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Using multiple remote sensing perspectives to identify and attribute land surface dynamics in Central Asia 2001–2013

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ABSTRACT

To understand the land surface changes that Central Asia experienced between 2001 and 2013, we applied a non-parametric change analysis method to the standard vegetation indices (NDVI and EVI), as well as to the MODIS Tasseled Cap indices Brightness, Greenness and Wetness. In addition, we evaluated the MODIS nighttime and daytime land surface temperature products and the MODIS evapotranspiration product. We compared the change results by country, land cover type, and anthropogenic biome, and we also evaluated the results according to an index of human influence (HII). We found that EVI, NDVI and Tasseled Cap Greenness reveal very similar changes ($r > 0.8$), while there was a much lower correlation between the vegetation indices and results based on other portions of the electromagnetic spectrum. Thus, we found it informative to expand the analysis beyond the optical and near infrared portions of the electromagnetic spectrum, into the thermal regions. We found that the majority of the changes occurred in Kazakhstan and Uzbekistan, while Turkmenistan, Kyrgyzstan and Turkmenistan appeared more stable during this period. The observed changes were attributable to a combination of anthropogenic changes and weather effects. For example, changes in crop type south of the Aral Sea were revealed as increases in vegetation indices but declines in evapotranspiration, resulting from a shift from cotton to wheat. Across Kazakhstan large patches of negative vegetation changes, combined with increasing temperatures and declines in evapotranspiration were attributable to persistent droughts. Generally, we found that most browning of vegetation occurred in areas with lower human influence (except for areas with very high human influence) and most greening of the vegetation occurred in the areas with intermediate human influence. The use of multiple indicators of significant trends improved trend interpretation and attribution of proximate causes.

1. Introduction

Central Asia has experienced significant and often serious land cover and land use changes over the past several decades (Klein, Gessner, & Künzer, 2014). The region is perhaps best-known for the massive decline of the Aral Sea, which is just one symptom of the many water related challenges the region is facing (Klein, Gessner, & Kuenzer, 2012). During the Soviet era, large swaths of steppe in northern Kazakhstan were converted to cropland, which were partly abandoned after the collapse of the Soviet Union (de Beurs & Henebry, 2004; Wright, de Beurs, & Henebry, 2012). The processes of cropland abandonment and degradation continue in some areas (Dubovyk et al., 2013; Dubovyk, Menz, & Khamzina, 2012; Tüshaus, Dubovyk, Khamzina, & Menz, 2014). Uzbekistan is particularly affected by land degradation resulting from secondary soil salinization (Sommer et al., 2013). Besides cropland abandonment, the region has also been affected by a partial rehabilitation of grasslands as a result of declining livestock numbers since 1990 (Karnieli et al., 2008). Climate change is expected to change the water availability with declining summer precipitation and potentially increasing winter precipitation (Lioubimtseva, de Beurs, & Henebry, 2013; Lioubimtseva & Henebry, 2009; Lioubimtseva, Kariyeva, & Henebry, 2014), which could significantly affect the precipitation sensitive vegetation in Central Asia (Gessner et al., 2013) as well as available water bodies (Klein et al., 2014), and has the potential to lead to cross-border water disputes (Bernauer & Siegfried, 2012; Groll, Opp, Kulmatov, Ikramova, & Normatov, 2015). However, the simulated precipitation in climate projections for this region remains highly uncertain in recent rounds of climate model intercomparisons (IPCC, 2013). The population of the region is highly variable with some areas extremely sparsely populated and others very densely populated. Areas with dense population are expected to experience tremendous growth over the next forty years (Siegfried et al., 2012).

Optical satellite data such as from AVHRR, MODIS and Landsat sensors are often applied in the analysis of land surface changes. Change analysis can be roughly divided into two groups. Approaches in the first group are focused on detecting change through post-classification comparison of two or more time periods to count differences in classes

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(Conrad, Colditz, Dech, Klein, & Vlek, 2011; Klein et al., 2012; Klein, Gessner et al., 2014; Wright et al., 2012). The second approach applies trend analysis and is focused more on gradual changes such as land degradation or recovery (de Beurs & Henebry, 2004; Eckert, Hüsler, Liniger, & Hodel, 2015; Tüshaus et al., 2014). Changes in the character of the vegetated land surface are most often expressed in terms of temporal changes in the Normalized Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI), or the Soil-Adjusted Vegetation Index (SAVI). Each index exploits the spectral contrast between red and near infrared reflectance to indicate the presence of green vegetation (Huete et al., 2002). SAVI and EVI are designed to reduce the influence of background soil reflectance (Huete, 1988; Huete et al., 2002).

In recent years, some papers have presented comparisons of trend results based on different vegetation indices (Dubovyk et al., 2012; Sonnenschein, Kuemmerle, Udelhoven, Stellmes, & Hostert, 2011; Tüshaus et al., 2014). One study used Landsat data to conclude that the trends for NDVI, SAVI, and Tasseled Cap Greenness indices were similar when gradual changes were observed (Sonnenschein et al., 2011). However, if disturbances were present, then the indices differed significantly (Sonnenschein et al., 2011). Another study compared the vegetation indices for croplands in Central Asia and found the trend results for NDVI and SAVI to be similar (Dubovyk et al., 2012, 2013). The trend results in the same area in Uzbekistan showed much greater variation, however, when compared using different sensors (MODIS vs MERIS) or when the MERIS-based Terrestrial Chlorophyll Index (MTCI) was evaluated (Tüshaus et al., 2014). In this study we confirm the existing literature by evaluating the standard vegetation indices (NDVI and EVI) and a MODIS version (Lobser & Cohen, 2007) of the Tasseled Cap Greenness index (Kauth & Thomas, 1976). We then determine whether there are meaningful significant differences in the changes observed by these indices by evaluating their statistical equivalency.

Changes in vegetation are both influenced by and have an influence on changes in land surface temperature. We expand our analysis by investigating the changes in MODIS nighttime and daytime land surface temperature products. Land surface temperature differs from air temperature in that it depends heavily on the radiative properties of the land surface, typically resulting in larger diel amplitudes than air temperature measurements. Some studies have indicated that changes in vegetation could significantly impact land surface temperature changes as well as observed evapotranspiration (ET; e.g., Peng et al., 2014). We compare the change results for the vegetation indices with daytime and nighttime LST as well as ET to determine whether a confluence of effects can be found.

Vegetation changes are also linked with changes in albedo and land surface wetness. We finalize our analyses by investigating the changes in Tasseled Cap Brightness and Wetness indices as proxies for albedo and vegetation wetness. Our ultimate objective is twofold. First, we want to confirm that for the Central Asia drylands, it is sufficient to select one of the vegetation indices (NDVI, EVI, or TC Greenness) for analysis. Second, we want to identify potential causes and consequences of well-studied vegetation changes by incorporating and investigating MODIS LST, ET and Tasseled Cap Brightness and Wetness data.

Changes in time series have often been summarized using the slope of a linear regression model based either on composited data or after application of seasonal correction models (e.g. de Jong, Verbesselt, Zeileis, & Schaepman, 2013; Eckert et al., 2015; Zhou et al., 2015). Yet, many factors can degrade the reliability of the parameter estimates (de Beurs & Henebry, 2004). Instead, we apply the Seasonal Kendall (SK) test corrected for first-order autocorrelation as a robust non-parametric alternative that relies on fewer statistical assumptions and is routinely used in analyses of climatological and hydrological time series (Hirsch, Slack, & Smith, 1982; de Beurs & Henebry, 2004; von Storch & Navarra, 1999). The SK test is well-equipped to pick up temporal changes that could result from shifts in aboveground biomass. It is important to distinguish the SK test from the Mann–Kendall test that is sometimes applied to satellite image time series (Schucknecht, Erasmi, Niemeyer, & Matschullat, 2013; Sobrino & Julien, 2011; Tüshaus et al., 2014). The Mann–Kendall test is not corrected for first-order autocorrelation; thus, it can suffer from an overestimation of trend significance due to high temporal autocorrelation. We apply trend detection methods to evaluate gradual changes, but we are well aware of the brevity of the currently available satellite time series. Trends are assessed by looking backward in time, and we emphasize that a detected significant trend is not a guarantee of a future tendency in the data – trends ought not to be extrapolated into the future. Land change dynamics are complex and require process modeling to capture and project future scenarios (Brown et al., 2014). We summarize and correlate the change results to determine the similarity and differences between the incorporated land surface metrics. Lastly, we evaluate the change results by country, land cover type, anthropogenic biome (Ellis & Ramankutty, 2008) and Human Influence Index (Sanderson et al., 2002; Wildlife Conservation Society - WCS & Center for International Earth Science Information Network - CIESIN - Columbia University, 2005).

2. Data and study region

2.1. Study region

In this paper we focus on the following five countries that comprised Soviet Central Asia: Kazakhstan, Turkmenistan, Uzbekistan, Kyrgyzstan, and Tajikistan (Fig. 1). Kazakhstan is the largest country (2,727,000 km^2) and Tajikistan is the smallest (142,000 km^2). The population density of the region varies greatly from less than 5 people per km^2 to as high as 7000 per km^2 in some areas of Uzbekistan.

Elevation increases to the east, from the coast of Caspian Sea in western Turkmenistan and Kazakhstan to the mountainous terrain in eastern Kazakhstan and Uzbekistan and across Kyrgyzstan and Tajikistan. The area generally ranges from semi-arid in the north to arid in the south, with the driest areas found in Northern Turkmenistan and Southern Uzbekistan. The wettest areas can be found in the mountainous areas of Kyrgyzstan and Tajikistan. Temperatures are very cold in the winter months (<-20 °C) in Northern Kazakhstan and increase towards the south. Rainfed agriculture dominates the northern portion of the region, while the southern region is well-known for its large scale irrigation. Agropastoralism is another widespread land use, both in the mountains and in the flatter grasslands of the region.

During the Soviet period, open pit mining, for example of uranium ore, was a fairly common activity in Kyrgyzstan and Tajikistan. But, the other countries in Central Asia are also still struggling with contaminated regions as a result of mining waste. Mining still continues in the region, for example for gold and silver.

2.2. Datasets for change analysis

Land surface change analysis is often carried out based on vegetation index data such as NDVI. Some recent studies have evaluated the differences and similarities between long term vegetation trends as observed by AVHRR sensors (e.g., GIMMS3g) and the MODIS sensors (e.g., Fensholt and Proud, 2012; Fensholt et al., 2012). These studies have reported general compatibility between these two datasets, although some variability is dependent on land cover classes. The general advantage of the data based on the AVHRR sensors is the duration of the record (starting in mid-1981). However, the AVHRR sensors record broad visible (580–680 nm) and NIR (725–1000 nm) bands. As result, the number of vegetation indices that can be calculated is limited and the band placement and width were not optimized for vegetation detection (Cracknell, 1997; Gitelson & Kaufman, 1998).

Here we have decided instead to investigate the changes on the land surface with a suite of MODIS products. We have chosen to work with the MODIS data products despite the shorter record, because it will enable us to evaluate how the land surface changes from multiple