threshold of plus and minus two standard deviations occupies 726,856 ha or 97.2% of the study area. No-changes are not colored, shown as gray-level values. The desert-steppe rocky terrain in the north, the mountain steppe in the southern and western fringes, and the desert sand dunes with shrubs and semi shrubs in the central-eastern and western parts of the Soum do not show significant changes. Contrary, LULCC in different levels are mostly occurred over the desert-steppe environment with herbaceous plants and semi-shrubs in the southeast and eastern portions of the study area.

About 16,696 ha (2.2% of the study area) were indicated as decreased NDVI from 1990 (wet year) to 2002 (drought year). The red in the NDVI differenced image represents high or severe rate of decreased NDVI (533 ha or 0.1% of the study area). The moderate (1,460 ha or 0.2% of the study area) and low (14,703 hectares that about 1.9% of the study area) decreases of NDVI values are shown as orange and yellow colors, respectively, in differenced image. Decreased NDVI values are found in the desert-steppe plain environment by a decline or reduction of natural vegetation. This happened in valleys, along temporal watering canals, and in an area of a lake.
(Ulaan-Nuur) that was dried up (Fig. D3b). Two reasons can be pointed out: (1) natural effect caused by difference in rainfall regime between the two years (Fig. D2b), since high correlation exists between the precipitation and NDVI (Tucker et al. 1991, Tucker and Nicholson 1999); and (2) anthropogenic effect of grazing pressure on the study area of domestic livestock. During the fieldwork, it was surveyed that roaming patterns of grazing livestock have been distributed mostly around the centers of Soum and Bags. Number of animals almost doubled from 1990. Due to limitation of drinking water over the pastureland in the far north of the study area and absence of grazing plants in the rocky-mountain areas and sand dunes in the west and east of the study area, grazing of the increased number of animals is mostly located over the south-eastern part of the study area. Therefore, it should be noted that the NDVI differencing could give significant LULCC in the plain desert-steppe environment due to the combined effects of drought and grazing.

Although there was less precipitation in 2002 (Fig. D2b), positive changes of NDVI are also observed. Only 4,355 ha (0.6% of the total study area) were detected as increased NDVI from the wet to drought year (Table D2). This highest level of LULCC was found around the dried lake Ulaan-Nuur. This phenomenon is explained by disappearing of the brackish-water and growing of worm weed shrubs such as Artemisia frigida, which is not palatable for the animals during an intensive growth period of plants in early autumn and summer times. The Artemisia frigida is one of indicator-species of land degradation processes since it is more resistant to degradation. Increasing of such worn weed plant over the dried-table of brackish-water is proved by the fieldwork in 2002. Moreover, areas with increased NDVI values between the study years are found over the valleys and canals that are near the Soum and Bag centers. This can be explained by extensions of invader plants such as a dwarf shrub, Iris Bungei, which is also not palatable during its growth period. This plant can grow up as relatively large bunches with diameters range in 0.5-2 m and height about 30-40 cm tall. From the fieldwork, it was observed that the Iris Bungei does not mix with other dwarf shrubs and has a significant association to soil moisture in sandy soil. In addition, cultivated irrigated areas near the Soum and Bag centers are observed with increased values of
NDVI. This type of LULCC is related to the irrigated-planting of vegetables that has become a new land use during the last a few years. Also, some increased NDVI values, which are observed in the floodplains of the Gobi Gurvan Saikhan Mountain in the west-south corner of the study area, were probably caused by flooding of local canals and ephemeral streams.

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<td></td>
<td>(hectare)</td>
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<tr>
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<td>Low</td>
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D5. Summary and conclusions

Changes of land-use and land-cover over the Bulgan Soum during a 12-year period (1990-2002) were detected and quantified by using high spatial resolution imagery of Landsat TM and ETM+ coupled with change detection method based on normalized difference vegetation index differencing. LULCC was caused by combination of anthropogenic (i.e., livestock grazing) and natural (i.e., precipitation deficit) effects.

As change-detection analysis between two dates with different rainfall regimes, it was shown that:

(1) Relatively large areas have been detected over the desert-steppe plain environment as decreased in NDVI. This phenomenon can be explained by ineffective grazing-management in the Bulgan Soum since livestock grazing has been intensified during the study period.
(2) Vanishing of the lake's water due to mismanaged human activities in the study area caused a suitable opportunity to unpalatable plants to grow in the dried-lakebed. Consequently, these species caused higher NDVI values in 2002 than in 1990.

This study demonstrates the potential for using remote sensing data and change detection method to identify LULCC in a selected area of Mongolia's desert steppe environment. Moreover, practical methodology of this study can probably be used as an example for regional level land cover monitoring system of the country. It is suggested that such a research on LULCC will be conducted on a regular interval, so that the information can be updated periodically. A further detailed investigation of LULCC in study area is necessary to use different change-detection techniques with integration of ancillary GIS datasets (e.g., environmental parameters such as elevation, slope, and aspect of the landscape and socio-economic information such as population and animal number) or sequential aerial photographs of the test area. Results of change detection analysis should be used as a tool for decision makers.
Impact, Relevance, and Technology Transfer

Mongolia is one of the countries that severely affected by droughts, desertification, and climate change processes. According to local measurements, regional climate warming in southern Mongolia has increased by 0.1 to 3.7°C during last sixty years. In this region, there is also evidence that spring precipitation has decreased by 17%, while summer precipitation has increased by 11%. It is likely that these changes in temperature and precipitation can intensify the occurrences of drought, especially during the vegetation green-up onset time. Moreover, it was reported that the frequency of drought in the spring and summer has increased from 1-2 to 3-4 times every five years in the Gobi region (Bolortsetseg et al., 2000). Drought has a disturbing effect not only on agricultural productivity and hydrological resources but also on the natural vegetation, and hence it may accelerate desertification processes when associated with destructive human activities (i.e., overgrazing) in semi-arid pastureland areas of Mongolian. Therefore it is very important to introduce new tools, such as remote sensing, image processing, and geographic information system (GIS) in order to analyze digital data from satellites over vast and remote areas such as the Gobi Desert.

In order to implement the above-mentioned goals, several items were purchased for the National Remote Sensing Center (NRSC) in Mongolia in framework of the current project. These are: (1) Linx-based satellite receiving station for acquiring digital images of the NOAA-AVHRR and SeaWiFS spaceborne systems; (2) 6 terra bit mass storage in order to store the data; (3) 4 desktop computers for process the images; and (ERDAS-Imagine and ARC/GIS software packages for processing the data. 

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Project Activities/Outputs

1) The following meetings were took place throughout the project:


- Progress meeting in July 2003, in Ulaan Batar, attendance: A. Karnieli (BGU), S. Kudulmur, M. Bayasgalan (NRSC/Mongolia).
- Progress meeting in October 2004, in Sede Boker (Israel), attendance: A. Karnieli (BGU), Y. Bayarjargal (NRSC/Mongolia), L. Remer (NASA/GSFC).

2) List of training:

Three students were involved in training at the Jacob Blaustein Institute for Desert Research. These are: (1) M. Bayasgalan, a PhD student at University of Mongolia and visited BGU twice for 3-month period each; (2) G. Chantuu was trained during two years and completed her master thesis at BGU, and (3) Y. Bayarjargal originally came for a Master program, but has stayed longer to complete his PhD at BGU.

3) List of publications:


**Project Productivity**

Based of the fruitful results, as are reflected in the scientific papers on one hand and the technology transfer on the other hand, we do believe that the project is extremely productive.

**Future Work**

The Mongolian and the Israeli teams are remained in close contact and looking forwards for future collaboration.
Literature Cited


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