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Land degradation assessment and monitoring of drylands

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1 Introduction

1.1 Drylands

Drylands cover about 41% of the earth's land surface, comprising hyper-arid to dry sub-humid climate zones which are defined by low mean annual precipitation amounts compared to potential evaporation, i.e. a ratio of mean precipitation to potential evaporation less than 0.65 (Safriel et al., 2005; Thomas and Middleton 1994; see figure 1). They include a large number of ecosystems which belong to the four broad biomes: forests, Mediterranean, grasslands, and deserts (Safriel, et al., 2005) and are home to about one third of the global population, with many residents directly depending on dryland ecosystem services including the provision of food, forage, water, and other resources (Millenium Ecosystem Assessment, 2005a). Drylands also provide ecosystem services of global significance, such as climate regulation by sequestering and storing vast amounts of carbon due to the large areal extent (Lal, 2004) (Table 1).

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Drylands are characterized by high variability in both rainfall amounts and intensities and the occurrence of cyclic and prolonged periods of drought. Most frequently, soils contain low nutritious reserves and have low contents of organic matter and nitrogen (Skujins, 1991). In addition, surface runoff events, soil-moisture storage, and groundwater recharge in drylands are generally more variable and less reliable than in more humid regions (Koofhafkan and Stewart, 2008).

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Water availability and the tolerance to periods of water scarcity are key factors in dryland productivity (Stafford Smith et al., 2009). In response to water scarceness and prolonged drought periods, fauna and flora of dryland ecosystems have adapted to these conditions following manifold strategies (morphological, physical, chemical), such as the development of drought-avoiding (i.e. ephemeral annual grasses) or drought-enduring (i.e. xerophytes) plant species as well as plant adaptations such as xeromorphological leaf structures. Fire is a further important element in functioning and maintenance of dryland ecosystems (Bond and Keeley, 2005).

1.2 Land use in dryland areas

For thousands of years humans developed strategies to use the goods and services provided by drylands in a sustainable way (Table 1), thereby responding to the level of aridity. Thus, land use systems in drylands are very diverse, including a variety of shifting agriculture systems, annual croplands, home gardens and mixed agriculture–livestock systems, including nomadic pastoral and transhuman systems (Koofhafkan and Stewart, 2008). The vast majority of dry-lands that support vegetation are used as rangelands (69%), which sustain about 50% of the world’s total livestock population, whereas 25% of the dryland areas are used as croplands (Reid et al., 2004). However, land use varies largely among dryland climates. The proportion of rangeland increases with aridity, from 34% in sub-humid regions to 97% in hyper-arid are-as (Millenium Ecosystem Assessment, 2005b), whereas arable cultivation is restricted to semi-arid and dry sub-humid regions (Koofhafkan and Stewart, 2008). Also the use of fire as a land use management tool has a history of millennia in drylands and includes the use of fire by pastoralists to improve rangeland conditions (Naveh, 1975), but also for slash and burn agriculture, honey collection, charcoal production and opening landscapes to facilitate hunting as practised in African Savannahs (Mbow et al., 2000). Even though dryland ecosystems are adapted to fires, changing fire regimes may cause land degradation and loss of biodiversity as they impact species composition and vegetation structure and severally affect nutrient cycling (e.g. Trapnell, 1959, Anderson et al., 2003).

Countries with drylands differ in their socio-economic development. Differences range from agrarian via industrialized to service oriented societies, whereby at least 90% of the dryland population lives in developing countries (Safriel, et al., 2005). The development stage defines to a large extent the land use systems and the corresponding process framework of land use/land cover changes (DeFries et al., 2004). Even though land use changes are affecting almost all terrestrial ecosystems, drylands are considered as most vulnerable to degradation processes. Thus, water scarcity, overuse of resources and climate change are a much greater threat for dryland ecosystems than for non-dryland systems (Millenium Ecosystem Assessment, 2005a).

1.3 Land degradation and desertification

Degradation of terrestrial dryland ecosystems, also termed desertification, is recognized as one of the major threats to the global environment impacting directly on human well-being (Millenium Ecosystem Assessment, 2005a) and threatening to reverse the gains in human development in many parts of world (UNU, 2006). The terms land degradation and desertification received worldwide attention following the prolonged Sahel drought during the 1970s and 1980s which caused a humanitarian catastrophe. As result of the United Nations Conference on Desertification (UNCOD) in 1977 a "*Plan of action to combat desertification*" was approved. Limited progress in reducing the problem of desertification since then, led the Rio Conference in 1992 to call on the United Nations General Assembly to prepare through intergovernmental negotiation a Convention to Combat Desertification (CCD). Thus, in 1994 the UNCCD (United Nations Convention to Combat Desertification) was adopted and brought into force in 1996 having received notification of the 50th ratification of the Convention, which by now has 193 signatory parties. The definition of both terms was subject to highly controversial debates (Hermann and Hutchinson, 2005).

A nowadays widely accepted definition of land degradation and desertification is provided by the UNCCD. According to the UNCCD (1994) land degradation is defined as "*the reduction or loss, in arid, semi-arid and dry sub-humid areas, of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns*". Desertification is defined as *"land degradation in arid, semi-arid and dry sub-humid areas, resulting from various factors, including climatic variations and human activities"* (UNCCD 1994). This definition aims to cover at large the broad range of complex processes that cause a sustained decrease of ecosystems services throughout all terrestrial ecosystems in drylands. Nevertheless, this also leaves room for interpretation and uncertainties concerning the terminology (Vogt et al. 2011) and, hence, also arouses different perceptions of the processes that lie behind these two terms.

1.4 Scientific perception of land degradation

In the past decades, the scientific communities' understanding has undergone a shift concerning the key factors that are required to allow for adequate assessment and monitoring of land degradation. The assessment of land degradation changed from a mere biophysical perception to a more holistic approach where human-induced or climate-driven underlying forces as well as spatial and temporal scale issues have been recognised as factors that should be considered to understand and identify land degradation processes (Vogt et al., 2011).
The understanding of land degradation processes, including their causes and consequences on ecosystem functioning as well as the identification of affected areas and regions at risk, are a prerequisite to develop strategies to mitigate and avoid land degradation. Accordingly, over the past decades many national and international research initiatives reviewed the status of land degradation sciences and identified gaps and developed strategies to assess and monitor land degradation and desertification.
This chapter provides an overview of important studies on remote sensing of land degradation in drylands. Section 17.2 presents general considerations regarding the assessment and monitoring of land degradation including suitable indicators as well as sensor systems. The following sections give a review of the state of the art on the assessment of land condition

(section 17.3), the monitoring of land use/land cover changes to assess land degradation processes (section 17.4) and the identification of human-induced drivers of land degradation using integrated concepts (section 17.5) whereas section 17.6 describes limits and uncertainties regarding dryland observation. This chapter concludes with a summary of land degradation assessment and monitoring by remote sensing techniques (section 17.7).

2 Remote Sensing of dryland degradation processes

Various scientific disciplines contribute valuable information that enhances the understanding of land degradation and desertification at different temporal and spatial scales. These include studies ranging from the plot scale to global assessments as well as the collection of biophysical or socio-economic data and the implementation of models to predict land use changes in future decades.

Earth observation is a tool that essentially contributes to the assessment and monitoring of ecosystems from a local to a global scale. Hence, information extracted from remote sensing data can be employed to: (i) assess the extent and condition of ecosystems, and (ii) monitor changes of ecosystems conditions and services over long time periods (Foley et al., 2005; Turner II et al., 2007). The use of earth observation data fundamentally contributes to the understanding of dynamics and responses of vegetation to climate and human interactions (DeFries, 2008).

Monitoring drylands requires observation data that are able to observe long-term trends and short-term disturbances across large areas. For this reason, remote sensing data are important components of monitoring strategies, as they provide objective, repetitive and synoptic observations across large areas (Graetz, 1996; Hill et al., 2004). Three major components are particularly important to provide (i) a comprehensive observation of dryland areas, (ii) ensure their relevance for policy and management and (iii) help preventing unsustainable use of ecosystems goods and services:

(i) Assessment of actual land condition, i.e. the capacity of an ecosystem to provide goods and services (compare 17.3),
(ii) monitoring of land cover changes and assessment of their implications for land condition separating natural processes, i.e. climate variability and fire, from human-induced land use/land cover-related processes (compare 17.4), and
(iii) integrated concepts that link remotely sensed results to the human dimension in order to identify drivers of land degradation (compare 17.5).

Neither the condition of ecosystems nor the processes affecting them can directly be measured by earth observation data. Rather, suitable indicators have to be identified (Verstraete, 1994) that (i) can be related to the status and processes and (ii) can be derived in standardized and replicable way.

2.1 Suitable remote sensing indicators for dryland observation

A range of approaches and models has been developed allowing to derive a variety of biophysical parameters appropriate for the observation of drylands (Hill, 2008; Lacaze, 1996). Depending on the spatial and spectral characteristics of the remote sensing data these qualitative and quantitative measures include vegetation indices related to greenness, vegetation cover, pigment and water content, soil organic matter of the topsoil, landscape metrics etc. (e.g. Blaschke and Hay, 2001; Hill et al., 2004).

Even though land degradation indicators related to soil have proven to provide important information on land degradation, vegetation cover hampers the remotely sensed assessment of soil properties. Thus, soil properties can only be reliably assessed at low vegetation cover (Jarmer et al., 2009). Furthermore, many of the proposed indicators, e.g. grain size distribution, mineral content and soil organic carbon, require hyperspectral data. To date, these data are mostly acquired using airborne systems, making them costly and only available for small areas. As a result, only few studies exist that use hyperspectral imagery for land degradation assessment (e.g. Shrestha et al., 2005, De Jong and Epema, 2011). However, various hyperspectral, space-borne missions are currently being developed, (e.g. EnMAP (Environmental Mapping and Analysis Program) under the lead of the German Aerospace Center (DLR), or HyspIRI (Hyperspectral Infrared Imager) by the National Aeronautics and Space Administration (NASA) and it is to be expected that the utilization of this hyperspectral imagery in the context of land degradation assessment will increase in the near future.

2.2 Biophysical remote sensing indicators for long-term dryland observation

The biological productivity of ecosystems is one of the key factors that describe the functioning of an ecosystem and it is also explicitly stated in the definition of desertification and land degradation of the UNCCD (Del Barrio et al., 2010). Parameters related to productivity such as greenness, vegetation cover and biomass can therefore serve as proxies to assess and monitor land degradation. These parameters are especially suitable for earth observation methods due to the distinct spectral signature of vegetation.

A commonly used vegetation index calculated from the red and near-infrared spectral information is the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974; Tucker, 1979). It was shown that the NDVI is a proxy for greenness and is linearly related to the fraction of absorbed Photosynthetic Active Radiation (faPAR) (Myneni and Williams, 1994, Fensholt et al., 2004) which in itself is an important factor of assessing the Net Primary Productivity (NPP). However, the NDVI has well-known weaknesses due to its sensitivity to soil background, especially when vegetation cover is low (Price, 1993, Elmore et al., 2000). Advanced vegetation indices overcome these problems, like the Enhanced Vegetation Index

(EVI) (Huete et al., 2002) and the Soil Adjusted Vegetation Index (SAVI) (Huete, 1988). More advanced methods to derive parameters that are related to vegetation are the Tasselled Cap Transformation (TC) (Kauth and Thomas, 1976) and Spectral Mixture Analysis (SMA) (Adams et al., 1986; Smith et al., 1990). The latter directly provides vegetation cover if correctly parameterized and is often used for Landsat-based land degradation assessment in drylands (Sonnenschein et al., 2011). Nevertheless, for temporal analysis it seems to be of more decisive importance to employ a robust and consistent measure (Udelhoven and Hill, 2009; Sonnenschein et al., 2011).

2.3 Earth observation platforms used in dryland observation

High variability of precipitation amounts infers also a high variability of vegetation cover and its vitality. Moreover, disturbances like fires create abrupt changes of vegetation cover. Dryland obervation requires to consider these variations by using long-term observation to separate gradual long-term trends from short-term variations. Among the numerous space-born sensors, only few satellites are fulfilling the two criteria of collecting data that (i) cover a long time period and (ii) provide a systematic global coverage. These systems can be distinguished in two major groups: the first provides a medium spatial resolution, but has a limited temporal resolution, the second provides a coarse scale resolution, but has a high temporal resolution. Table 2 gives information of important sensors and derived archives, which are presented in more detail in the following sections.

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2.3.1 Medium spatial resolution sensors

The Landsat program consists of a series of multi-spectral optical sensors that record the reflected radiance in the visible to middle infrared domain (complemented by band(s) in the thermal domain) which allows the derivation of several surrogates related to vegetation properties (Fang et al., 2005). Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+) and Operational Land Imager and Thermal Infrared Sensors (OLI/TIRS), respectively are providing data of the earth's surface with a spatial resolution of 30 m x 30 m since 1982 (Goward and Masek, 2001). The temporal revisit rate of the sensor is 16 days and could theoretically provide a time series of earth observations with similar density compared to those provided by coarse scale sensors, but also in many dryland areas cloud cover impedes the acquisition of utilizable images. Thus, often only few images of sufficient quality can be acquired per season.

The SPOT (Satellite Pour l'Observation de la Terre) satellites operated by Centre National d'Études Spatiales (CNES) provide multi-spectral data since 1986 with a spatial resolution of 6 m x 6 m up to 20 m x 20 m with a revisit rate of 26 days. The SPOT system is operated commercially, which offers the possibility to prioritize the observation of specific areas. Whereas the Landsat sensors are restricted to Nadir-acquisition, the SPOT sensors are able to incline the sensor allowing for the acquisition of data for specific areas more often than these 26 days. At the same time this means that other areas are not recorded on a regular basis.

2.3.2 Coarse spatial scale satellite sensors

Regional to global dryland studies are mostly based on coarse-scale imagery with higher temporal resolution. Due to the long legacy of the mission, the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) sensor series is one of the most important sensors in this context. Within the Global Inventory Monitoring and Modeling System (GIMMS) project, the most commonly used global NOAA AVHRR time series are provided. The recent version NDVI3g (third generation GIMMS NDVI from AVHRR) spans the time period from 1981 to 2012 and consists of bi-monthly measurements of the NDVI data at a pixel size of about 8 km x 8 km.

Higher resolution NOAA AVHRR archives data are available for some parts of the world, such as the Mediterranean Extended Daily One-km AVHRR Data Set (MEDOKADS). The archive consists of a 10-day maximum value composite of full resolution NOAA AVHRR channel data covering the whole Mediterranean region from 1989 to 2004 with a spatial resolution of about 1 km^2 (Koslowsky, 1996). Another regional datasets is for example a 1-km^2 dataset covering Australia (BOM, 2014).

A prerequisite for long-term observation analyses are well-calibrated data archives. This is especially demanding in case of the NOAA AVHRR data archives as pre-processing comprises the correction of effects caused by orbital drift of the sensor (i.e. changing overpass time) as well as the inter-calibration of the spectral channels between the different AVHRR sensors employed to create the long-term archives. Due to the limited spectral properties of the NOAA AVHRR sensors the derivation of biophysical parameters is limited and usually based on the NDVI.

The Moderate-resolution Imaging Spectroradiometer (MODIS) provides a better spatial and spectral resolution and which allows to derive more enhanced biophysical surrogates. NDVI and EVI are provided as standard vegetation parameter products. Moreover, the sensor properties facilitate the provision of a consistent high quality data archive including the possibility to derive Bi-directional Reflectance Distribution Function (BRDF) corrected data (Strahler et al., 1999). Other sensors delivering time series suitable for land degradation assessment are e.g. Satellite Pour l'Observation de la Terre (SPOT) Vegetation, Sea-Viewing Wide Field-of-View Sensor (SeaWIFS), and Medium Resolution Imaging Spectrometer (MERIS). However, in comparison to the NOAA AVHRR data sets these archives are still confined to rather short observation periods. Several studies aimed at combining different data archives to overcome the different spectral responses, differing observation characteristics including observation geometry and diverging spatial resolutions of the sensor systems (Ceccherini et al., 2013).

2.3.3 Recent developments for obtaining medium spatial and high temporal resolution time series

Although both coarse and medium sensor types provide data that allow for adequate dryland observation, there is a trade-off between geometric and spectral level of detail, areas covered and temporal resolution that needs to be considered. With the planned launch of the ESA (European Space Agency) Sentinel-2 satellites in 2015 and 2016, two additional Landsat-type sensors will be available. Together with the Landsat OLI the repetition rate of acquiring data from the entire globe will be much higher, augmenting also the probability of cloud-free observations. Another promising technique is the fusion of Landsat and MODIS images with the Spatial and Temporal Adaptive Reflectance Fusion Model STARFM (Gao et al., 2006) aiming at providing time series with a temporal resolution of MODIS but the spatial resolution of Landsat. The approach was applied successfully to dryland areas (Schmidt et al., 2012; Walker et al., 2012) and offers the possibility to monitor land degradation processes in more detail. One drawback of this procedure is that the fusion can only be performed after the launch of MODIS Terra in the year 2000.

2.3.4 Analysis techniques

Long term monitoring requires accurate geometric and radiometric correction of the data to reduce noise that originates from observational conditions including observation geometry, atmospheric conditions and sensor degradation. A meaningful analysis necessitates a rigorous pre-processing scheme for all the time series images (Röder et al., 2008a).

The creation of a medium resolution time series is challenging because images should originate from comparable phenological stages. Therefore, many of the early studies investigating time trajectories of vegetation based on Landsat time series are confined to only one observation per season (e.g. Hostert et al., 2003; Röder et al., 2008a).

The opening of the Landsat archives distributed by the United States Geological Survey (USGS) has enabled new opportunities to assess land cover changes based on the full range of available data from the archive, including images with high cloud cover. Thus, new approaches move from image based analysis towards pixel based analysis. This comes along with new methodologies that allow for pre-processing and analysing the data in an automated way. It includes the provision of geometrically corrected Landsat L1T data by USGS, cloud detection via fmask (Zhu and Woodcock 2012) and automated radiometric correction schemes like the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al., 2006) or the Australian BRDF correction scheme (Flood et al., 2013). Recently, the U.S. Geological Survey (USGS) has embarked to distribute higher-level Landsat data products, e.g. Landsat Surface Reflectance Climate Data Record (CDR) and Landsat Surface Reflectance Derived Spectral Indices (http://landsat.usgs.gov/CDR_ECV.php). For Queensland, Australia a Fractional Vegetation Cover product is available since 1986 providing seasonal images for the entire state (http://www.auscover.org.au).

With the changes in data policy and increases in data quality as well as computational improvements, time series approaches were developed that allow for the detection of gradual or abrupt changes, or both simultaneously. Several methodologies and tools were published, e.g. Landsat based detection of trends in disturbance and recovery – LandTrendr (Kennedy et al., 2010), the Vegetation Change Tracker – VCT (Huang et al., 2010), Breaks For Additive Seasonal and Trend – BFAST (Verbesselt et al., 2010), Continuous Monitoring of Forest Disturbance Algorithm – CMFDA (Zhu et al., 2012) and Continuous Change Detection and Classification – CCDC (Zhu and Woodcock, 2014). Many of these approaches were implemented and tested in boreal and temperate forest ecosystems (e.g. Griffiths et al., 2011, Schroeder et al., 2011). In such ecosystems the vegetation signal is high and yearly variations are small compared to dryland areas. Moreover, vegetation communities in drylands are often very complex and the spatial arrangement of the landscape very heterogeneous. These factors plus the occurrence of fires hamper the detection of subtle modifications of vegetation cover due to land degradation processes. Therefore, enhanced time series analyses tools are gaining more and more importance as they allow for monitoring not only the overall increase or decrease of greenness, but also more complex change patterns including its character, i.e. gradual and abrupt changes (De Jong et al., 2012). This represents reality better as trends are rarely uniform during a long observation period, e.g. due to droughts, fire events and macro weather situations.

The techniques that are used to explore the coarse scale data archives are very similar to the ones used to examine Landsat time series. Additionally, due to the dense temporal resolution, the phenology of vegetation and its changes can be portrayed by deriving phenological metrics using specialised software like for instance Timesat (Jönsson and Eklundh, 2002) and Timestats (Udelhoven, 2011).

3 Assessing land condition

Land degradation may be defined as a long-term loss of an ecosystem’s capacity to provide goods and services. Therefore, a major component of a comprehensive dryland observation is the assessment of land condition which can be linked to ecosystem status. Even though land degradation is recognized as a severe threat, only few global land degradation assessments have been carried out until today (Millenium Ecosystem Assessment, 2005a; Vogt et al., 2011).

The first global assessment of land quality was provided in the framework of the GLASOD project (Global Assessment of Human-Induced Soil Degradation, 1987-1990) where human-induced soil degradation (extent, type and grade) was mapped at a scale of 1:10 million based on expert judgement (Oldeman, et al., 1990). Another global assessment was provided by Dregne and Chou (1992) who also integrated information on vegetation status based on secondary sources. Whereas the map provided by GLASOD indicated that 20% of soils in drylands were degraded, Dregne and Chou estimated that 70% of dryland areas were affected either by degradation of soil or vegetation. A more recent study (Lepers, 2003) prepared for the Millenium Ecosystem Assessment covered over 60% of all dryland areas. Several data sources, including remote sensing data, were integrated in the analyses and indicated that 10% of the observed area was affected by land degradation. One of the major points of criticisms related to the subjectivity of the studies which impede operational use or comparability (Millenium Ecosystem Assessment, 2005a). In recent years, different concepts were developed and implemented to assess land condition which will be described in the following part. A selection of studies and the techniques used is summarized in table 3.

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3.1 Assessment of land condition related to the biological productivity of ecosystems

In recent years, the assessment of land condition has been primarily related to the biological productivity of ecosystems. The concept is based on the fact that land degradation, which might be caused by a wide variety of climate- and human-induced processes, results in a decline of the potential of the soil to sustain plant productivity (Del Barrio et al., 2010). Using the example of rangelands, figure 2 clearly illustrates the dependence of biological productivity on grazing pressure, rainfall and soil properties. In this respect, soil properties like water holding capacity and nutrient supply are essential factors that directly affect primary productivity. Ongoing overgrazing drives feed-back loops between vegetation and soil, resulting in a degradation of these soil properties and triggers a sustained decrease of the soil's capacity to sustain primary productivity. As a consequence, the ecosystem's capacity to utilize local resources (such as soil nutrients and water availability) in relation to its potential capacity may be defined as land condition. This in turn allows drawing conclusions on the degradation status of observed areas (Boer and Puigdefabregas, 2005). Hence, biological productivity is considered a suitable surrogate to assess land condition and surrogates derived from remote sensing are predestined to support this assessment.

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At local scale Boer and Puigdefabrégas (2005) conceptualized and implemented a spatial modelling framework to assess land condition based on climate data as well as on NDVI data derived from the Landsat sensor, which served as a proxy for primary productivity. The approach is based on the assumption that in arid and semi-arid areas water availability is the major limiting factor of productivity and furthermore, that the water balance, which depends on rainfall, soil properties (evaporation), vegetation (interception and transpiration) and discharge, reflects land condition. Based on this theoretical concept they proposed a long-term ratio of mean actual evapotranspiration and precipitation to assess land condition.

Prince (2004) and Prince et al. (2009) introduced the Local Net Primary Productivity Scaling (LNS) method where the actual NPP is compared to the potential NPP of the corresponding Land Capability Class (LCC). The LCCs are homogenous areas that are determined by climate, soils, land cover and land use, and are independent of actual NPP. The magnitude of the difference provides a measure of land degradation and at the same time the loss of carbon sequestration. The actual NPP is derived for each pixel from multi-temporal earth observation data. The potential NPP, i.e. the NPP that could be expected without human land use, equals the maximum NPP found in the corresponding LCC and enables to implement this approach for large physical heterogeneous areas. The implementation of this method for Zimbabwe (Prince et al., 2009, see figure 3) showed that only 16% of the land cover reached the level of the potential NPP whereas over 80% were found to have an actual NPP far below the potential one suggesting a loss of carbon sequestration of 7.6 Mio. tons C yr^{-1}. Similar methodologies were developed by Bastin et al, (2012) and Reeves and Baggett (2014) to identify rangeland conditions in Queensland, Australia and the southern and northern Great Plains, USA, respectively.

3.2 Assessment of land condition including climate and its variability

Wessels et al. (2007) used a residual trend analysis (RESTREND) to identify potentially degraded areas by decoupling the NDVI signal from rainfall variability based on NOAA AVHRR data. This methodology identifies areas were a reduction in productivity per unit rainfall has occurred by comparing modelled accumulated NDVI values based on rainfall data to the observed NDVI. While the method proved capable of identifying potentially degraded areas in South Africa, Wessels et al. (2007) stressed that the cause of the negative trend cannot be explained solely by this approach, but needs detailed investigation. Li et al. (2012) transferred the RESTREND methodology to a rangeland area in Inner Mongolia, China. Their results showed that until the year 2000 heavy overgrazing deteriorated rangelands in this area, but grasslands recovered afterwards due to the implementation of new land use polices. The authors concluded that the methodology is useful to identify human-induced changes in drylands, but also underlined that the results need careful interpretation.

Other developed approaches make use of the concept of Rain Use Efficiency (RUE), which was introduced by Le Houérou (1984). RUE is defined as the ratio of NPP to precipitation over a given time period and may be interpreted as being “proportional to the fraction of precipitation released to the atmosphere” (Del Barrio et al., 2010). Several studies explored RUE in dryland areas based on remote sensing (e.g. Prince et al., 1998; Bai et al., 2008) causing debates between scientists due to supposed weaknesses in the rationale (Hein and de Ridder, 2006; Prince et al., 2007; Wessels, 2009). In the framework of the LADA (Land

Degradation Assessment in Drylands) project Bai et al. (2008) proposed a methodology to assess and monitor land condition by deriving RUE based on the global NOAA AVHRR GIMMS dataset. The implemented methodology and the results were criticized (Wessels, 2009) because rainfall is not a limiting factor in more humid areas and moreover, RUE values are dependent on precipitation amounts and thus impede the direct comparison of RUE values from regions of diverging aridity level. Fensholt et al. (2013) proposed to only use NPP-proxies that are positively linearly correlated to precipitation and to only consider the rainy-season-variation of NDVI for those areas where the correlation between RUE and annual precipitation is close to zero.

Del Barrio et al. (2010) presented an approach which takes the dependency of RUE on aridity into account. The approach was implemented for the Iberian Peninsula based on 1 km^2 NOAA AVHRR NDVI data and spatially interpolated climate data. Due to the strong climatic gradient across the Iberian Peninsula, the derived RUE values were in a first step de-trended for aridity to ensure the comparability of the derived data between different climatic zones. In a next step, statistically derived boundaries of minimum and maximum RUE were employed to calculate relative RUE values. Based on the assumption that healthy and undisturbed vegetation is characterized by a maximum RUE value the relative RUE can be treated as a measure for land condition. Results of this study indicated that land condition of the Iberian Peninsula was better than expected with localised areas of ongoing land degradation caused by current or recent intensive land use (Del Barrio et al., 2010; see figure 4). This study also focussed on the monitoring of changes in primary productivity and considered effects of climatic variations. The results suggest that areas already in good conditions further improved whereas degraded areas remained static. One disadvantage of this approach is the statistical determination of land condition lacking absolute references of vegetation performance comparable to the LNS method.

4 Monitoring of land use/land cover changes to assess land degradation processes

Land cover is defined by the attributes of the land surface including all aspects such as flora, soil, rock, water and anthropogenic surfaces whereas land use has been defined as the purpose for which humans employ land cover (Lambin et al., 2006). Changes in land use are often accompanied by alterations in land cover that always imply changes in ecosystem functions, such as for instance primary productivity, soil quality, water balance and climatic regulation (e.g. Foley et al., 2005; Turner II et al., 2007). The monitoring of landscape dynamics forms therefore an essential component for dryland observation as it provides information about the nature and extent of the changes and allows for the evaluation of the consequences for ecosystem functions.

Land cover changes can be distinguished in two major groups: (i) conversion and (ii) modification (Lambin et al., 2006). Land use conversion commonly involves the replacement of one land use/land cover class by another (e.g. shrublands with arable land) whereas modification is usually related to gradual changes within one thematic class (e.g. shrub encroachment within natural ecosystems). The assessment of both conversion and modification is important to provide a comprehensive picture of land use/land cover changes. The assessment of land use/land cover conversion is often based on land use change detection performed at defined years of interest. Several strategies and methods were developed to optimise the results of change detection analyses. A detailed overview of change detection techniques and their application, potentials and limits is for instance given in Hecheltjen et al. (2014).

The assessment of modifications is a crucial element in dryland areas, because land cover changes related to land degradation are often associated with a modification of the landscape (Lambin, et al. 2006; Lambin and Geist, 2001). These include for instance vegetation cover loss due to overgrazing or primary or secondary succession on abandoned fields and rangelands. The detection and monitoring of a modification is often more challenging as changes of biophysical properties have to be observed and distinguished from inter-annual variability. This is especially important for dryland areas where primary productivity is dependent on the highly variable climatic conditions in terms of rainfall (Turner II et al., 2007). Time series analysis of remote sensing archives is a suitable methodology to assess gradual changes of land cover (Udelhoven, 2010), providing means to delineate inter-annual variability from long-term trends. This requires consistent long-term data of biophysical parameters connected to surface properties, such as those provided by the broad remote sensing data sources described in the previous chapter.

The high geometric detail of Landsat data often matches the scale of land management decisions (Cohen and Goward, 2004; Lambin et al., 2006), whereas coarse scale NOAA AVHRR data are more suitable to cover large areas providing a much higher temporal repetition rate. These data archives therefore permit the detection of changing parameters connected to vegetation cover as well as the deduction of changes in phenology (e.g. Andres et al., 1994; Brunsell and Gillies, 2003, Stellmes et al., 2013). Numerous studies exists that assess landscape dynamics in dryland areas based on these data sources, giving useful insights on process-patterns from local to regional and global scales (see table 4).

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4.1 Local scale studies to detect land degradation related modifications

At a local scale, many studies focused on monitoring both long-term and abrupt modifications using Landsat time series. In this context, the impact of grazing pressure on vegetation cover has been analysed in different parts of the world, e.g. in Bolivia (Washington-Allen et al., 2008), Greece (Hostert et al., 2003; Röder et al., 2008a; Sonnenschein et al., 2011) and Nepal

(Paudel and Andersen, 2010). These studies used either vegetation indices like the NDVI or enhanced parameters such as proportional vegetation cover derived from Spectral Mixture Analysis. Degradation processes were identified in all study areas and often additional information layers were used to explain these findings. Washington-Allen et al. (2008) assessed the effect of an El Niño-Southern Oscillation (ENSO) induced drought on a rangeland system in Bolivia employing Landsat time series. This study showed that the decrease in vegetation cover of the rangelands resulted in an increased risk of soil erosion. In northern Greece (Röder et al., 2008a) patterns of over- and undergrazing were identified following changed rangeland management practices from transhumance to sedentary pastoralism (see figure 5). Similar patterns were observed on the island of Crete, Greece (Hostert et al., 2003). Another important dimension in land degradation science is the understanding of impacts of land use/land cover changes on ecosystems. Hill et al. (2014) used the ecosystem services concept (Millenium Ecosystem Assessment 2005a) to estimate changes in ecosystems services introduced by land use/land cover changes detected using a Landsat TM/ETM+ time series in Inner Mongolia, China between 1987 and 2007.

Other studies were focusing on abrupt changes caused by fires, including studies on mapping fire patterns (Diaz-Delgado and Pons, 2001; Bastarrika et al., 2011) or post-fire recovery (e.g Viedma et al., 1997; Röder et al., 2008b). Yet, assessments of the relationship of gradual and abrupt vegetation changes in the Mediterranean are largely missing (Sonnenschein, 2011).

While many studies focused on local areas, i.e. covering one Landsat scene, operational systems for the monitoring of rangeland areas have been set up in Australia during the last decades (Wallace et al., 2006; 2004). Several regional projects use parameters derived from Landsat time series to monitor land cover changes and land condition, which are integrated in the Australian Collaborative Rangeland Information System (ACRIS) on a nationwide level. Furthermore, the software tool VegMachine was developed where satellite imagery and expert knowledge are combined to assess the health status of grazing grounds and to support pastoral producers as well as management decisions (CSIRO, 2009).

4.2 Regional to global scale studies to detect land degradation related modifications

Most studies covering large dryland areas (including continental and global studies) are based on NOAA AVHRR archives or similar sensor systems. Many of these studies focussed on ordinary least-square regression or non-parametric trend tests such as the Mann-Kendall-test on NDVI values, which were often seasonally aggregated and served as a proxy for NPP (e.g. Eklundh and Olsson, 2003; Anyamba and Tucker, 2005) or other parameters related to greenness (e.g. Lambin and Ehrlich, 1997; Cook and Pau, 2013). Only in recent years, changes in phenological metrics were analysed to monitor dryland areas (e.g. Heumann et al., 2007; Stellmes et al., 2013, Hilker et al., 2014) and change detection techniques were applied to also describe non-linear trends (e.g. Jamali et al., 2014).

A major concern of monitoring dryland areas is the distinction between land cover changes driven by climatic fluctuations and those caused by human intervention. Various techniques were employed for assessing the effect of climatic variabilty such as the before-mentioned RUE (Geerken and Ilaiwi, 2004; Fensholt et al., 2013) and RESTREND methodology (Wessels et al., 2007), but furthermore linear regression analysis (Helldén and Tottrup, 2008), distributed lag models (Udelhoven et al., 2009), multiple stepwise regression (Zeng et al., 2013) and dynamic factor analysis (Campo-Bescós et al., 2013). of teleconnections of macro weather situations (Williams and Hanan 2011) and global sea surface temperature (Huber and Fensholt, 2011).

Many of the large-scale studies focused on Africa, especially on Sub-Saharan Africa including the Sahel region. Droughts in the first decades of the 20th century as well as in the 1960s to 1980s caused disastrous famines in the Sahel zone and had a strong impact on vegetation cover. Yet, resilience in these systems often led to recovery under more profitable climatic conditions, while the term desertification involves a permanent and irreversible reduction in vegetation productivity. In the 1990s remote sensing studies started to support the analysis based on time series analyses. Recent studies dealing with greening trends in the Sahel found vegetation recovery in most parts of the Sahel (e.g. Eklundh and Olsson, 2003; Herman et al., 2005). Heumann et al. (2007) showed that both annual and perennial vegetation recovery processes drive the observed greening and Dardel et al. (2014) demonstrated that soil type and soil depth are important factors for recovery. Jamali et al. (2014) implemented an automated approach to account for non-linear changes. Results showed a dominance of positive linear trends distributed in an east-west band across the Sahel whereas regions of non-linear change occur only in limited areas, mostly on the peripheries of larger regions of linear change (see figure 6). These studies all implied that vegetation recovered after the severe droughts in the 1970s and 1980s and that land degradation not related to water availability/droughts is not a widespread phenomenon but is confined to smaller areas (Fensholt et al., 2013).

Also in other parts of the world a large proportion of dryland areas showed “greening-up” trends (e.g. Helldén and Tottrup, 2008; Hill et al., 2008; De Jong et al., 2012; Fensholt et al., 2012; Stellmes et al., 2013). The global study of Cook and Pau (2013) focussed on rangeland productivity between 1982 and 2008 and indicated that almost 25% of the rangelands were affected by significant trends. These trends were found to be mostly with increasing productivity whereas decreasing productivity related to land degradation was found in rather isolated spots, mainly in China, Mongolia and Australia. Whereas in many other regions rainfall was the dominant factor influencing NDVI, in Mongolia 80% of the decline in greenness could be attributed to an increase in livestock (Hilker et al., 2014).

Generally, a comprehensive analysis of land degradation needs to include, also at regional to global scale, the fire regime and possible inter-linkages to land use and land cover, e.g. by analysing recovery after fire events (Katagis et al., 2014). The two MODIS fire products, Active Fire and Burned Area, allow monitoring of important variables of fire regimes (Justice et al., 2006; Loboda et al., 2012), such as fire frequency, fire seasonality and fire intensity and allow for identifying drivers (Archibald et al., 2009) and model potential changes (Batllori et al., 2013).

5 Integrated concepts to assess land degradation

The previous sections have illustrated that time series analysis allows to discriminate human-induced land cover changes and changes caused by inter-annual climatic variability. Beyond this, a crucial element of land degradation assessment is the identification of underlying and proximate causes of human-induced changes (e.g. Reynolds et al., 2007). Only in this manner the coupled human-natural character of land cover changes can be understood and an identification of the mechanisms that drive land degradation is possible. This knowledge provides the foundation to support the development of sustainable land management strategies.

A comprehensive framework designed to capture the complexity of land degradation and desertification was provided by Reynolds et al. (2007). They introduced the term "Drylands Development Paradigm" (DDP), which "*represents a convergence of insights and key advances drawn from a diverse array of research on desertification, vulnerability, poverty alleviation, and community development*" (Reynolds et al., 2007). The DDP aims at identifying and synthesizing those dynamics central to research, management, and policy communities (Reynolds et al., 2007). The essence of this paradigm, which consists of five principles, builds on the assumption that desertification cannot be measured by solitary variables, but that it has to consider biophysical and socio-economic data at the same time

(Vogt et al., 2011) as well. A limited number of “slow” variables (e.g. soil fertility) are usually sufficient to explain the human-natural system dynamics. These slow variables possess thresholds and if these thresholds are exceeded the system moves to a new state. “Fast” variables, for instance climatic variability, often mask the slow variables and thus, aggravate the assessment of the slow variables, which is a prerequisite to understand the ecosystem behaviour. Moreover, it is important to consider that human-natural systems are “hierarchical, nested, and networked across multiple scales” (Reynolds et al., 2007). Accordingly, both the human component, e.g. stakeholders at different levels, and the biophysical component, e.g. slow variables at one scale can be affected by the change of slow variables operating at another scale (Reynolds et al., 2007).

Prior to the DDP, Geist and Lambin (2004) examined the main mechanisms that trigger land degradation processes and conclude that these processes, which often manifest in land use/land cover changes, are governed by proximate causes (immediate human and biophysical actions) which in are depending on underlying drivers (fundamental social and biophysical processes). Figure 7 illustrates the dependencies of land use/land cover changes from proximate causes and underlying drivers. Furthermore, alterations of ecosystem services caused by land use/land cover changes can again alter underlying drivers, proximate causes and even external constraints, hence, resulting in a feedback loop. Policy plays an important role in avoiding positive feedback mechanisms which can accelerate unsustainable land use (Reid et al., 2006).

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5.1 Integrated studies at local scale

Several local studies linked the biophysical dimension of land use/land cover changes to the human dimension in various dryland areas such as Spain (Alvarez-Martinez et al., 2014;

Améztegui et al., 2010; Serra et al. 2008), Greece (Lorent et al., 2008), Kenya (Were et al., 2014), China (Li et al., 2012), Mongolia (Hilker et al., 2014), and Uzbekistan (Dubovyk et al., 2013). Regression-based models are the most widely used approach to identify the major drivers of change (Were et al., 2014) and mostly rely on land cover changes derived from land use/land cover classifications at several time steps. However, time series of remotely sensed data were only rarely used (Lorent et al., 2008; Dubovyk et al., 2013). The drivers of land use/land cover change depend very much on the contextual framework of the study area including physical and socio-economic characteristics. Therefore, it is essential to first set up a hypothesis that identifies major underlying drivers of land use/land cover change. For instance, in Spain and Greece the Common Agricultural Policy (CAP) subsidies of the European Union (EU) were identified as one of the important drivers. These largely influenced agricultural developments like intensification and land abandonment, where abandonment of marginal areas involved forest expansion and bush encroachment. (Améztegui et al., 2010; Lorent et al., 2008; Serra et al., 2008). In the grasslands of Inner Mongolia/China many factors explained observed grassland degradation between 1990 and 2000 and the reduced degradation rate between 2000 and 2005, which were altitude, slope, annual rainfall, distance to highway, soil organic matter, sheep unit density, and fencing policy. Fencing policy was negatively correlated suggesting that fencing of sensitive areas can reduce land degradation. The analysis of cropland degradation in the Khorezm region, Usbekiztan, based on MODIS time series (Dubovyk et al., 2013) revealed that one third of the area was characterized by a decline of greenness between 2000 and 2010. Ground-water table, land use intensity, low soil quality, slope and salinity of the ground water were identified as the main drivers of degradation. These examples show that the combination of remote sensing supported land use/land cover change and underlying and proximate causes may reveal the most important drivers of land degradation. However, this analysis is often hampered by the fact that for each study area (i) all potential and relevant drivers have to be identified and (ii) spatially explicit information of each driver or a proxy has to be available with a sufficient spatial resolution.

5.2 Integrated studies at regional to global scale

Another approach capable to support land degradation assessment is the syndrome approach which has been developed in the context of global change research (Cassel-Gintz and Petschel-Held, 2000; Petschel-Held et al., 1999). It aims at a place-based, integrated assessment by describing global change by archetypical, dynamic, co-evolutionary patterns of human-nature interactions instead of regional or sectoral analyses. In this framework, syndromes (as a "combination of symptoms") describe bundles of interactive processes ("symptoms") which appear repeatedly and in many places in typical combinations and patterns. Sixteen global change syndromes were suggested and distinguished into utilisation, development and sink syndromes. Downing and Lüdeke (2002) applied the approach to land degradation. Based on the set of global change syndromes they identified the syndromes that are of relevance in dryland areas and linked vulnerability concepts to degradation processes. The syndrome concept is considered a suitable interpretation framework that allows for an integrated assessment of land degradation (Sommer et al., 2011; Verstraete et al., 2011). This concept was transferred to earth observation based studies and implemented for Spain based on NOAA AVHRR data between 1989 and 2004 (Hill et al., 2008; Stellmes et al., 2013) thus enabling to monitor changes in land cover after the accession of Spain to the European Union (see figure 8). In these studies, the focus was not on the identification of land cover changes, but also on the link of these findings to underlying causes enabling the designation of syndromes of land use change. The main findings of the two studies comprise three major land cover change processes caused by human interaction: shrub and woody vegetation encroachment in the wake of land abandonment of marginal areas, intensification of nonirrigated and irrigated, intensively used fertile regions, and urbanization trends along the coastline caused by migration and the increase of mass tourism.

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At a global scale LADA has recently implemented a Global Land Degradation Information system (GLADIS), which provides information on land degradation with a spatial resolution of 8 km x 8 km. The interpretation of ecosystem changes in GLADIS includes RUE, NPP and climatic variables and is based on an integrated land use system map. This map entails information about the main proximate causes of LUCCs such as livestock pressure and irrigation. The major constraints of this approach concerns the derivation of the RUE and the NPP from the GIMMS NOAA AVHRR dataset (compare section 3) (Wessels, 2009) and the coarse spatial resolution that hampers the detection of land cover changes (Vogt et al., 2011). Nevertheless, Vogt et al. (2011) emphasized that this assessment is a first step towards an integrated assessment.

Another spatially explicit assessment concept that was not specifically designed in the context of land degradation, but was adapted and implemented, is the Human Appropriation of Net Primary Production (HANPP, Erb et al., 2009; Haberl et al., 2007). HANPP represents the aggregated impact of land use on biomass available each year in ecosystems as a measure of the human domination of the biosphere. Global maps of the parameter were prepared based on vegetation modelling, agricultural and forestry statistics and geographical information systems data on land use, land cover, and soil degradation (Erb et al., 2009; Haberl et al., 2007). In a global study Zika and Erb (2009) estimated the annual loss of NPP due to land degradation at 4% to 10% of the potential NPP of drylands, ranging up to 55% in some degraded agricultural areas.

6 Uncertainties and limits

Manifold methods were developed for assessing and monitoring land degradation ranging from detailed local to broad global studies. Nevertheless, until today no comprehensive picture of the state of drylands is available. This results from different aspects some of which shall be discussed here.

6.1 Uncertainties regarding the definition of land degradation and its derivation

Monitoring of drylands is often based on analysing indicators related to the productivity of vegetation. Thereby, the loss of productivity is considered to be linked to degradation processes. However, it should be stressed that the decrease of primary productivity does not necessarily imply land degradation processes. This was for instanced illustrated by an example in Syria where unsustainable irrigation agriculture was transformed to near-natural rangelands in Syria (Udelhoven and Hill, 2009). In turn, a positive trend of productivity is not always an indicator for improving land condition, a greening-up of, for instance, rangelands, does not necessarily imply an improvement of pastures (Miehe et al., 2010). In marginal areas of the European Mediterranean, greening-up has been shown to be caused by bush encroachment due to land abandonment and the consequences for ecosystems are heavily discussed (Stellmes et al., 2013). Thus, on the one hand soils can be stabilized and soil erosion can be reduced (Thomas and Middleton, 1994), more carbon can be sequestered (Padilla et al., 2010), but on the other hand run-off and groundwater recharge is reduced (Beguería et al., 2003), biodiversity is altered (Forman and Collinge, 1996) and the fire regime changes (Duguy et al., 2007). Thus, including additional information sources, for instance on land use, is required to allow a meaningful interpretation of time series results (Vogt et al., 2011). The same is also true in case of fires which strongly affect the time series signal, e.g. induce short-term decreases in productivity and subsequent increase in productivity due to vegetation recovery.

6.2 Uncertainties regarding remote sensing data

6.2.1 Remote sensing archives and their analysis

Uncertainties in remote sensing observations pose a set of methodological and practical challenges for both the analysis of long-term trends and the comparison between different data archives. Creating consistent remote sensing time series is challenging and the prerequisite for a meaningful trend analysis. Using combined data from different sensors affording high temporal resolution such as AVHRR, MODIS and SPOT-VGT in principle allow for the construction of time-series in surface reflectance and related changes back to the early 1980s. However, this is hampered by several sources of uncertainties in the comparability between different sensor products (Yin et al., 2012). Comparison of the absolute NDVI values from different archives as well as the derived trends showed strong differences; where a good correspondence of derived NDVI trends was found at the global scale, while spatial trends at the local to regional scale often showed remarkable discrepancies (Beck et al., 2011; Fensholt and Proud, 2012; Hall et al., 2006; Yin et al. 2012). Beck et al. (2011) found, amongst others, good agreements between GIMMS, PAL, FASIR, Land Long Term Data Record version 3 (LTDR v3), see table 2, in Australia and tundra regions, moderate consistency for North America and China but inconsistent trends for Europe and Africa including the Sahel zone. A comparison with Landsat NDVI showed that MODIS data performs better than any of the NOAA AVHRR archives. Also the trends of NDVI between GIMMS and SPOT-Vegetation considerably disagreed for different land use systems across Northern China (Yin et al., 2012) indicating that trends have to be interpreted with caution and bearing in mind the limitations of the datasets. LTDR v3 showed apparent trends within the Sahara (Beck et al., 2011), which hints on calibration problems. A new and enhanced version of the GIMMS data set was published in June 2014 (http://ltdr.nascom.nasa.gov/cgi-bin/ltdr/ltdrPage.cgi), but still regional inconsistencies with MODIS data appear (figure 9).

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As an example, figure 9 shows trends derived from NOAA NDVI3g and MODIS MOD13Q1 NDVI data covering the same observation period (2001-2011) of the eastern Sahel. Even though the general picture is quite similar for the mean annual NDVI trends, a more detailed analysis reveals a considerable disagreement between both datasets that also addresses the temporal trends for a phenological parameter (i.e. the amplitudes of the annual NDVI cycle). Possible explanations for these incoherencies include different data pre-processing schemes for different sensors. The effects of sensor degradation on the captured signal are different and AVHRR data need to be additionally corrected for orbital drift effects that introduce systematic changes in the bidirectional characteristics of surfaces. Another factor are different spectral mixture effects in heterogeneous regions effects that arise from the different spatial resolutions of the GIMMS and MODIS data products.

The comparability of many studies is additionally hampered by the fact that the used methods and techniques, vegetation proxies and thresholds to exploit the time series are very diverse, since the implemented methods are often adapted to specific objectives and certain study areas. This is often necessary as drylands are very diverse concerning the degradation processes and the environmental settings including climate, soil, geology, fauna and flora.

6.2.2 Observation period

As outlined before, rainfall variability is a key driver of variability of vegetation productivity within drylands. In consequence the observation period will substantially influence the derived trends depending on the assembly of drier and wetter periods. Figure 10 illustrates the difference of trends for different observation periods derived from the NOAA NDVI3g archive.

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This underlines that drylands monitoring should always consider rainfall variability, e.g. implemented in the RESTREND method (Wessels et al., 2007). Hereby, similar to remote sensing archives, the homogeneity and reliability of the precipitation time series is of utmost importance. Even though some authors generated interpolated precipitation fields for their studies themselves (Wessels, 2007; Del Barrio, 2010) diverse global and regional gridded precipitation data are available, e.g. Global Precipitation Climatology Centre (GPCC) (Meyer-Christoffer et al., 2011) and ARC2 (Novella and Thiaw, 2013). The choice of an appropriate dataset should be based on plausibility checks (e.g. Anyamba et al. 2014). Tozer et al. (2012) demonstrated for three monthly gridded Australian rainfall datasets that interpolated data are rather restricted as a useful proxy for observed point data, although these grids are "based" on observed data. Gridded datasets often significantly vary from gauged rainfall datasets, and they do not capture gauged extreme events. Apart from observation errors these uncertainties are mainly introduced by the spatial interpolation algorithms, which always introduce some artificiality. Furthermore, it is difficult to verify the "ground truth" of the gridded data in areas or epochs with sparse observation gauges. Tozer et al. (2012) recommend always to acknowledge these uncertainties in using gridded rainfall data and to try to quantify and account for it in any study, if possible.

6.2.3 Spatial Scale

One drawback of regional to global studies is the coarse pixel resolution which often impedes the monitoring of small-scale land degradation processes (e.g. Stellmes et al., 2010; Fensholt et al., 2013) as illustrated in figure 11.

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Moreover, species composition cannot be identified and vegetation structure is not resolved, and often the focus is put on green vegetation cover even though dry vegetation is an important component in drylands. Some approaches try to solve some of these gaps, e.g. decomposition of time series to assess woody and herbaceous components (Lu et al., 2001) or using a clumping index to estimate woody cover from MODIS data (Hill et al., 2011). Other methods make use of alternative sensor systems such as passive microwave radar to derive Vegetation Optical Depth (VOD), which is sensitive to both photosynthetic active and non-active biomass (Andela et al., 2013) or combine the analysis of optical and radar imagery (Bucini et al., 2010).

Methods like STARFM or the improved availability of Landsat-like medium resolution data (e.g. Sentinel-II mission) will only partially solve the problem, since dryland observation requires long term archives. However, these sensors and methods will improve the situation over the long term. The same is true for operational satellite-based hyperspectral data that will allow for the development and application of enhanced indicators for dryland observation.

7 Summary and Conclusions

The definition and perception of land degradation and desertification have undergone a substantial transformation within the past decades. While in the beginning the biophysical assessment of degradation processes, which often focused on soil degradation, was the primary objective of many research initiatives, in recent years the necessity to investigate the mechanisms of human-environmental systems as a prerequisite to create a comprehensive understanding of land degradation processes has been recognized. This is considered essential to understand the impacts of land degradation on the provision of ecosystem goods and services and thus, its impact on human well-being (Millenium Ecosystem Assessment, 2005a). In recent years, great efforts were put into developing methodologies to enhance the understanding of coupled human-environmental systems and the influence of natural climatic variations.

One of the major challenges that remains is to link these observations with socio-economic data, thus connecting biophysical and socio-economic information to yield combined information of land change processes and their underlying causes. This proves especially crucial for large scale assessments of land degradation from national to global scales. This intricacy even increases if degradation is not only defined as a loss of productivity of ecosystems but as the decline of important ecosystem services as suggested by the Millennium Ecosystem Assessment (2005a). Even though this definition further increases the complexity of dryland assessment, it might be more compliant with the needs of policy makers and land management to develop and establish sustainable land use practices.

This complexity might also explain that until today no comprehensive picture of dryland condition is available, even though manifold methods were developed for assessing and monitoring land degradation ranging from detailed local to broad global studies. Moreover, dryland studies differ in implemented techniques, indicators, observation periods, thresholds and significance levels as well as the spatial and temporal resolution and the spectral characteristics of the sensor, hampering a comparison of the studies to form a picture of global dryland condition. Therefore, it is of utmost interest to promote international cooperation in order to harmonize dryland studies, such as the initiative to compile a new World Atlas of Desertification (WAD) under lead of the United Nations Environment Programme (UNEP) and the European Commission Joint Research Center (EC-JRC). In particular, it is not likely that one singular methodology will be sufficient to comprehensively analyse drylands; rather, depending on the respective physical and socio-economic framework, complementary approaches have to be applied as introduced in the preceding sections.

The land degradation and desertification topic is part of the more broadly perceived debate on global change. Thereby, climate change and its environmental and economic consequences are major environmental issues of global interest. Human activities have transformed a major part of the earth's terrestrial ecosystems to meet rapidly growing demands for food, fresh water, timber, fibre and fuel. Land use practices have not only affected global and regional climate due to the emission of relevant greenhouse gases, but also by altering energy fluxes and water balances (Foley et al., 2005). Additionally, even seemingly "unaffected" areas are also influenced and altered indirectly through pollutants and climate change (DeFries et al., 2004; Foley et al., 2005).

Whereas in the past, conservation of ecosystems was given priority to maintain ecosystem services, in the face of global change it cannot be assumed that the future behaviour of ecosystem responses to changes will be the same as in the past (Chapin III et al., 2010). Instead, the challenge of future land use management will include the assessment of trade-offs between acute human needs and the long-term capacity of ecosystems to provide goods and services (DeFries et al., 2004; Foley et al., 2005).

It is essential to consider that ecosystem responses to land use changes vary in time and space and moreover, analysis should encompass larger areas with sufficient spatial resolution to ensure that on- and off-site ecosystem responses are detected. Sustainable management of ecosystems requires information concerning the actual conditions and furthermore, alterations of ecosystems in relation to reference states. Such information allows for a thorough analysis of ecosystem functionality and enables rating trade-offs between ecosystem services which policy decisions (where necessary considering climate change scenarios) could impose by inducing land use changes (DeFries et al., 2004). The understanding of the impact of land use/land cover changes is even more urgent in the context of climate change, and the prospect land use will be further intensified to satisfy humanities' growing demand for resources (Foley et al., 2011). Especially when considering the expected rise to 10 billion people by the end of the 21st century (Lee, 2011), pressure on dryland ecosystems could further increase, making the development of integrated, multi-component dryland observation and management even more important.

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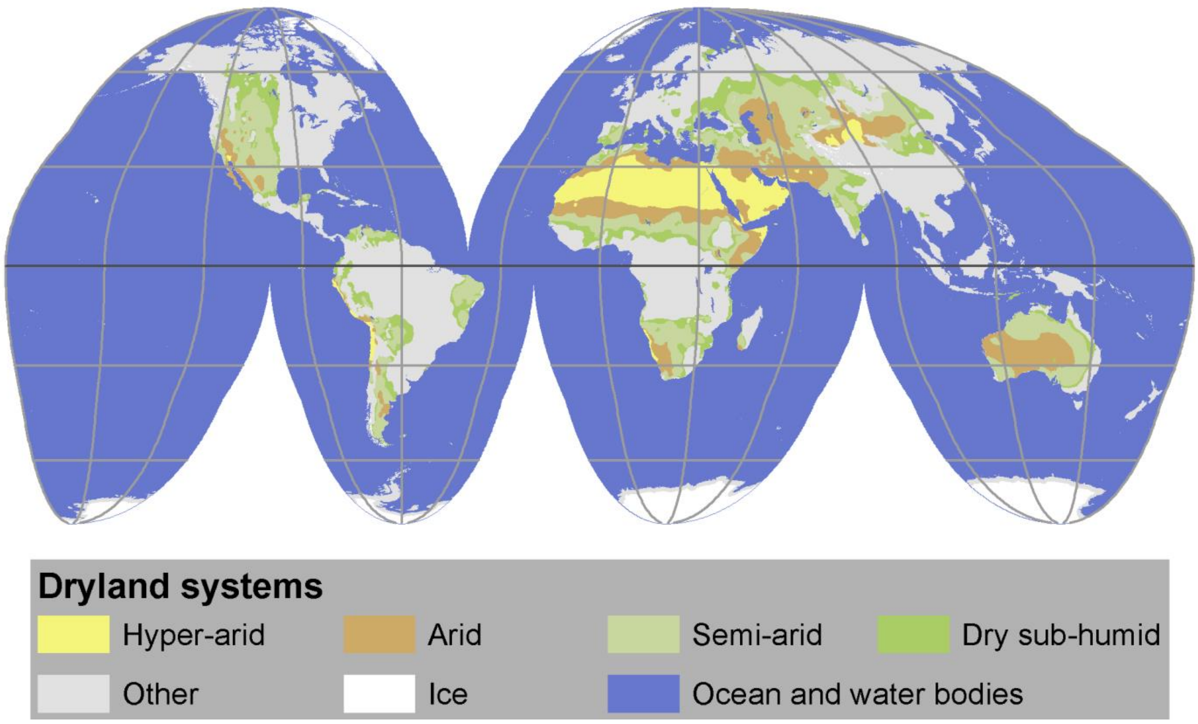

Figure 1: The spatial extent of drylands based on the aridity index (AI equals ratio of rainfall (P) and Potential Evapotranspiration (PET) for the period from 1951 to 1980). Hyper-arid: $P/PET < 0.05$; arid: $0.05 \leq P/PET < 0.20$; semi-arid: $0.20 \leq P/PET < 0.50$; dry sub-humid: $0.50 \leq P/PET < 0.65$. Projection Goode Homolosine (source: UNEP (2014): The UNEP (United Nations Environment Programme) Environmental Data Explorer, as compiled from UNEP/DEWA/GRID-Geneva: http://geodata.grid.unep.ch, ESRI Data & Maps).

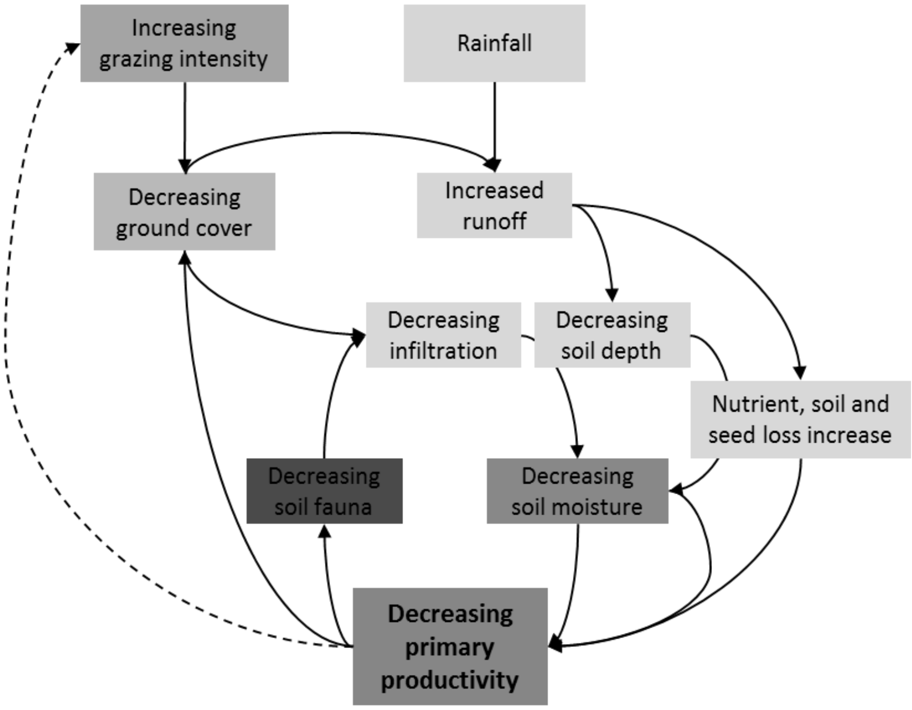

Figure 2: Aspects of landscape function using the example of grazing. Changes of ground cover, which are at shorttime scales mainly driven by rainfall variability and grazing pressure, can affect soil properties negatively. If thresholds are crossed the cycle moves towards a new state that is characterized by degraded soil properties and a long-term loss in productivity. Even though a negative feedback exists to grazing intensity, management interventions often weaken this mechanism by maintaining constant stock numbers (modified from Stafford Smith et al., 2009).

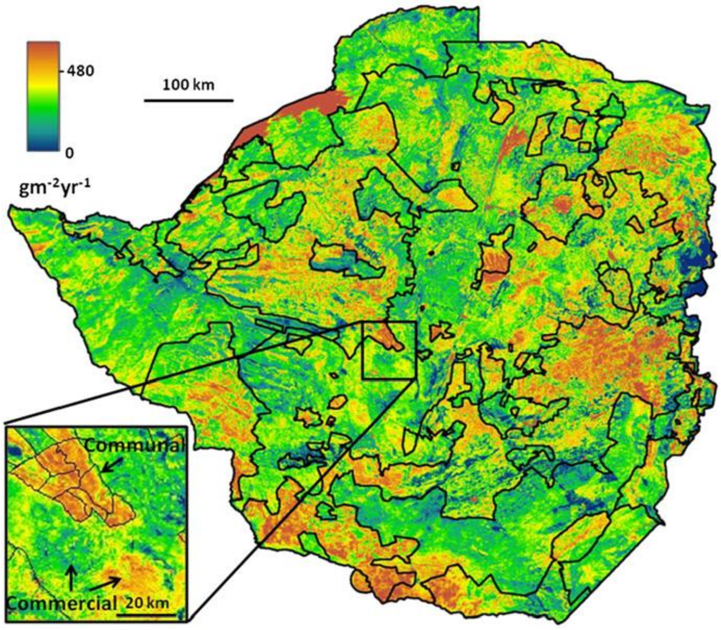

Figure 3: Local NPP Scaling (LNS) of Zimbabwe, where LNS provides the NPP lost as a result of degradation. Communal and commercial area boundaries are in black. Inset, higher resolution segment SWof Gweru showing communal area degradation (top left) and commercial area degradation (lower right). (from Prince et al., 2009).

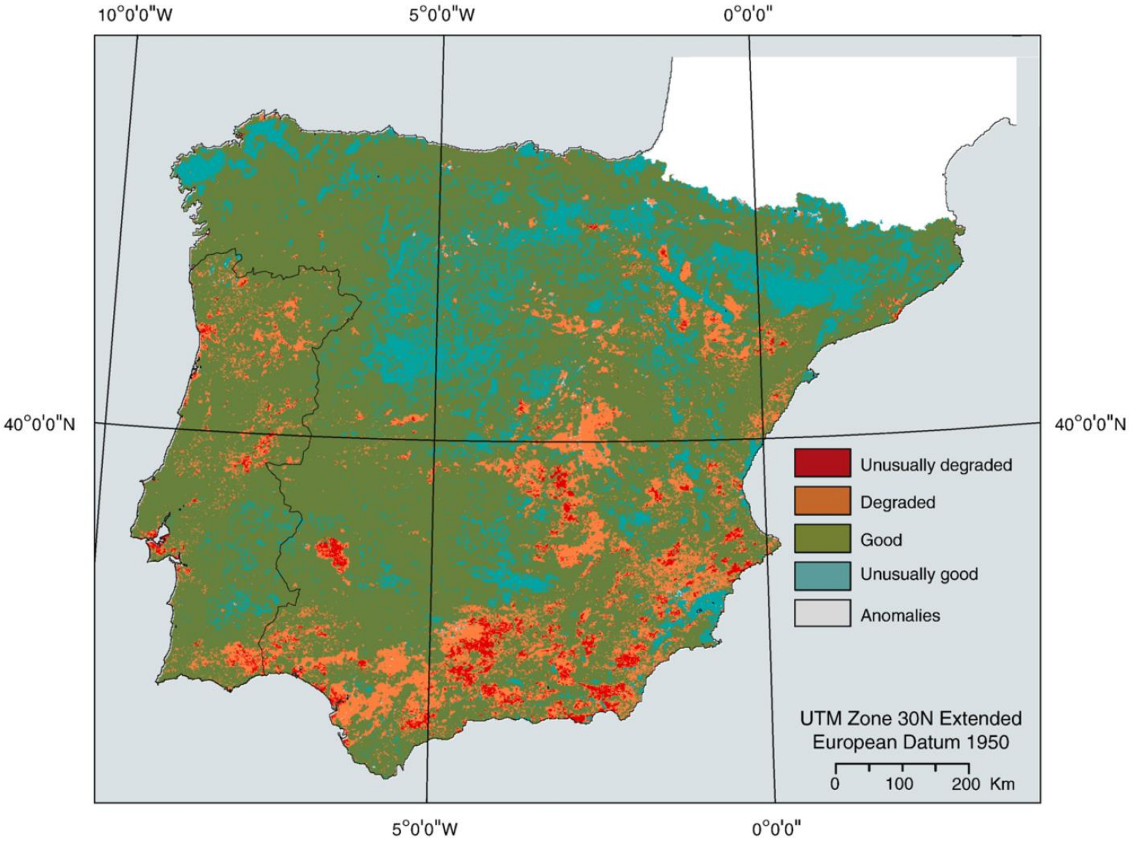

Figure 4: Assessment of land condition in the Iberian Peninsula (1989–2000) (from Del Barrio et al., 2010).

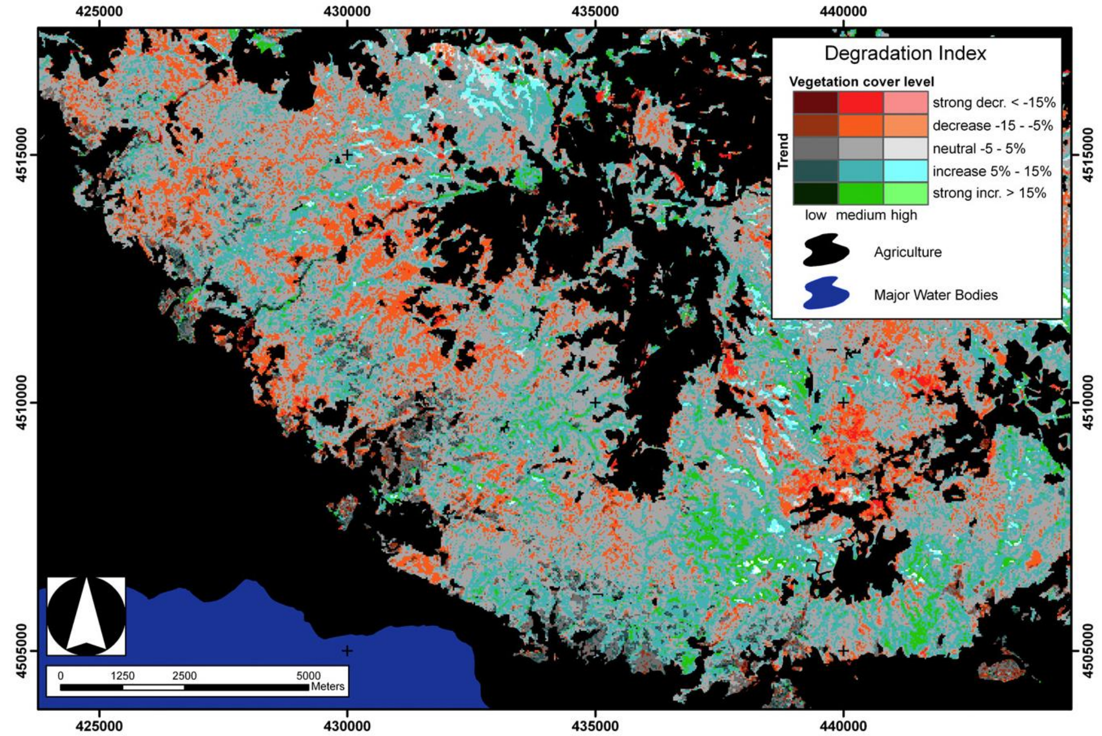

Figure 5: Degradation index map integrating the gain coefficient and average value derived from linear trend analysis of the Landsat-TM/-ETM+ time series for the rangelands of Lagadas Greece; agricultural areas were masked out (black) (from Roeder et al., 2008).

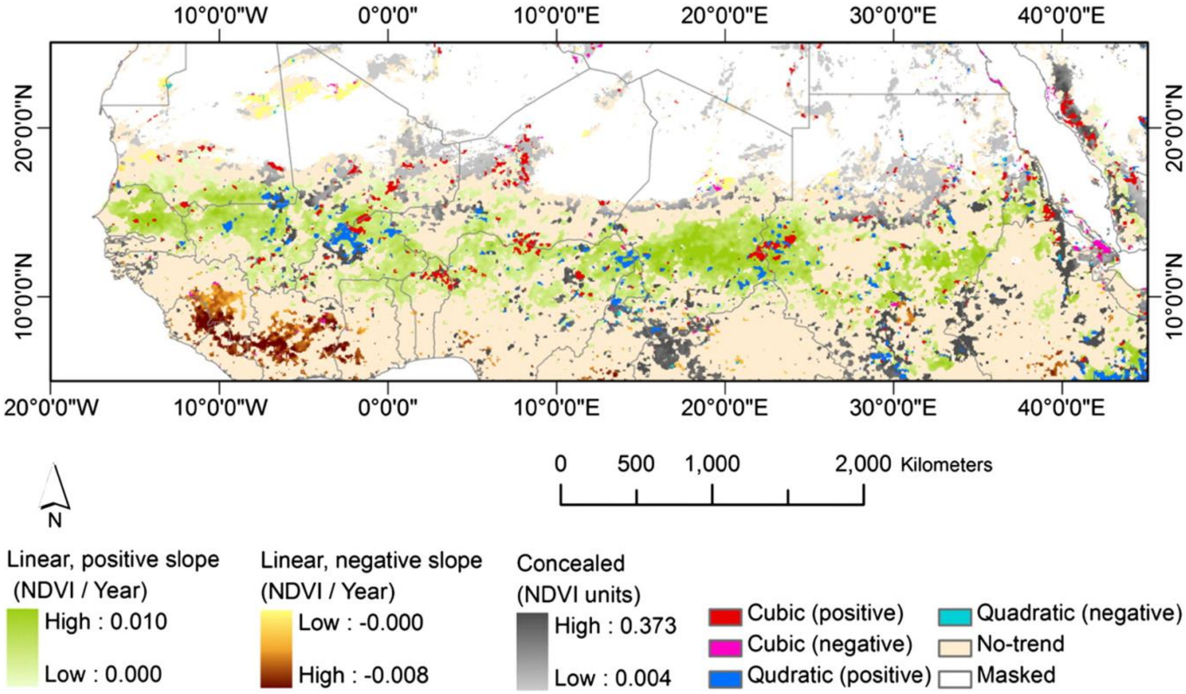

Figure 6: Results of a polynomial fitting-based approach to account also for non-linear trends (Jamali et al., 2014). Trend slope for the linear trends, range of annual variations of NDVI for the concealed trends and trend sign for the cubic and quadratic trends obtained by using the annual GIMMS–NDVI data series for the Sahel (1982–2006) in the trend classification scheme. Concealed trends are indicating that no net change in vegetation productivity has occurred, but the curve exhibits at least one minimum or maximum. Areas with a mean yearly NDVI < 0.1 were masked out (from Jamali et al., 2014).

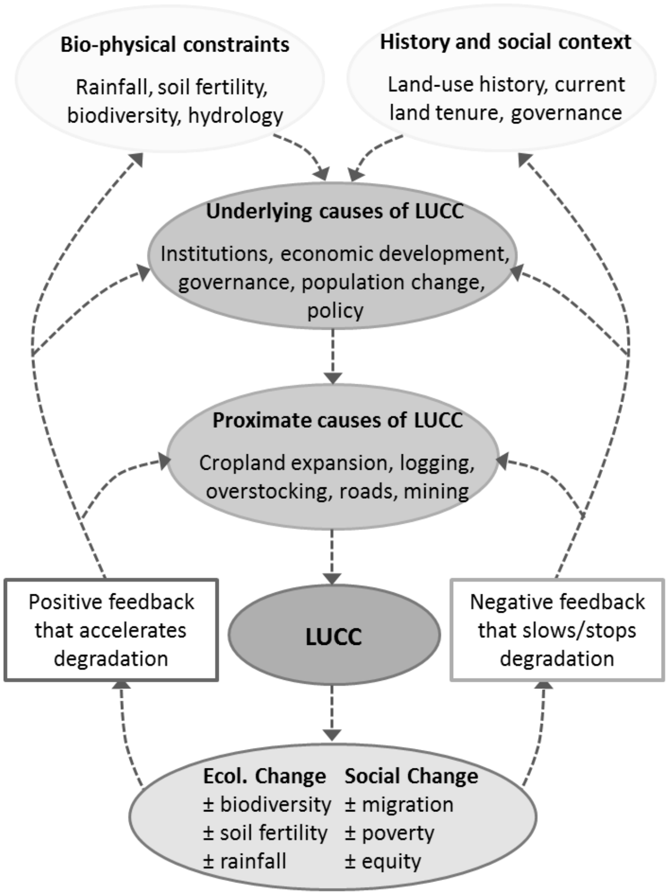

Figure 7: Conceptual model illustrating the feedback loop of Land Use/Land Cover Changes (LUCC), its consequences and the underlying and proximate causes (modified from Reid et al., 2006).

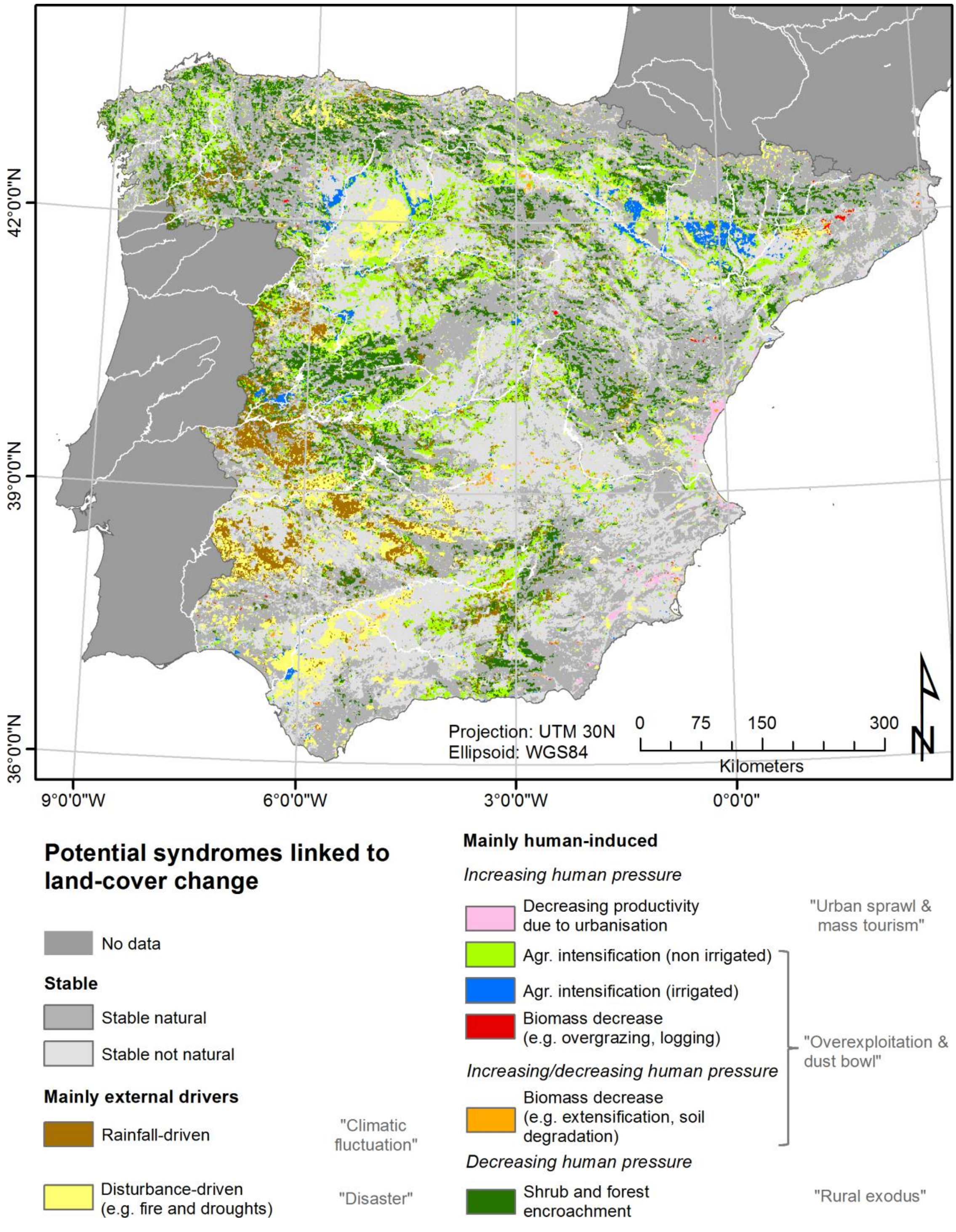

Figure 8: Syndromes and main drivers of the identified land cover changes in Spain derived from MEDOKADS NDVI data, 1989-2004 (from Stellmes et al., 2013)

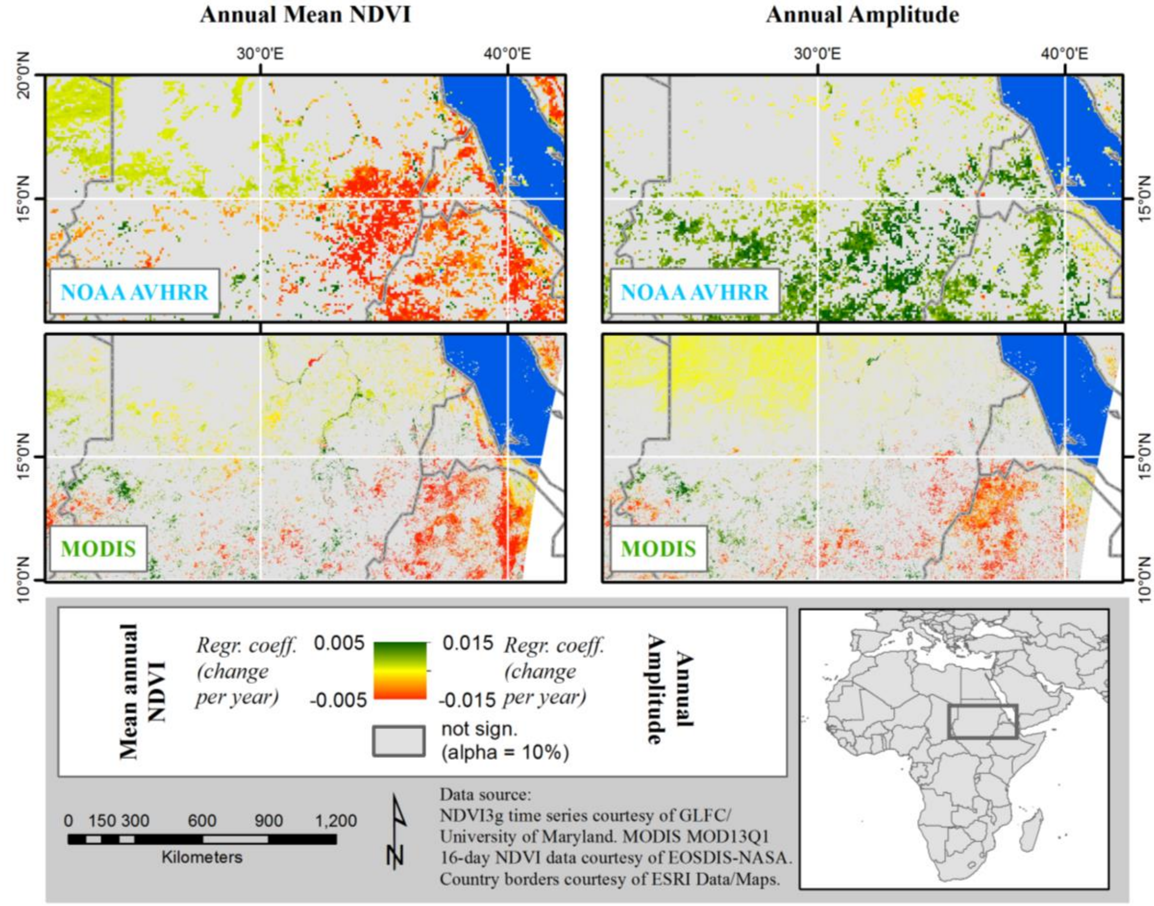

Figure 9: Trends derived from linear regression analysis for the annual total sum of NDVI based on the NOAA NDVI3g archive (upper panels) and MODIS MOD13Q1 NDVI time series (lowest panel) for the Eastern Sahel from 2001 to 2012. Time series analysis performed with Timestats (Udelhoven, 2010).

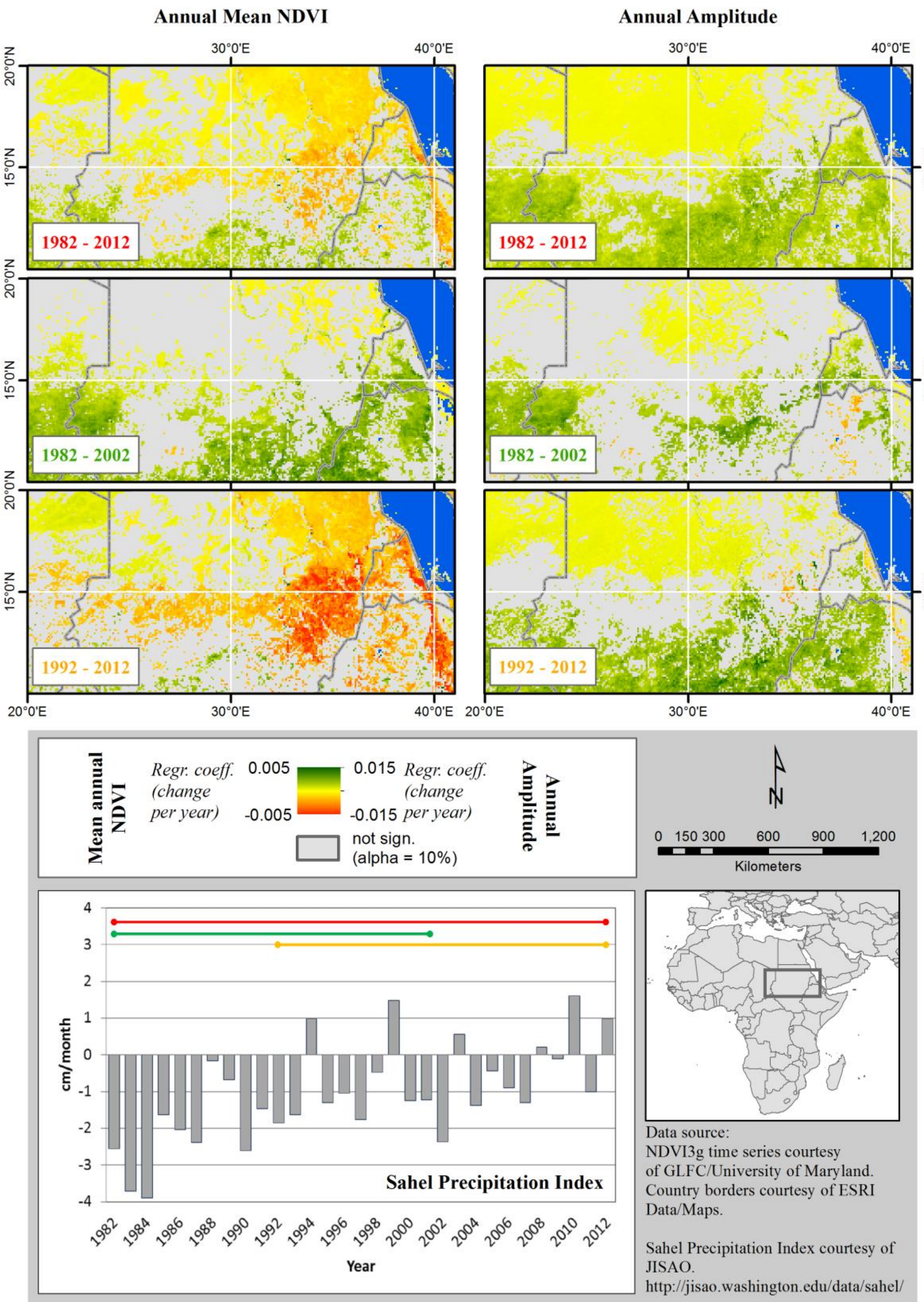

Figure 10: Change of the NDVI derived for three different observation periods based on the NOAA NDVI3g archive and Sahel Precipitation Index from 1982 to 2012 (Janowiak 1988). Time series analysis performed with Timestats (Udelhoven, 2010).

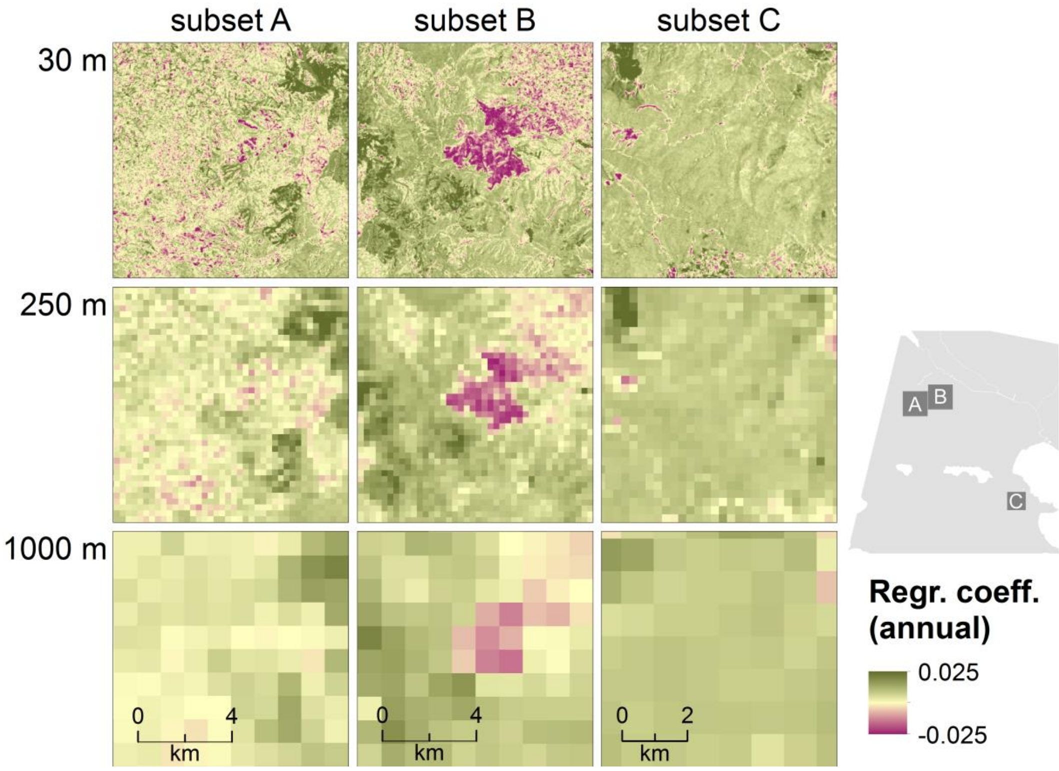

Figure 11: Effects of spatial degradation of Landsat TM/ETM+ time series (1990-2000) from a geometric resolution of 30 m x 30 m to 1000 m x 1000 m on the derived regression coefficient of a linear trend analysis. The three presented subsets represent different types and scales of land cover change (modified from Stellmes et al., 2010).

Table 1: Key dryland ecosystem services (after Millenium Ecosystem Assessment 2005a).

Supporting Services Services that maintain the conditions for life on earth		
- Soil development (conservation, formation) - Primary production - Nutrient cycling - Biodiversity		
Provisioning Services Goods produced or provided by ecosystems	**Regulating Services** Benefits obtained from regulation of ecosystem processes	**Cultural Services** Nonmaterial benefits obtained from ecosystems
- Provision derived from biological productivity: food, fibre, forage, fuelwood, and biochemicals - Fresh water	- Water purification and regulation - Pollination and seed dispersal - Climate regulation (local through vegetation cover and global through carbon sequestration)	- Recreation and tourism - Cultural identity and diversity - Cultural landscapes and heritage values - Indigenous knowledge systems - Spiritual, aesthetic and inspirational services

Table 2: Selection of important sensors and available data products suitable for dryland monitoring. Archives marked with an asterisk are/were often used in dryland studies (as of 2014):

Sensor	**Coverage**	**name**	**Source**	**Observation period**	**Spatial Resolution**	**Temporal resolution**	**Indicator**
Coarse resolution							
NOAA AVHRR	global	PAL	GES-DAAC, NOAA/NASA *James and Kalluri (1994); Smith et al. (1997)*	1981-2001	8 km	10-daily	NDVI
		FASIR (ISLSCP II)	ISLSCP II *Sietse (2010)*	1981-1998	8 km	monthly	NDVI
		GIMMS*	GLFC, University of Maryland *Tucker et al. 2005*	1981-2006	8 km	bimonthly	NDVI
		GIMMS3g*	GLFC, University of Maryland *Pinzon and Tucker 2014*	1981-2012	8 km	bimonthly	NDVI, LAI, faPar
		LTDR v4	NASA/GFSC; University of Maryland *Pedelty et al. 2007*	1981-present	0.05°	daily	NDVI
	regional	NDVI (Australia)	Bureau of Meteorology; AusCover *BOM (2014)*	1992-present	0.01°/0.05°	10-daily/monthly	NDVI
		MEDOKADS (Mediterranean)	Freie Universität Berlin *Koslowsky (1998)*	1989-2005	1 km	10-daily	NDVI
SeaWiFS	global	L3 Land- NDVI	NASA/GFSC *OceanColor WEB (http://oceancolor.gsfc.nasa.gov/)*	1997 - 2010	4 km/9 km	daily, 8-daily, monthly, annual	NDVI
		faPAR	EC-JRC *Gobron et al. (2006)*	1997 - 2006	0.01°	10-daily	faPAR
SPOT Vegetation		VGT-S10	VITO; CNES *Achard et al. (1995)*	1998 - present	1 km	10-daily	NDVI
Envisat-MERIS	global	EM-10	VITO; ESA; Belspo; EC-JRC *Gobron (2011)*	2002 - 2012	1.2 km	10-daily	NDVI; faPAR
		MGVI	ESA/JRC-EC *Gobron et al. (1999)*	2002 - 2012	1.2 km	10-daily	faPAR
MODIS Terra/Aqua	global	MOD/MYD13Q1*	NASA LP DAAC *Huete et al. (1999)*	2000 - present	250 m - 1 km	16-daily/monthly	EVI, NDVI
		MOD/MYD/MCD15A	NASA LP DAAC *Knyazikhin et al. (1999); Myneni et al. (2002)*	2000 - present	1 km	4-daily/8-daily	faPAR
		MOD/MYD17A	NASA LP DAAC *Running et al. (2000)*	2000 - present	1 km	8-daily/annual	GPP/NPP
		TIP.faPAR	EC-JRC Pinty et al. (2011)	2000 - present	1 km	16-daily	faPAR

Combined							
NOAA AHRR/MODIS	global	LTDR v3	NASA/GFSC; University of Maryland *Pedelty et al. 2007*	1991-2012	0.05°	daily	NDVI
SeaWIFS/MERIS		faPAR	EC-JRC *Ceccherini et al. (2013)*	1997-2012	1.2 km	10-daily	faPAR
Moderate resolution							
Landsat	local	Individual*	Individually; USGS *e.g. Röder et al. (2008), Sonnenschein et al. (2011)*	1982 to present	30 m	multi-seasonal to annual	Vegetation indices, SMA
		Surface Reflectance Climate Data Record (CDR)	USGS-ESPA *Masek et al. (2006)*	1982 to present	30 m	multi-seasonal to annual	Vegetation indices
	regional	Seasonal Fractional Vegetation Cover, Queensland (Australia)	JRSRP; DSITIA; AusCover *Danaher et al. (2010), Flood et al. (2013), Muir et al. (2011)*	1986 to present	30 m	multi-seasonal	Fractional vegetation cover
	global	WELD v1.5 Product	NASA LP DAAC/USGS *Roy et al. (2010)*	2002 to 2012	30 m	annual	Tree cover
SPOT	local	individual	Individually; CNES ASTRIUM (http://www.astrium-geo.com/)	1986 to present	6 m /20 m	multi-seasonal to annual	Vegetation indices

Table 3: Selection of studies evaluating land condition using remote sensing data.

Extent	Study area	RS data and Indicator	Methodology	Observation period	Result	References
Local						
	Spain	Landsat NDVI	Water balance model	1993-1994	Long-term ratio of mean actual evapotranspiration and precipitation able to assess land condition, e.g. poor land condition due to soil erosion	Boer and Puigdefabregas 2005
Regional						
	Zimbabwe	MOD13Q1 NDVI	Local NPP Scaling (LNS)	2000-2005	Over 80% were found to have an actual NPP far below the potential one	Prince 2004, Prince et al. 2009
	North east Queensland, Australia	Landsat Persistent Ground Cover time series	Automated detection of rangeland condition based on reference areas.	1986-2008	Management-related change in ground cover in savanna woodlands at three spatial scales was detected.	Bastin et al. 2012
Regional to global	Great Plains, USA	MOD13Q1 NDVI	Rangeland productive capacity is derived relative to reference conditions	2000-2012	16% of the northern and 9% of the southern study area are degraded	Reeves and Baggett 2014
	Bishri Mountain, Syria	NOAA AVHRR NDVI	Residual trend analysis	1981-1996	Areas showing a negative temporal trend in residuals of NDVImax and rainfall coincide with areas that are most heavily used by humans.	Geerken and Ilaiwi 2004
	South Africa	NOAA AVHRR VI	Residual trend analysis (RESTREND)	1985-2003	Identification of potentially degraded areas in South Africa	Wessels et al. 2007a
	Inner Mongolia China	GIMMS NDVI	Residual trend analysis (RESTREND)	1981-2006	Heavy overgrazing deteriorated rangelands in this area but grasslands recovered afterwards due to the implementation of new land use polices	Li et al. 2012
	Sahel, Africa	GIMMS NDVI(NPP)	Rain use efficiency (RUE)	1982-1990	Systematic increase of RUE in the Sahel; recovery of vegetation after the severe drought	Prince et al. 1998
	Spain	MEDOKADS Green Vegetation Fraction	Rain use efficiency (RUE)	1989-2000	Ongoing land degradation appeared only in localized areas caused by current or recent intensive land use	Del Barrio et al. 2010
		GIMMS NDVI; MODIS MOD13C1 NDVI	Rain use efficiency (RUE), Residual trend analysis	1982-2007	Very limited anthropogenic land degradation in the Sahel-Sudanian zone could be observed by trend analyses.	Fensholt and Rasmussen 2011
	Sahel, Africa	GIMMS3g NDVI (SPOT Vegetation NPP)	Rain use efficiency (RUE)	1982-2010	Only few areas (0.6%) were affected by land degradation processes	Fensholt et al. 2013
Global						
	60% of global drylands covered	Several (meta analysis)	Expert judgement	1980-2000	Sahel not a hot spot of land degradation, Asia shows largest area of degradation but other drylands are not covered well by studies	Lepers 2003
		GIMMS NDVI (MOD17 NPP)	Rain use efficiency (RUE)	1981-2003	Declining rain-use efficiency-adjusted NDVI on ca. 24% of the global land area	Bai et al. 2008

Table 4: Selection of studies monitoring land degradation in drylands.

Extent	Study area	RS data and indicator	Methodology	Time range	Result	References
Local						
Grazing induced vegetation loss/gain in rangelands						
	California, USA; Utah, USA	Landsat SAVI/ SSI time series	Trend analysis based on SAVI/SSI (soil stability index)	1982-1997	Landscape showed an increased susceptibility to soil erosion due to drought events and grazing	Washington-Allen et al. 2006, 2010
	Crete, Greece	Landsat SMA time series	Trend analysis based on SMA-derived vegetation abundances	1984-2000	Pattern of over- and undergrazing as a result of rangeland management practices from transhumance to sedentary pastoralism	Hostert et al. 2003
	Lagadas, Greece	Landsat SMA time series	Trend analysis based on SMA-derived vegetation abundances	1984-2000	Pattern of over- and undergrazing as a result of rangeland management practices from transhumance to sedentary pastoralism	Röder et al. 2008a
	Crete, Greece	Landsat vegetsation proxy time series	Comparative trend analysis based on SMA, NDVI and TC	1984-2006	Different vegetation estimates result in similar vegetation trend pattern	Sonnenschein et al. 2011
	Nepal	Landsat NDVI time series / GIMMS NDVI	Landsat: Trend analysis based on NDVI; GIMMS: residual trend analysis	1976-2008/ 1981-2006	Inter-annual vegetation variability driven by annual precipitation, degradation result of overgrazing or other processes	Paudel and Andersen 2010
Fire regime						
	Catalonia, Spain	Annual NDVI Landsat images	NDVI time series to generate a map series of fire history	1975-1993	Methodology to create maps of fire distribution	Diaz-Delgado and Pons 2001
	Portugal, Southern California	Multiseasonal Landsat imagery	Two-step approach to detect fires at medium resolution	1993	The algorithm showed a good agreement with the official burned area perimeters was shown	Bastarrika et al. 2011
	Alicante, Spain	Landsat NDVI time series	Nonlinear regression analysis of NDVI values and time elapsed since the fire event	1984-1994	After fire events two recovery trends were found that can be explained by species type	Viedma et al. 1997
	Ayora, Spain	Landsat SMA time series	Trend analysis and diachronic thresholding to procure a fire perimeter data base and depict post-fire dynamics	1975-1990	Typical recovery phases were described by exponential functions and were related to plot-based botanical information	Röder et al. 2008b
	Peloponnese, Greece	Landsat time series/MODIS NBR time series	Analysis of the temporal dimension of assessing burn severity	2006-2008	Within the limitations of available Landsat imagery, caution is recommended for the temporal dimension when assessing post-fire effects	Veraverbeke et al. 2010
Relationship of vegetation trends and climatic factors						
	Altiplano,Bolivia	Landsat time series	Mean-variance analysis	1972-1987	Landscape showed an increased susceptibility to soil erosion during ENSO-induced droughts	Washington-Allen et al. 2008

Regional to global						
Change of vegetation cover						
	Sub-Saharan Africa	NOAA AHRR NDVI and surface temperature	Seasonal analysis of Surface temperature-NDVI trajectories	1982-1991	Only 4% of the study area showed consistent trends (increase/decrease) of vegetation cover.	Lambin and Ehrlich 1997
	Sahel, Africa	PAL NDVI	Trend analysis of NDVI	1982-1999	Increase in seasonal NDVI was observed over large areas in the Sahel	Eklundh and Olsson 2003
	Sahel, Africa	GIMMS NDVI	Trend analysis of NDVI/ Residual trend analysis with gridded rainfall data	1982-2003	Rainfall was found to be a major reason for the increase in vegetation greenness and most of the Sahel does not show large scale human-induced land degradation	Herman et al. 2005
	Sahel, Africa	GIMMS NDVI	Trend analysis of NDVI	1981-2003	NDVI data indicate a gradual and slow but persistent recovery from the peak drought conditions that affected the region in the early to mid-1980s.	Anyamba and Tucker 2005
	Sahel, Africa	GIMMS NDVI3g, MOIS MOD12C2 NDVI	Trend analysis of NDVI	1981-2011	Recovery rate of vegetation is dependent on factors like soil type and soil depth	Dardel et al. 2014
	Sahel, Africa	GIMMS NDVI3g	Trend analysis of growing season averages of NDVI	1981-2012	NDVI behaviour reflects the variability of rainfall condition such as the drought in the 1980s and the weather conditions starting in 1994; data might be used as a land surface climate data record in a semi-arid areas where detailed ground-based meteorological data are missing	Anyamba et al. 2014
	Sahel, Africa	GIMMS NDVI	Automated mapping of vegetation trends with polynomials	1982-2006	Dominance of positive linear trends distributed in an east-west band across the Sahel. Regions of non-linear change occur on the peripheries of larger regions of linear change.	Jamaili et al. 2014
	Global, Pastures	GIMMS LAI3g	Trend analysis of maximum LAI; correlation analysis with rainfall and temperature	1982-2008	Degradation of pastures is not a globally widespread phenomenon but an increase of greenness in many areas was observed; precipitation was the dominant climate control on inter-annual variability of LAImax in pastures	Cook and Pau 2013
	Global	GIMMS NDVI	BFAST was used to map gradual an abrupt changes of NDVI and breakpoints	1982-2008	Abrupt greening prevailed in semi-arid regions, probably due to their strong reactions to climatic variations. These abrupt greening events were often followed by periods of gradual browning.	De Jong et al. 2012
Change in phenologocal characteristics						
	Sahel and Soudan, Africa	GIMMS NDVI	Trend analysis of Phenological metrics derived with Timesat	1981-2005	Significant positive trends for the length and the end of the growing season for the Soudan and Guinean regions were detected but not in the Sahel; this can be attributed to two types of greening trends associated with rainfall change since the drought in the early 1980s	Heumann et al. 2007
			Trend analysis of Phenological metrics for an integrated analysis		listed in table 5	Hill et al. 2008; Stellmes et al. 2013
						Hilker et al. 2014

Relationship of vegetation trends and climatic factors						
			RUE		listed in table 3	
			RESTREND		listed in table 3	
	Major areas of global drylands	GIMMS NDVI	Linear regression models	1981-2003	A strong general relationship between NDVI and rainfall over time characterizes large parts of the drylands; no large scale land degradation was observed but rather an increase of vegetation cover	Helldén and Tottrup 2008
	Spain	MEDOKADS NDVI	Distributed lag models	1989-1999	Significant relationships between lagged NDVI and rainfall anomalies up to 3 months are confined to sub-humid/semi-arid areas; severe drought periods might have an enduring influence on biomass production in subsequent years	Udelhoven et al. 2009
	Global semi-arid areas	GIMMS NDVI	Correlation analysis of NDVI and precipitation/air temperature	1981-2007	Semi-arid areas, on average, experience an increase in greenness; similar increases in greenness may have widely different explanations	Fensholt et al. 2012
	Okavango, Kwando, upper Zambezi, Africa	GIMMS NDVI3g/ MODIS MOD13A3 NDVI	Dynamic factor analysis	1982-2010 /2001-2010	The spatial distribution of soil moisture and precipitation as determinants of NDVI is important in areas with mean annual precipitation under 750 mm	Campo-Bescós et al. 2013
	Global	GIMMS NDVI3g/MODIS MOD and MYD13C2	Multiple stepwise regression	1982-2010	Precipitation showed the highest correlation to temperate to tropical water-limited herbaceous systems where rainfall partially explains more than 40% of NDVI variability	Zeng et al. 2013
Teleconnections						
	Sahel, Africa	GIMMS NDVI	Correlations between NDVI and climate indices and global sea surface temperatures	1982-2007	Global SST anomalies and Sahelian NDVI showed strong correlations with different characteristics for western, central and eastern Sahel	Huber and Fensholt 2011
	Africa	GIMMS NDVI/MODIS NDVI for correction	Land surface model driven by meteorological data and NDVI o analyze response of photosynthesis to macro weather situations	1982-2003	ENSO and IOD induce large seasonal anomalies of precipitation, vegetation, humidity as well as , photosynthesis across the main part of Africa	Williams and Hanan 2011
Fire reegime						
	Central Asia	MODIS Active Fire and Burnded Area product	Validation of MODIS products and mapping of fire occurrence	2001-2009	In average about 15 million ha of land burns annually across Central Asia with the majority of the area burned in August and September in grassland areas.	Loboda et al. 2010
	Southern Africa	MODIS Burnded Area product	Random forest regression tree procedure to determine the factors of wild fires	2003	Areas where identified where fire is rare due to low rainfall regions, regions where fire is under human control and higher rainfall regions where burnt area is determined by rainfall seasonality.	Archibald et al. 2009
	Mediterranean Biomes	MODIS Active Fire product	Statistical fire-climate models driven by ensembles of climate projections under the IPCC A2 emissions scenario	2001-2007	Fire activity was found to be sensitive to environmental changes and productivity may be the key to future fire occurrence in this biome	Battlori et al. 2013

Table 5: Selection of studies evaluating land degradation based on integrated concepts and use of remote sensing products.

Extent	Study area	RS data	Methodology	Observation period	Result	References
Local						
	North-West Spain	Time series of orthorectified aerial photographs	Species Distribution Modelling techniques (MaxEnt and BIOMOD)	1956-2004	Land-use history primarily controlled forest expansion rates, as well as upward altitudinal shift	Alvarez-Martinez et al. 2014
	North-East Spain	Bi-temporal analysis of aerial photographs	Logistic regression models	1956-2006	Effects of several topographic and socio-economic variables were analyzed; patterns of observed forest expansion are highly related to patterns of farmland abandonment	Améztegui et al. 2010
	Lagadas, Greece	Landsat SMA image	Cost surface modelling to understand the influence of grazing management on vegetation cover.	2000	Uneven distribution of livestock causes both over- and undergrazing to occur in close proximity, which negatively affects the ecosystem through various feedback loops	Roeder et al. 2007
	North-East Spain	Landsat MSS and TM land cover maps	Multiple logistic regressions (MLOR) combining biophysical and human variables	MSS: 1977-1993; TM: 1991-1997	EU subsidies were one major driver of land use/cover changes, e.g. intensification of subsidised herbaceous crops on the coastal agricultural plain.	Serra et al. 2008
	Lagadas, Greece	annual Landsat TM/Etm+ vegetation fraction time series	Combined use of household-level land-use data, remote sensing products, and standardised socio-economic data	1984-2000	Major driver of land use/cover changes were EU subsidies, e.g. lowprofit farmers maintained extensive farming activities on the most erodible, steep-sloped land due to subsidies	Lorent et al. 2008
	Xilinhot, Inner Mongolia, China	Landsat TM/ETM+ land use and NDVI (three time steps)	Multinomial logistic regression model	1991-2005	Main drivers of observed trends in rangelands were altitude, slope, annual rainfall, distance to highway, soil organic matter, sheep unit density, and fencing policy	Li et al. 2012
	Lake Nakuru drainage basin, Kenya	Landsat TM/ETM+ land use maps (three time steps)	Logistic regression models	1985-2011	Major drivers of forest-shrubland conversions, grassland conversions and cropland expansions were identified; significance of the influential factors varied depending on the time period observed and the land cover change type	Were et al. 2014
Regional						
	Mongolia	MODIS daily 1B data (MYD021KM), NDVI MAIAC	Regression analysis between variables on a provincial level	2002-2012	About 80% of the decline in NDVI explained by increase in livestock; 30% of changes across the country by precipitation	Hilker et al. 2014
	Uzbekistan	MOD13Q1 NDVI	Spatial logistic regression modeling	2000-2010	One third of the area was characterized by a decline of greenness. ground-water table, land use intensity, low soil quality, slope and salinity of the ground water were identified as the main drivers of degradation	Dubovyk et al. 2013

	Spain	MEDOKADS NDVI	Syndrome approach	1989-2004	Only few areas affected by land degradation in the sense of productivity loss; shrub and woody vegetation encroachment due to land abandonment of marginal areas, intensification, urbanization trends along the coastline caused by migration/increase of mass tourism	Hill et al. 2008 Stellmes et al. 2013
Global						
		SPOT Vegetation Global land cover map 2000 (GLC2000)	HANPP	~2000	Annual loss of NPP due to land degradation at 4% to 10% of the potential NPP of drylands, ranging up to 55% in some degraded agricultural areas	Zika and Erb (2009)
		NOAA AVHRR NDVI and MOD17A	GLADIS: NPP trend detrended via RUE and RESTREND; biomass, soil quality, water quantity, biodiversity, economic and social services are used as indicators to describe the status of land degradation	1981-2003 (with MODIS 1981-2006)	Degraded lands are found to be highly variable; degraded land occurs mostly in drylands and steep lands; the capacity to deliver ecosystem services is also generally less in developing countries as compared to industrial nations	Nachtergaele et al. 2011