The role of Remote Sensing in land degradation assessments: opportunities and challenges

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ABSTRACT

Land degradation (LD) is one of the biggest global challenges for the people’s livelihoods and environment. Remote Sensing plays an unprecedented role in LD mapping, assessment and monitoring at multiple spatial and temporal scales. Regardless of a big potential of Remote Sensing to support LD studies, there are still quite a few challenges that impede its successful application. This paper provides a logical synthesis of the role of Remote Sensing for LD assessments. First, background information on definition of LD and existing assessment frameworks are provided. This follows with the synthesis of the areas of application of Remote Sensing for LD analysis and a brief review of the major Remote Sensing variables used in LD studies. The paper further argues for multi-scale and cross-scale LD assessments calling for application-oriented solutions and highlighting the need of in situ data for validation of Remote Sensing-based LD maps. This claim is illustrated by an example of a case study in Uzbekistan.

INTRODUCTION: PROBLEM OF LAND DEGRADATION

Land degradation (LD) is one of the biggest challenges for the people’s livelihoods and environment all around the world (Figure 1). The concerns of the world community about this issue resulted in proclamation of the United Nations Convention to Combat Desertification (UNCCD) in 1994 (http://www.unccd.int/) which aims at a reduction of LD and desertification in all affected countries. Likewise, the United Nation’s Conference on Sustainable Development (“Rio + 20”) has requested to set up the goal of Land Degradation Neutrality, calling for a compensation of degrading lands through land improvement (UNCCD, 2014). Furthermore, the sustainable development goals (SDGs) of the 2030 Agenda for Sustainable Development adopted by world leaders in September 2015 documents the need to address the problem of LD. There is also an Economics of Land Degradation (ELD) initiative, which is a global partnership aiming to establish a comprehensive framework for the evaluation of the economic losses due to LD in order to assist the decision-making process (Nkonya et al., 2016).

The effective implementation of these international frameworks as well as well-informed planning and policy decisions, which are related to the sustainable land management (SLM) and to “zero net land degradation” target, require, however, credible and spatially explicit information on degraded lands (Stavi & Lal, 2015). The availability of spatial data on LD is also a precondition for the implementation of land rehabilitation measures (Winslow et al., 2011).

Even with the existing demand for LD-related spatial information, there is still no global agreement on the definition of LD and standardized methodology for its assessment at different spatial scales, while the reliability of the existing maps is often questioned (Higginbottom & Symeonakis, 2014; Metternicht, Zinck, Blanco, & Del Valle, 2010). The reasons behind are the differences in definition of LD, methods for LD mapping and field data scarcity. The existing global assessments differ in the selection of measurable attributes of LD, in their spatial coverage, and in the quality of the data sets used (Le, Nkonya, & Mirzabaev, 2016; Safriel, 2007). These estimates derived from coarse resolution satellite data and/or expert opinions are not suitable for policy-making or for scientific investigations of the potential land rehabilitation measures (Dubovyk et al., 2013a). Moreover, the coarse spatial resolution of global LD maps is not appropriate to support region-based sustainable land use planning, while national maps are not always in place for all countries.

A need to develop a standardized methodology for LD assessment is also due to the necessity to support the SDG 15. The SDG 15 aims “to protect, restore and promote sustainable use of terrestrial ecosystems, to sustainably manage forests and combat desertification, as well as to halt and reverse LD and halt biodiversity loss” (UN, 2015, p. 14). The recently proposed indicator to assess achievements related to the SDG target 15.3 “proportion of land that is degraded over total land...
“area” has been just confirmed by both the Inter-Agency and Expert Group on SDG indicators (IAEG-SDGs). There is, however, currently no approved recommended methodology by the UNCCD to calculate this indicator. Preliminary, the IAEG-SDGs agreed that the indicator 15.3 would be derived by summing all areas subject to change, which conditions are considered negative due to LD, namely (i) land cover and land cover change, (ii) land productivity and (iii) carbon stocks above and below ground.

The above-mentioned three sub-indicators, proposed to measure the SDG 15.3, underline the importance of spatiotemporal monitoring of land cover dynamics and land productivity for LD assessments.

In this light, the role of Earth Observation (EO; or Remote Sensing; these two terms are used interchangeably in this paper) has gained unprecedented importance. Remote Sensing is a discipline that employs theories and methods related to extraction of information about surfaces through the interaction of electromagnetic radiation with matter (Li, Shan, & Li, 2009a). Remote Sensing also studies the fundamental issues related to the capturing, storing and analyzing Remote Sensing data. With the launch of the first EO satellites in 1970s, satellite Remote Sensing was established leading to an unprecedented opportunity for people to observe their planet from space. Currently, Remote Sensing data are featured by satellite multi-platforms, multi-sensors and multi-scale sensors’ capabilities covering a wide spectrum of electromagnetic radiation characterized by a range of temporal, spatial and spectral resolutions that are used for various applications in different domains. These observations allow for past, present and near-real-time monitoring of Earth processes (Li et al., 2009a).

The data archives from the EO sensors allow retrospective analyses of the state and development of land on different spatial scales. Satellite imagery confirms to the principles of repetitiveness, objectivity and consistency, which are preconditions in the framework of LD monitoring. Therefore, Remote Sensing provides important information for integrated approaches combining satellite data with specific tools, geographic information system (GIS) analysis and modeling techniques (Röder et al., 2008). Among different methods for studying and monitoring LD, Remote Sensing provides a cost-effective evaluation over extensive areas, whereas in situ process studies are resource demanding, and thus, are usually conducted at a field level (e.g. Bai & Dent, 2009; Prince et al. 2009; Gao & Liu, 2010; Vlek, Le, & Tamene, 2008). In addition, satellite-based assessment is currently the only means for LD monitoring at different spatial and temporal scales in a spatially explicit and continuous manner, specifically in the less developed countries where funds for SLM programs are often limited (Sivakumar and Stefanski 2007).

The main aim of this paper was to provide an overview as well as to discuss the role of Remote Sensing for LD monitoring and assessment. The
specific aim was to show the importance of multi-scale and cross-scale analysis in Remote Sensing-based LD assessments. Following an introduction, the definition of LD as well as causes (or factors) of LD processes were elaborated. In the subsequent section, the role of Remote Sensing for LD assessment was defined and further demonstrated using a case study. The detailed overview of the most common Remote Sensing-based variables as a proxy for LD was also presented. In the discussion section, the current gaps of Remote Sensing for LD assessment and monitoring were critically discussed. We further argued on the importance of multi-scale and cross-scale analysis in Remote Sensing-based LD assessments. The discussion was followed by the concluding remarks and the paper’s outlook for the future research directions outlined as necessary ones to increase the role of Remote Sensing in LD assessments.

Setting the scene

Definition of LD

LD itself is a complicated area of research due to its interdisciplinary nature incorporating geographical, ecological, climatic and social perspectives (Vogt et al., 2011). This complexity partly arises due to an ongoing discussion on the definition of what actually constitutes degradation and how it should be measured (Reynolds et al., 2011). There are many definitions of LD (Herrmann & Hutchinson, 2005; Nicholson, Tucker, & Ba, 1998). For example, the definition by UNCCD refers to LD as the “reduction or loss 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” (§ 5, UNCCD, 1994) (Figure 1).

The definition proposed by the Millennium Ecosystem Assessment (MEA), also followed in this research, refers to LD as “a persistent net loss of capacity to yield provisioning, regulating, and supporting ecosystem services” (p. 16, Adeel, Safriel, David, & White, 2005); while MEA refers to desertification as the same process in drylands (i.e. semi-arid, arid and dry sub-humid zones). In the ecosystem services framework, “land” is recognized as a terrestrial ecosystem that includes not just soil resources, but also vegetation, water, other biota, climatic factors, landscape setting and ecological processes that operate within one system ensuring its functions and services (MEA, 2005).

The definition of MEA considers the ability of land to support primary production as a key ecosystem service. Thus, a reduction in net primary productivity (NPP) at a site is often viewed as LD (Reynolds et al., 2007). Therefore, the MEA’s definition of LD emphasizes the leading role of primary production among other services as it generates products of biological origin on which other ecosystem services depend. The primary production regulates energy, water and nutrient flows in land ecosystems, sequestrates carbon dioxide, and it is the basis of food production and generally provides habitats for species (MEA, 2005). This notion forms the theoretical framework on which the majority of Remote Sensing-driven assessments of LD are based (Bai, Dent, Olsson, & Schaepman, 2008; Le et al., 2016; Wessels, Prince, Frost, & van Zyl, 2004).

Factors of LD

Degradation of land is caused by various factors, including climatic variations and human-induced activities. Human-induced LD occurs mainly due to overexploitation of land resources for cropping and livestock farming, including irrigation practices, over-grazing of rangelands and fuelwood exploitation (Adeel et al., 2005). A drastic example of human-induced LD is shown in Figure 2. The “man-made” Aralkum desert, being a striking example of human-induced desertification, is a young desert located in the former seabed of the Aral Sea. It has evolved due to unsustainable water withdrawal for irrigation agriculture purposes (Dukhovny & de Schutter, 2011; Glantz, 1999). According to the ELD approach, the causes of LD are divided into proximate and underlying causes (Nkonya, Mirzabaew, & von Braun, 2016b). Proximate causes of LD are those that directly cause LD; and they are further subdivided into two categories:

- Biophysical factors (e.g. steep slopes, land use, extreme climate events, soil erodibility)
- Unsustainable land management practices (e.g. monocropping, excessive fertilizer application, unsustainable irrigation practices, land clearing)

The underlying causes include policies, institutions and other socio-economic factors that affect the proximate causes of LD (Nkonya et al., 2011). Local policies and institutions have a large impact on sustainability of land management practices, and thus, could either have a direct or indirect impact on behavior of land users. For example, the policy promoting payments for ecosystem services will encourage SLM in the area of their implementation. National-level policies and the presence of international and national organizations, which build the capacity of the local institutions on land management and support extension services, play important role to prevent and forestall LD. In
general, top-down policies are found to lead to LD (Mirzabaev et al., 2016).

The role of Remote Sensing in LD assessments

**General overview**

The areas of Remote Sensing applications in LD assessment were grouped in this paper into two groups: (i) applications where Remote Sensing plays the leading role and (ii) applications where Remote Sensing could support the assessments that preliminary rely on other data sets and methods. Following the framework of ELD assessment, the main role of Remote Sensing reveals in the assessments of the different levels of LD that is mapping of its extent, types and severity at different spatial scales (Figure 3). The supporting role of Remote Sensing manifests in the studies that deal with:

- analyses of driving factors of LD (Dubovyk, Landmann, Dietz, & Menz, 2016a; Li, Ma, Xu, Wang, & Zhang, 2009b; Mirzabaev et al., 2016; Zhou et al., 2015);
- spatial decision support of land rehabilitation activities (Buenemann et al., 2011; Dubovyk et al., 2013b; Thomas, Quillerou, & Stewart, 2013; Vlek et al., 2008);
- spatial assessments of the impacts of either LD or land rehabilitation activities (Bai & Dent, 2009; CACILM, 2006; Cano, Mermut, Arocena, & Silla, 2009; Liu et al., in press).

![Figure 2. The former seabed of the Aral Sea in the harbor city of Moynaq in Uzbekistan. The shipwrecks indicate the former seashore line.](image)

**Figure 2.** The former seabed of the Aral Sea in the harbor city of Moynaq in Uzbekistan. The shipwrecks indicate the former seashore line.

![Figure 3. The contribution of Remote Sensing in LD assessments based on the example of the economics of land degradation framework (re-drawn and modified after Nkonya et al., 2016b).](image)

**Figure 3.** The contribution of Remote Sensing in LD assessments based on the example of the economics of land degradation framework (re-drawn and modified after Nkonya et al., 2016b).
To date, several spatial assessments have been conducted to map LD globally. For example, the Global Assessment of Human-induced Soil Degradation (Oldeman, Hakkeling, & Sombroek, 1991) estimates 15% of the Earth’s surface and 60% of drylands as being degraded. Other examples are the Land Degradation Assessment in Drylands (Bai et al., 2008), and the most recent global assessment of global LD hotspots (Le et al., 2016). For a detailed review on conducted LD assessment, the reader is directed to Nkonya, Mirzabaev, and von Braun (2016a).

**Remote Sensing-based variables as a proxy for LD**

The earlier generation of above-mentioned LD assessments were constrained by lack of quantitative data available for LD mapping, and thus largely relied on expert opinions, such as by Oldeman et al. (1991). The developments in satellite Remote Sensing (Table 1) allowed the later studies to utilize satellite image data, such as from the Advanced Very High Resolution Radiometer (AVHRR). The evolution of the Remote Sensing-based methods for LD mapping, monitoring and assessment is summarized in Table 1.

Among different Remote Sensing methods developed for LD studies, analysis of vegetation cover dynamics and vegetation decline analysis are the most commonly applied ones. The short description of some of these methods is provided below.

**Vegetation cover dynamics**

Changes and modifications of vegetated land surfaces, such as habitat loss and LD, are regarded as the primary cause for global environmental change as they reduce ecosystem services and impair ecosystem function (Gillanders, Coops, Wulder, Gergel, & Nelson, 2008). Vegetation cover functions as an integrated indicator of vegetation responses to environmental factors including rainfall, temperature, soil and topography, as well as factors related to human activities, which are typically derived from land cover and land use (LULC) information (e.g. irrigated agriculture). Linking vegetation cover dynamics with climatic and anthropogenic factors facilitates an improved understanding of vegetation cover changes as well as ecosystem’s feedbacks to natural stresses (e.g. droughts) and human activities (Brown, de Beurs, & Vrieling, 2010). Moreover, some changes in LULC are sometimes regarded as LD-enabling factors (i.e. deforestation or encroachment of invasive species). Therefore, Remote Sensing-based monitoring of vegetation cover dynamics at a variety of scales provides crucial information required to assist in SLM decisions (Walker, de Beurs, & Henebry, 2015).

Several systematic techniques were developed to perform vegetation dynamics analysis and change detection using as an input satellite images (time series or multi-temporal images). The most popular ones are methods that first calculate vegetation-related parameters, such as phenometrics (Parples, Dubovyk, Tewes, Mund, & Schellberg, 2016), and then analyze their spatio-temporal dynamics over the given observation period (Nagai, Nasahara, Inoue, Saitoh, & Suzuki, 2016). In relation to the temporal dimension of such analyses, they can be performed in bi-temporal, multi-temporal or hyper-temporal manner (Dubovyk et al., 2016a).

**Vegetation productivity and cover decline**

LD manifests itself in the reduced productive potential of a particular landscape or land unit (Reynolds

| Table 1. The evolution of Remote Sensing data and methods used for land degradation assessment. |
|-----------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| Input data                                    | Methods (examples)                              | Methods (examples)                              | Methods (examples)                              |
| Multi-spectral images, aerial photos          | Visual interpretation of aerial photos, photo-grammetric methods, manual mapping | Image classification, map digitalization, expert mapping, photo-grammetric methods, manual mapping | Time series analysis, data fusion, LD modeling, image classification, spectral transformation, change detection, participatory mapping methods |
| Multi-spectral images, aerial photos and derivatives, vegetation indices | Landsat TM, SPOT, AVHRR | Landsat ETM/ETM+, SPOT, ASTER, AVHRR | Landsat TM; Landsat MSS; GeoEye, ICெNOS, Quickbird, GeoEye, Hyperion, UAV |
| 1 m to 8 km, increasing number of bands        | Landsat TM; Landsat MSS; GeoEye, ICெNOS, Quickbird, GeoEye, Hyperion, UAV | Landsat TM; Landsat MSS; GeoEye, ICெNOS, Quickbird, GeoEye, Hyperion, UAV | Landsat TM; Landsat MSS; GeoEye, ICெNOS, Quickbird, GeoEye, Hyperion, UAV |
| 0.01 m to 8 km, increasing number of bands     | Landsat TM; Landsat MSS; GeoEye, ICெNOS, Quickbird, GeoEye, Hyperion, UAV | Landsat TM; Landsat MSS; GeoEye, ICெNOS, Quickbird, GeoEye, Hyperion, UAV | Landsat TM; Landsat MSS; GeoEye, ICெNOS, Quickbird, GeoEye, Hyperion, UAV |
| PCA: principal component analysis; SMA: spectral mixture analysis; NPP: net primary productivity; AVHRR: Advanced Very High Resolution Radiometer; MODIS: Moderate Resolution Imaging Spectroradiometer; MERIS: Medium Resolution Imaging Spectrometer; Landsat MSS: Multispectral Scanner; Landsat TM: Thematic Mapper; Landsat ETM: Enhanced Thematic Mapper; SPOT: Satellite for Observation of Earth; ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer; UAV: unmanned aerial vehicle. |
et al., 2007). A gradual loss of vegetation productivity and cover over time is often used as a proxy of LD when Remote Sensing is used for its assessment.

Remote Sensing-based analyses of vegetation productivity decline and vegetation cover decline rely on a wide range of change detection methods (Dubovyk, Menz, Conrad, Thonfeld, & Khamzina, 2013c; Higginbottom & Symeonakis, 2014). The gradual LD processes within one land cover class are commonly detected by applying algorithms that reveal negative changes in vegetation cover and productivity parameters between image acquisition dates (Lambin & Strahlers, 1994; Stellmes, Udelhoven, Röder, Sonnenschein, & Hill, 2010; Zhao, Lin, & Warner, 2004). Another approach is based on image classification when multi-temporal LULC maps are compared to identify changes in the mapped LD class (Li et al., 2009b; Yiran, Kusimi, & Kufogbe, 2011). The classification-based analysis, however, fails to evaluate gradual LD processes within one land cover class. Moreover, these change maps can lead to high mapping inaccuracies due to error propagation between classification results. Trend analyses of multi-year satellite images allow capturing the gradual LD processes (Ghazaryan, Dubovyk, Kussul, & Menz, 2016; Le et al., 2016). Trend analyses were routinely employed for LD assessment using coarse- and multi-scale imagery (Ibrahim, Balzter, Kaduk, & Tucker, 2015; Santos, Dubovyk, & Menz, 2017; Tüshaus, Dubovyk, Khamzina, & Menz, 2014). For a recent review of available Remote Sensing methods for assessing LD using vegetation index data reader is referred to Higginbottom and Symeonakis (2014).

The following case study will demonstrate the application of different sources of satellite data for vegetation decline analysis as a manifestation of LD at multiple spatial scales. Furthermore, the set of biophysical and socio-economic data sets were used to reveal causes of LD in the study region.

**Case study: multi-scale assessment of vegetation dynamics and degradation**

In this case study, multi-temporal spatial information on vegetation condition was generated and subsequently analyzed to support site-specific sustainable agricultural management. The study was conducted within the irrigated croplands of Khorezm region and southern Karkalpakstan Republic of Uzbekistan where ongoing LD in the form of secondary soil salinization is an acute problem, triggered by unsustainable irrigation and land management practices (Ibrakhimov et al., 2007). This study demonstrates the use of multi-temporal and multi-scale satellite images for assessment of vegetation dynamics and degradation. As a major input for analysis, high spatial resolution (10 m) SPOT-4/5 image data for the years 1998, 2006 and 2010 were fed in an integrated change vector analysis and spectral mixture analysis (CVA-SMA) procedure (Dubovyk et al., 2013c, 2015b). In addition, multi-temporal Landsat images with the spatial resolution of 30 m and 16-day Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI time series for the same observation period were used for cross-scale comparison of the mapping results and maps validation. The same CVA-SMA procedure was applied to Landsat data to generate vegetation cover change maps, while linear trend analysis of MODIS-NDVI time series were conducted to detect negative trend in vegetation productivity in the irrigated cropland area of the case region (Figure 4).

Prior to analysis, the cadastral maps were collected from local land administration authorities and subsequently digitized. These parcel-specific data sets were used as a mask for satellite image-based analysis allowing generating the maps of vegetation cover changes within a land parcel (Figure 5). The secondary data sets on soil properties, ground water level and salinity, and crop type maps were additionally collected. All the secondary data were linked to the digitized cadastral parcel-maps through an attribute table in GIS. The attribute secondary data stored in the cadastral parcel layer allowed analysis of the reasons behind the mapped vegetation changes and linking them to biophysical properties of land (soil properties, ground water levels) as well as crop management, such as crop rotations.

Results of the satellite-based mapping analysis allowed to identify the overall trend in vegetation dynamics between 1998 and 2010 as well as to highlight the land parcels where vegetation cover have decreased in the analyzed years (Figure 5). The cross-comparison of the overall SPOT-based change direction map (1998–2010) with the MODIS-based LD trend map (2000–2010) indicated an agreement of 84% between both maps, while the overall agreement of 82% was achieved between SPOT-based and Landsat-based map (1998–2009). The comparison between three maps, however, yielded relative low user’s and producer’s accuracies (in the range from 62–75%) for the class “vegetation decrease”, which was used as a proxy of LD. This underestimation of vegetation cover decline in both SPOT and Landsat-based maps in comparison to MODIS-based map, or overestimation of vegetation cover decline by trend analysis of MODIS-NDVI time series, clearly demonstrates the disadvantages of both change detection approaches used calling for application-oriented solutions and highlighting the need of in situ data for validation of Remote Sensing-based LD maps.

**Discussion**

**Call for multi-scale assessment of LD**

Currently, there are still ongoing discussions and unresolved questions related to the use of satellite Remote Sensing to address LD, including but not limited to methodological issues, such as
Figure 4. The workflow of the satellite image analysis to derive multi-scale information on vegetation cover changes in the study area in Uzbekistan.

Figure 5. SPOT-based vegetation cover change map (1998–2010) calculated based on CVA-SMA approach.
• choice of LD proxy when mapping vegetation cover and productivity changes at different spatial/temporal scales (Prince, Wessels, Tucker, & Nicholson, 2007; Tüshaus et al., 2014);
• data/method selection for multi-temporal analysis (Le et al., 2016; Wessels, van den Bergh, & Scholes, 2012);
• analysis of the drivers of LD at different spatial/temporal scales (Bai et al., 2008; Gao & Liu, 2010; Reed et al., 2011);
• decoupling environmental signals due to short-term climatic variability and land management from long-term resource degradation (Nkonya et al., 2016a; Stavi & Lal, 2015); and
• validation of the Remote Sensing results against *in situ* data (Karnieli et al., 2013; Le, Tamene, & Vlek, 2012; Safriel, 2007).

The first reason behind the outlined research needs is a complexity of the process of LD, which manifests differently across various spatial and temporal scales (Figure 6). The hierarchy theory emphasizes this notion, arguing further that to explain the patterns observed at a given level, it is important to perform multi-scale assessment that includes both levels below and above the focal level (Reed et al., 2011). For example, widespread cropland degradation at the village level is largely an aggregate of unsustainable land management of households within the village, which in turn is a function of polices and laws at province and country level. The importance of the multi-scale assessment and analysis of the cross-scale linkages in LD research is also highlighted in the Driving Forces-Pressures-States-Impacts-Responses framework (Burkhard & Müller, 2008), and in the Drylands Development Paradigm (Reynolds et al., 2011).

In LD research, two broad categories of scale are defined depending on either their relevance with regard to human impacts (farm/household, community, district/provincial and national/international) or their relevance with regard to environmental impacts (patch, local, landscape, regional and global) (Reynolds et al., 2011). The latter corresponds to ecological view on scale, while the former reflects a planning notion. A good example of the first category of scale is a level system that is often used in spatial planning and management. A second category is more applicable when the focus is on environmental processes that are not bounded by administrative units.

Both types of scale are equally important in LD-based assessment. However, the choice of the relevant scale(s) depends on the study’s aims and specific applications. For example, the scale relevant with regard to human impacts should be selected for analysis when the strong accent set on the applicability of the research results to support sustainable land planning and management. The examples are a province-wide study on land suitability assessment for afforestation of degraded cropland to support SLM of degraded arable land (Dubovyk, Menz, & Khamzina, 2016b), and regional-based assessment of land productivity decline in Eastern Africa (Landmann & Dubovyk, 2014). At the same time, Figures 6 and 7 shows clearly differences between geographical, ecological and planning perspective on

![Figure 6. Schematic representation of different spatial and temporal resolution of satellite imagery and their relation to various spatial and temporal scales of environmental and human processes linked to land degradation (a) spatial and temporal resolution of selected satellite imagery; (b) simplistic representation of hierarchy theory diagram showing that human (H) and environmental (E) processes influence land state (degraded or non-degraded) through land management activities. The indicated scales are not absolute. The listed processes at one specific scale may also occur at other scales. Sub-scales could be identified for each mentioned scale (re-drawn and modified after Buenemann et al., 2011).](image-url)
scale and the challenge of finding suitable satellite data sets to perform analysis at multiple scales. In such complex situation, the analyst should be guided by the main scope of the assessment and its application.

Another reason for the existing challenges of Remote Sensing of LD refers to a mismatch between spatial and temporal resolution of currently available satellite imagery and ecological and socio-economic scales of LD processes and its drivers (Figures 6 and 7). For example, to assess LD at a landscape scale, high spatial resolution imagery, such as from Sentinel program, is not always available at frequent and repeatable intervals over long periods that are required for trend analysis. Because of this, no optimal method exists to assess LD at present. Furthermore, the choice of a particular technique often depends on the scale of the analysis, application, data availability and quality, and the analyst’s experience (Radke, Andra, Al-Kofahi, & Roysam, 2005). The wide adaptation of trend analysis approach based on vegetation index data for LD assessments could become possible when the high spatial resolution time series such as from the Landsat mission or, even from the Sentinel mission, will become available for all geographical areas in the world at frequencies required for time-series analysis (Wulder, Masek, Cohen, Loveland, & Woodcock, 2012).

Consequently, there is currently a research need in assessments of LD and its drivers at different spatial scales and across various ecosystems, which are largely predefined by existing local differences and locally specific problems that have to be prioritized. It is equally important to explore further Remote Sensing-based scale transfer approaches and methodologies to understand the relationship between locally observed LD processes and their aggregation at different spatial scales.

As an example, the multi-scale assessment of LD is described in Graw, Oldenburg, and Dubovyk (2016), where the authors applied multi-scale mapping approach to produce a series of bush encroachment maps at local level based on multi-source imagery: aerial photos, Landsat level (30 m spatial resolution) and MODIS level (250 m spatial resolution). Another example is a series of publications of Dubovyk et al. (2016a), Dubovyk et al. (2015b), and Dubovyk et al. (2013a). Dubovyk et al. (2015b) analyzed vegetation cover decline at sub-field level within several districts in Uzbekistan, followed by the province-wide study of cropland degradation in Uzbekistan based on Dubovyk et al. (2013a) and a regional assessment comprising five post-Soviet Central Asian countries of vegetation dynamics and its triggers (Dubovyk et al., 2016a). The publications by Dubovyk et al. (2013c) and Dubovyk et al. (2015b) investigated the cross-scale linkages by comparing cropland degradation estimates derived from high resolution imagery (Landsat and SPOT with 30 and 10 m pixel size, respectively) and mapped degraded cropland from MODIS with 250 m pixel size for the same area of the irrigated-agro-ecosystems in Uzbekistan.

**Other methodological challenges and gaps**

In addition to aforementioned need of multi and cross-scale assessments, there is currently a call for continuing long-term observations of LD over extended geographical areas characterized by various types of LD (Vogt et al., 2011) based on long-term satellite time-series data. This demand results from strong environmental and socio-economic differences between the different regions. Such macro-scale observations are needed to account for the...
high environmental variability and to distinguish between the impacts of climate variability and human actions on LD processes. Likewise, there is a need to consider both natural and transformed environments (e.g., irrigated croplands) (Aw-Hassan et al., 2016) and to analyze the losses and gains resulting from land transformation processes (Landmann & Dubovyk, 2013).

Besides mapping LD patterns, it is equally important to go one step further and to analyze the drivers of these processes for a correct interpretation of the produced maps of degraded land (Dubovyk et al., 2015a; McDowell et al., 2015). Remote Sensing and GIS provide an opportunity to link the mapped patterns of LD to their proximate causes using spatially explicit analysis. Due to the nature of underlying causes of LD, Remote Sensing-based tools and techniques usually have a limited applicability for their assessments. However, due to the nature of underlying causes of LD, that the impact of underlying factors like land policies, land tenure, poverty, economic pressures, migration and others are often not directly investigated in LD assessment (Nkonya et al., 2013). This holds true also for inclusion of the impact of stressors such as drought, or the impacts of the atmospheric CO₂ concentration on LD. The main reason for this is a lack of needed image data sets for LD analysis at the required spatial and temporal scales.

As in the case of scale dependency when mapping degraded areas, the factors that drive vegetation dynamics and degradation are also scale-dependent: for example, gross basal area of pasture is a slow variable at the household scale. At the same time, it is a fast variable at the national scale (Reynolds et al., 2011). Many important issues, therefore, arise from conflicts between scales and a lack of suitable multi-scale data sets needed for analysis, for example, when agricultural policies at national level do not allow for appropriate local management decisions.

**Conclusions and outlook**

LD is taking place in all agro-ecological zones and has long-lasting impacts on people and the environment. Despite the importance of the problem of LD and its acknowledgment at a global level, to date no consensus has been achieved on systematic and standardized approaches that can be utilized for its assessment and monitoring at different spatial scales. Furthermore, the absence of accurate up-to-date spatial information on the extent of LD as well as on its triggers forestalls implementation of land rehabilitation measures, which in turn threatens environmental sustainability and people’s livelihoods. The provision of spatially explicit information on degraded land and identification of the LD causes would make it possible to indicate areas for targeted mitigation efforts and to prioritize those in need of immediate policy attention at different spatial scales. Consequently, there is a pressing need to improve (rather than develop new approaches and methods) existing methods as well as to calibrate them using *in situ* data and to consolidate existing methods for derivation of the accessible and accurate measurements on the extent of degradation at multiple spatial scales to satisfy environmental and natural resource management, policy and research needs.

The herein presented paper has also pointed out the existing research needs. The concept of ecosystem services is adopted for LD definition in most of Remote Sensing studies. Accordingly, LD is measured as a “loss of ecosystem productivity” and uses vegetation cover and productivity loss over time as a proxy of LD. Degradation of valuable resources, such as biodiversity, may not necessarily result in productivity loss, while some LD manifestations such as bush encroachment, often result in gain of vegetation cover and productivity. Therefore, an accurate localized calibration of Remote Sensing-based information against field data including vegetation cover and productivity, soil fertility and soil compaction is an issue that should not be overlooked. Another important consideration refers to a difficulty to disentangle productivity changes attributable to proximate causes from those, which may have been caused by underlying causes of LD, such as policy decisions favoring one crop versus another, market access, technological change or shifts in import/export opportunities. Therefore, there is a need to link generated spatial information and a variety of environmental and socio-economic data in one integrative framework for comprehensive LD assessment. It is also important to continue long-term LD observations based on multi-scale image time series as well as harmonize the methodology for Remote Sensing-based LD assessments. The latter will be possible when medium to high spatial resolution data archives, such as from Landsat and Sentinel missions, will be available at required resolutions for all geographical areas in the world.

From a research perspective, the integrative mapping approaches comprising the synergetic use of multiple Remote Sensing perspectives and different types of observations could be one way forward in Remote Sensing-based LD assessment. This is not only important for mapping applications, but also for correctly attributing the factors of the changes for a better-informed decision-making. There is also a need for further integration of Remote Sensing-based approaches and data with the existing process-based LD models and socio-economic approaches for LD assessment in order to capture interdisciplinary nature of this phenomenon.

This paper also emphasized the importance of the multi-scale and cross-scale analyses based on multi-source Remote Sensing data sets to respond to the
needs of the potential users, and to fill the gap between the scales of environmental and socio-economic processes and the spatial and temporal resolution of satellite images. The inherent challenge of Remote Sensing-based multi-scale and cross-scale assessments refers to the mismatch between spatial and temporal resolution of currently available satellite imagery and other geospatial data sets, and the required scales for LD assessment along with fast and slow variables (with emphasis on the latter) that trigger these processes.

As outlook, currently we are facing an era of “big data” or the era of the “fourth paradigm” (Sellars et al., 2013) with more and more data available for research and applications, including data from new satellites placed in the orbit, comprehensive networks of ground measurements collecting meteorological data, ecological observatories, results of model simulations and forecasts amongst others. The important question arises, how to smartly deal with such big data sets with the purpose to manipulate and extract usable information from this overwhelming amount of image data and numerous other data sets, and how to produce useful information for science and society for different applications in general, and for LD assessments in particular.

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