

A New Era of Earth Observation for the Environment: Spatio-Temporal Monitoring Capabilities for Land Degradation 24

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#### Abstract

Land degradation can be defined as a persistent reduction or loss of the biological and economic productivity resulting from climatic variations and human activities. To quantify relevant surface changes with Earth observation sensors requires a rigorous definition of the observables and an understanding of their seasonal and inter-annual temporal dynamics as well as of the respective spatial characteristics. This chapter starts with brief overviews of suitable remote sensing sources and a short history of degradation mapping. Focus is on arising possibilities with the new European Sentinel satellite fleet, which ensures unprecedented spatial, spectral, and temporal monitoring capabilities. Synergistic retrieval of innovative degradation indices is illustrated with mapping examples from the SPACES II (Science Partnerships for the Adaptation/Adjustment to Complex Earth System Processes) SALDi (South Africa Land Degradation Monitor) and EMSAfrica projects plus South African contributions. Big data approaches require adapted exploration techniques and infrastructures—both aspects conclude this chapter.

# 24.1 Introduction

Land degradation (LD) is a global problem affecting approximately 70% of drylands with 73% of Africa's agricultural lands already degraded (DFFE 2018). The narrative of land degradation, its location and causes are evolving over time (Scholes

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2009; von Maltitz et al. 2019). From a government perspective, concerns such as soil erosion are being viewed as less important in the immediate time frame, compared to issues such as bush encroachment and the invasion of alien plants, which are becoming the most prominent current degradation concerns (von Maltitz et al. 2019; O'Connor et al. 2014). Since the middle of the twentieth century, the term land degradation in South Africa had been linked to veld and soil degradation and has been addressed by numerous measures (Hoffman and Todd 2000; Hoffman and Ashwell 2001).

Target 15.3 of the Sustainable Development Goals (SDG) aims to achieve Land Degradation Neutrality (LDN) worldwide by 2030. Three global indicators for assessing land degradation are suggested in the LDN Scientific Conceptual Framework: land cover (physical land cover class), land productivity (net primary productivity, NPP), and carbon stocks [soil organic carbon (SOC) stocks] (Orr et al. 2017; Cowie et al. 2018). The South African LDN target setting process during 2017/2018 showed that these global indicators are not appropriate to fully describe the nature, extent, and location of degradation in South Africa (von Maltitz et al. 2019, see also Chap. 3). Global satellite-based NPP time series, for example, indicate areas of negative trends that clearly differ from perception-based assessments of land degradation. Reasons might be that some degradation aspects such as bush encroachment and invasive alien species can result in increased plant cover and NPP; also, high inter-season variability of rainfall and its impact on plant productivity impedes identifying management-related land degradation (Wessels et al. 2012). Thus, it is rather suggested to locate land degradation hotspots and respective target intervention areas based on the results of the perception-based assessments such as the Land Degradation Assessment in Drylands (LADA) Project (Lindeque and Koegelenberg 2015), in combination with issue-specific maps, even though currently such maps are hardly available (von Maltitz et al. 2019).

Land degradation processes in South Africa are as complex as the country's ecosystems and are intricately linked to food security, poverty, urbanization, climate change, and biodiversity. Therefore, South African authors contribute their experience and emerging tools. The chapter starts with a brief overview of Earth observation (EO) sensors suitable for degradation monitoring, followed by historic and emerging EO strategies for the following six LD topics: vegetation development and cover change, woody cover trends, bush encroachment, invasive species, drought and soil moisture assessments, and overall degradation. A summarizing table to highlight the achievements and perspectives from the Copernicus programme and other international emerging technologies concludes the chapter. The SPACES II SALDi-project's methodological implementations are described for representative regions in Chap. 29.

# 24.2 Overview of Satellite Earth Observation Data Sources Suitable for Degradation Monitoring

Until the mid-2010s, the most common satellite datasets used for degradation mapping were time series of Moderate Resolution Imaging Spectroradiometer (MODIS)  $(250-500 \text{ m}^{-1} \text{ km})$ , Satellite Pour l'Observation de la Terre-VEGETATION (SPOT-VGT) (1 km), and Advanced Very High Resolution Radiometer (AVHRR) (1–8 km), as well as Landsat and aerial images which were usually not available in the form of time series but rather as mono- or irregular multi-temporal acquisitions. Even though important and highly valuable Earth-observation based analyses have been conducted based on these datasets, one major challenge remained: The relatively coarse spatial resolution of these time-series data and the irregular temporal availability of higher spatial resolution imagery resulted in general difficulties to assess degradation processes where small-scale landscape elements and patterns show distinct seasonal or multi-annual dynamic behaviour.



**Fig. 24.1** Overview of EO-satellites with potential for degradation assessment. Satellites are shown which allow time-series assessments at medium to high spatial resolution (<=300 m) and where data can (partly) be accessed free of charge

With the launch of the Copernicus Sentinel satellite fleet in 2015 freely available radar and since 2017 optical Earth observation data can be used (Aschbacher 2017), which fulfil the requirements of a reliable observation system as proposed by Main et al. (2016), e.g. Woody Cover mapping based on the data's high geometric (10 m and 20 m) and temporal (5–12 days) resolutions, plus the guarantee of decades of data consistency due to the commitment of the European Commission to the Copernicus Programme (Article 4(1) of Regulation (EU) No 377/2014). As can be seen in Fig. 24.1, the increasing availability of free Earth observation data during recent years introduces new challenges and opportunities in the development of synergistic approaches combining optical and microwave information, e.g. Sentinel-1/-2 and NASA's Landsat-8.

New lidar sensors, specifically NASA's Global Ecosystem Dynamics Investigation (GEDI), complement surface monitoring capabilities by adding a vertical component, thus making 3-dimensional monitoring of vegetation structure feasible. Figure 24.1 also illustrates the rich heritage of radar sensors in space, which are being continued and extended by an increasing number of space agencies. The Sentinel-1 fleet constitutes the break-through to operationalizing microwave remote sensing, known to deliver information about vegetation volume and soil moisture estimates. New hyperspectral sensors in space (the German EnMAP was launched on 1 April 2022) deliver a wealth of spectral signatures to support degradation monitoring as described, e.g., by Oldeland et al. (2010) or assembled by Cawse-Nicholson et al. (2021).

The need for analysis-ready data (ARD) in the optical and especially radar domain has been recognized and formerly complex information is increasingly easy to be used and applied (e.g. through companies such as SINERGISE and Google Earth Engine). Various processing tools are accessible without cost for large datasets (e.g. PyroSAR, SNAP).

# 24.3 History, Opportunities, and Challenges for Degradation Monitoring in South Africa

Von Maltitz et al. (2019) developed five major assessment goals for land degradation monitoring strategies: rangeland degradation, bush encroachment, degradation of croplands, vegetation cover change, and alien species. Accordingly, the SPACES II project SALDi defined a workflow to generate the necessary indicators by exploiting Sentinel-1 and -2 time series as well as additional products, e.g. rainfall estimates from rain gauge and satellite observations [i.e. Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)] (Fig. 24.2).

The following sections explain the retrieval of EO products with further contributions from South African authors leading to (1) vegetational development, (2) woody cover trends, (3) bush encroachment, (4) invasive species, (5) drought and soil moisture assessments, and (6) overall degradation, thus covering the degradation aspects exemplified in Sect. 24.1 and summarized in Sect. 24.5.



**Fig. 24.2** Workflow of deriving land degradation indicators from Sentinel-1 and Sentinel-2 time series with additional products to deliver maps of four major degradation aspects. How these maps contribute to von Maltitz's assessment goals is indicated by coloured asterisks

### 24.3.1 Vegetational Development

Degradation processes related to vegetation development and productivity have been analysed in different studies based on EO data. A common way is the multitemporal analysis of vegetation index data as derived from multispectral sensors which can measure aspects of ecosystem health and changes (e.g. Higginbottom and Symeonakis 2014; Wessels et al. 2004). Multi-annual analyses usually include the identification of trends and/or of abrupt changes in a given temporal behaviour. Up to the release of NASA's Landsat archive in 2008 and the computational advancements required to process it, the key optical sensor used for such analyses was AVHRR, due to its long temporal coverage and short repeat cycles, but also MODIS, SPOT-VGT, and Proba-V were used. These datasets allow for a large spatial and temporal coverage, but have clear limitations with respect to their spatial resolution of 250–1000 m. Early analyses though with 1 km AVHRR data from South Africa showed that Normalized Difference Vegetation Index (NDVI) growing season sums are in many cases lower than in non-degraded areas (Wessels et al. 2004). For Kruger National Park, these growing season sums were related to herbaceous biomass and its inter-annual variations, but sub-pixel heterogeneity of the coarse data as well as considerable scale differences to in situ data hindered the production of reliable biomass estimates (Wessels et al. 2006).

In South Africa, large portions of rangelands have seen extensive modifications from centuries of livestock farming (Hoffman and Ashwell 2001), alien plant species have invaded extensively in mountainous, riparian, and coastal regions (Van Wilgen and Wilson 2018), and natural fire regimes have seen major disruptions in grassy biomes and the Fynbos (Slingsby et al. 2020a, b). The ecological condition in these modified areas ranges from near natural to heavily modified depending

on the degree to which ecosystem structure, function, and composition have been altered. Unfortunately, mapping these degrees of degradation is not easy, because one is dealing with continuous variation in the degree of modification rather than relatively distinct classes. These difficulties have led to some distinction between land cover mapping and degradation mapping in southern Africa.

A critical aspect when interpreting temporal changes of remotely sensed vegetation development with regard to human-induced degradation in arid and semi-arid areas is considering the influence of precipitation on observed vegetation trends and changes. This is particularly relevant for those large areas where rainfall is both highly variable and significantly influences vegetation productivity. The effect of precipitation can, for example, be considered in multiple regression analyses (e.g. Wessels et al. 2007a) or by comparing trends in time series of vegetation data and climate variables (e.g. Niklaus et al. 2015). Further prominent approaches are RUE (Rain-Use Efficiency) or RESTREND (Residual Trends). Using 1 km AVHRR-NDVI data and modelled 8 km NPP data, Wessels et al. (2007b) found RESTREND being better suited than RUE for the assessment of degradation in South Africa. However, several years later, Wessels et al. (2012) conducted a detailed study on the sensitivity of AVHRR-based trend and RESTREND analyses for degradation assessment and found these methods not capable of indicating land degradation with 1 km resolution NDVI data for a north-eastern study region in South Africa. Higginbottom and Symeonakis (2020) analysed changes in NASA's Goddard Space Flight Center (NASA/GSFC) Global Inventory and Modelling Studies (GIMMS) NDVI and RUE time series for break points and trends using Breaks for Additive Season and Trend (BFAST). They concluded that in southern Africa, constant positive trends in RUE combined with varying trend types of NDVI may be indicative of shrub encroachment, but they likewise highlighted difficulties in correct interpretation of drivers and processes. High-resolution trend analyses for South Africa were conducted using a 30 m Landsat EVI (Enhanced Vegetation Index) time series (Venter et al. 2020). The authors revealed patterns of degradation (e.g. bush encroachment) and restoration for some landscapes and thus demonstrated the high potential of such trend analyses with higher spatial detail. But at the same time, they underlined that Landsat data scarcity in the 1980s is a potential source of error.

Many approaches to time series analysis were developed in economics, social sciences, and engineering, and later found their way into phenology and thus remote sensing. While most models in the aforementioned disciplines try to come up with a prediction, many applications in remote sensing look for times when a break and change in a cycle (breakpoints) has occurred. The basic assumption of many methods is the notion that time series can be decomposed into three components: a seasonal, trend, and residual component. For land degradation issues, it is the trend component that provides information on whether fluctuations or even changes in the seasonal component are associated with a long-term change, or are just a one-time event that settles back to the old cycle after a certain time. Such analyses can be performed using the BFAST (Breaks for Additive Season and Trend) algorithm (Verbesselt et al. 2010), a well-established method for characterizing break points



Fig. 24.3 BEAST-based breakpoint determination of Sentinel-2 NDVI time series. The area displayed is characterized by intensive forestry and located near the southern border of Kruger National Park. Left: Google Maps Overview. Centre: BEAST classification with year of major breakpoints. Right: Location map, white square indicating position of sub-scene

and associated trends. Considerations to reduce the computational effort led to the evaluation of a method capable of processing no-data values (reduction of preprocessing) and a faster determination of breakpoints using a different approach. For the map displayed in Fig. 24.3, the Bayesian ensemble algorithm of Zhao et al. (2019) called Bayesian Estimator of Abrupt change, Seasonality, and Trend (BEAST) was chosen to establish break points in a Sentinel-2 NDVI and Bare Soil Index (BSI) time series. Evaluation of the BEAST products show that the accuracy of the results varies with land cover type. Changes in forestry or fire scars are picked up as homogenous areas, whereas patterns over open grassland with shrubs are irregular. This kind of analysis also requires very good data preparation, because results are sensitive to outliers (e.g. undetected clouds) leading to negative spikes in time series, which might be mistaken for real events.

To evaluate Sentinel-1 time series to detect surface changes, irregularities in the radar backscatter and coherence time series were analysed. The processing procedure is based on the recurrence plot analysis (Marwan et al. 2007) followed by the detection of breakpoints using a Sobel filter. The aim is to identify regions where possible degradation processes take place, such as land-use changes susceptible for erosion (e.g. clearings for macadamia plantations), fallow farmland or shrub encroachment (compare Chap. 29 for slangbos mapping). The method for detecting breakpoints is initially based on a pixel-based smoothing procedure using a median filter over the period under investigation, here March 2015 to March 2020, followed by the identification of breakpoints in the time series using the Sobel filter. Figure 24.4 shows examples of Sentinel-1 breakpoint maps for the SALDi project regions Ehlanzeni and Sol Plaatje illustrating the detection of surface changes.

In addition to spatial and temporal resolution issues, several authors underlined, that degradation identified by EO-based vegetation products—even though corrected for rainfall influences—can likewise result from other processes. Southern Africa is comprised of largely open vegetation with low tree cover, often a high





fraction of bare soil and complex natural dynamics due to fire, rainfall sensitivity, and seasonality (Bond 2019). Local investigations and expert knowledge are thus an indispensable complement to EO time-series analyses for correctly distinguishing degradation from other processes (e.g. Wessels et al. 2007b; Prince et al. 2009).

Recently, Slingsby et al. (2020b) developed an approach that identifies degradation processes in the Fynbos biome of South Africa by identifying anomalies in observed MODIS NDVI relative to the expected NDVI produced by a hierarchical Bayesian time-series model. The model predicts the natural dynamics (postfire recovery rate, seasonality, maximum NDVI) based on abiotic environmental data (climate, soils, topography) and fire history, allowing identification of alien species invasions, drought or pathogen driven mortality, vegetation cover loss or fire. Their proof of concept including Landsat and high-resolution satellite data leading to an operational near-real-time change detection system for land managers and policy makers is being implemented as "Ecosystem Monitoring for Management Application" (http://emma.eco/). The same approach can be applied to other ecosystems if their natural dynamics can be suitably characterized with a time-series model. It is of great importance, that the dynamical features are based on factors such as fire and postfire recovery, a greater contribution of bare soil to observed vegetation indices, as well as high sensitivity to rainfall and a strong seasonality. This allows to monitor and detect abrupt or gradual changes in the state of an ecosystem in near-real time by identifying areas where the observed vegetation signal has deviated from the expected natural variation.

Moncrieff (2022) focusses on a different degradation process: the complex landscape changes of the Renosterveld. This is a hyperdiverse, critically endangered shrubland ecosystem in South Africa with less than 5–10% of its original extent remaining in small, highly fragmented patches. His work demonstrates that direct classification of satellite image time series using neural networks can accurately detect the transformation of Renosterveld within a few days of its occurrence, and that trained models are suitable for operational continuous monitoring if based on daily, high-resolution Planet satellite data. The convolutional neural network was applied to Sentinel 2 data and indices and resulted in correct identifications of up to 89% of land cover change events. There is thus a great potential for supervised approaches to continuous monitoring of habitat loss in ecosystems with complex natural dynamics.

#### 24.3.2 Woody Cover

Woody cover encroachment has increased throughout southern Africa, which led to substantial environmental, land cover as well as land-use changes (Eldridge et al. 2011; O'Connor et al. 2014; Stevens et al. 2016). Woody cover intensification in rangelands by slangbos (*Seriphium plumosum*), black wattle (*Acacia mearnsii*), etc., will result in enlarged pressure on open grassland areas, which become vulnerable to overgrazing thus increasing the potential of land degradation (Snyman 2012; Oelofse et al. 2016). In protected areas and national parks, the knowledge of woody plants abundance and change are essential information for park management and

conservation efforts. An intensification of woody plants will likely cause a reduction in grass and herbaceous biomass (Berger et al. 2019), which has direct influence on grazing animals, their territories, and migration as well as predators seeking herbivores (Munyati and Sinthumule 2016).

The high potential of combining multispectral and radar data for woody cover assessments has been illustrated in several studies. As an often-referenced example, Bucini et al. (2010) utilized Landsat Enhanced Thematic Mapper (ETM)+ (2000–2001) and radar data Japanese Earth Resources Satellite (JERS-1, 1995–1996) jointly with field measurements to map woody cover for Kruger National Park at 90 m spatial resolution. Skowno et al. (2017) combined Advanced Land Observing Satellite (ALOS) Phased Array L-band Synthetic Aperture Radar (PALSAR) data with national, Landsat-derived land cover maps to quantify changes in woodlands and grasslands of South Africa between 1990 and 2013.

Another example of synergistic radar/multispectral analyses is the work of Higginbottom et al. (2018) who predicted woody cover at 30-120 m spatial resolution for the South African province Limpopo by fusing Landsat Thematic Mapper (TM)/ETM+ and ALOS-PALSAR data and aerial imagery. Urban et al. (2020) generated a woody vegetation cover map at four different spatial resolutions (10 m, 30 m, 50 m, 100 m) for Kruger National Park based on Sentinel-1 data in combination with airborne lidar measurements. Holden et al. (2021) mapped invasive alien trees in the Boland mountains of the Fynbos biome, a key driver of biodiversity loss and run-off reduction in the region, at 10 m using a combination of Sentinel-1 and Sentinel-2 data. Multispectral time series from multiple resolution sensors were used, e.g., in a multi-scale analyses of woody vegetation cover in Namibian savannas by Gessner et al. (2013), including MODIS, Landsat, and very high-resolution satellite data. As woody cover is considered as an essential biodiversity variable (EBV) (Pettorelli et al. 2016), EO time series are key to develop wall-to-wall monitoring strategies (Urban et al. 2020). However, current remote sensing techniques are not likely to replace field measurements completely, as sustainable validation strategies for EO-derived woody vegetation composition with in situ data is still of very high importance (Kiker et al. 2014).

SALDI's woody cover retrieval for Kruger National Park used an airborne Light Detection and Ranging (LiDAR) strip from 2014 with a 2 m spatial resolution, made available through SANParks Scientific Services. These LIDAR data were converted to a woody cover percentage map with 10 m resolution to match Sentinel-1 and -2 pixel sizes and were then used in a random forest, machine learning (RF-ML) approach as training input. The resulting map products are shown in Figs. 24.5 and 24.6, illustrating the advantage of joint radar-optical analyses and additionally—with the new Copernicus satellites—achieving at the same time greatly improved spatio-temporal resolutions. In order to compare different sites in the future and over time, a uniform training data set is necessary, as now being available with NASA's Global Ecosystem Dynamics Investigation Lidar (GEDI), launched in 2018. This latter procedure has been applied to map woody cover changes illustrated in Fig. 24.7.

The woody cover estimates based on Sentinel-1 (radar) and Sentinel-2 (optical) data show generally similar patterns and overall agreement in Fig. 24.5. The radar



**Fig. 24.5** Woody cover for the southern Kruger National Park region derived from a single airborne Lidar strip (small stripe in centre) and (upper map) Sentinel-1 time series 2016–2019 and (lower map) Sentinel-2 time series 2016–2017. The two products show complementarities and thus the need for radar-optical synergy. Waterbodies, built-up areas, and cultivated areas were masked using the National Land Cover 2017/2018 product (LRI 2018)



**Fig. 24.6** Detailed view of Sentinel-1 vs. -2 woody cover estimates (green maps on left) and very high-resolution images (Google Earth Pro [GU1]) for the red-framed subset in Fig. 24.5, exemplifying advantages and disadvantages of either method. See text for further information



**Fig. 24.7** Deriving woody cover change between 2016 and 2019 of the southern Kruger National Park and surrounding areas using Copernicus Sentinel-1 data and NASA's GEDI LiDAR at 50 m spatial resolution. Left side: box 1—woody cover decline due to harvested forest plantations, subimages: Google Earth (Maxar Technologies), right side: box 2—woody cover regrowth after fire, subimages: NASA Landsat-8, RGB = Bands 5-4-3 (EO Browser/Sinergise Ltd.)

product, though, exhibits more contrast between areas of high and low woody cover in flat terrain, but is still more affected by topography despite radiometric corrections. This finding is exemplified in Fig. 24.6: Sentinel-1 shows more contrast in flat areas, where areas of high and low woody cover are better discernable than in the optical dataset (framed box on the right). Sentinel-2 better detects

differences in mountainous areas (framed box on the left). Here, the Sentinel-1 map contains uniformly high woody cover, whereas in reality denser woody coverages are only found on slopes oriented towards west and south. This spatial pattern is well represented in the Sentinel-2-derived map. This example underlines the high synergistic potential of using optical and radar sensors jointly for taking advantage of the respective strengths of each EO method.

When looking at change, it is feasible to explore either radar or optical products to not merge error sources and to rather cross-compare each change map to distinguish between consistent change areas and sensor-specific detections. Figure 24.7 illustrates a Sentinel-1 SALDi change product.

# 24.3.3 Bush Encroachment

There have been a number of studies on bush encroachment in southern Africa based on Earth observation data. Aerial images have been employed for mapping bush encroachment in several projects (e.g. Hudak and Wessman 1998, 2001; Stevens et al. 2016; Ward et al. 2014; Wigley et al. 2010), sometimes also in combination with very high-resolution (<2 m) satellite data (e.g. Shekede et al. 2015). These datasets have the advantage of allowing detection of individual bushes (compare also Sect. 24.3.7), and aerial images often date back to decades where space-borne EO data were not available yet. At the same time, their analysis is hindered by the enormous efforts for data pre-processing and because quantitative inter-image comparisons are hardly possible or extremely time-consuming for large areas due to missing radiometric comparability (Hudak and Wessman 2001). Furthermore, the low temporal frequency of multiple years between airborne campaigns does not allow the needed temporal monitoring of bush encroachment processes.

With respect to multispectral remote sensing analyses at spatial resolutions of 30 m or less, usually selected radiometrically optimal acquisitions were analysed prior to the availability of dense satellite time series such as now being recorded by the two Copernicus Sentinel-2 satellites A and B since 2016 resp. 2018. Earlier examples are studies using SPOT (e.g. Munyati et al. 2011) and Landsat (e.g. Symeonakis and Higginbottom 2014; Ng et al. 2016) to identify spreading bush areas or for mapping the distribution of encroaching bush species in southern Africa. Cho and Ramoelo (2019) have developed a methodology for detecting increasing tree and bush cover in the grassland and savanna biomes of South Africa using MODIS data despite its coarser geometric resolution. The methodology is based on asynchronous NDVI phenologies of grasses and trees in these semi-arid systems. Using a 16-day NDVI time series generated from MODIS NDVI data between 2001 and 2018, the authors first determined the best time for mapping tree cover in the region, which turned out to be a narrow period from Julian day 161-177 (June 10-26). This is the period of maximum contrast between grasses and trees. Eight tree-cover maps (2001–2018) were generated using linear regression models derived from Julian day 161 for each year.

In rarer cases, radar satellite data were applied: Main et al. (2016) combined time series of the European Space Agency's (ESA's) Envisat Advanced Synthetic

Aperture Radar (ASAR) and airborne LiDAR data for 2006–2009 to analyse woody cover in Kruger National Park and surrounding areas with a spatial resolution of 75 m, Urban et al. (2021) synergistically combined Sentinel-1 radar and optical Sentinel-2 time-series data to monitor slangbos encroachment, a woody shrub, on arable land (see Chap. 29).

## 24.3.4 Invasive Species (Acacia mearnsii)

The invasion of productive lands by alien plants is an important contribution to land degradation. Large monocultures of alien species have a negative impact on water resources, pasture and crop production and biodiversity. This is the case with Black Wattle, Acacia mearnsii, a prominent invasive alien species in South Africa. Remote sensing of invasive species is mainly aimed at mapping the extent of the invasion, quantifying their biomass, and highlighting invasion hotspots. Masemola et al. (2019, 2020a, b) conducted numerous studies to: (1) explore the utility of hyperspectral data to discriminate A. mearnsii from native species, (2) determine the optimal period to spectrally distinguish A. mearnsii from native plants, (3) determine if vegetation indices related to the unique biological traits of A. mearnsii have the potential to distinguish it from native species, (4) assess the potential of multispectral Sentinel-2 data to map the distribution at the landscape level, and (5) explore the applicability of radiative transfer model (RTM) simulations to characterize the differences between A. mearnsii and native species. Through this multi-step approach, Acacia mearnsii could be distinguished from native species with overall accuracies ranging from 75% to 90%.

# 24.3.5 Drought and Soil Moisture

Southern African biomes are particularly prone to drought because more than 65% of the area is semi-arid and thus environmental conditions alternate strongly in space and time. Monitoring and spatio-temporal assessment of drought impacts is a challenge due to a limited number of weather stations. In addition, drought monitoring is difficult, since effects can accumulate over time. Droughts have major impact on ecosystems, such as fire severity (Mukheibir and Ziervogel 2007), biodiversity and ecosystem functioning (Masih et al. 2014; Graw et al. 2017), and economy, e.g. food production (Verschuur et al. 2021). Therefore, analysing surface moisture dynamics is of high importance, as it is also highly correlated to vegetation and soil respiration, which represents both root and microbial respiration, and is one of the main ecosystem fluxes of carbon (Makhado and Scholes 2011).

Various studies focus on the development of drought monitoring concepts using EO data from different sources (AghaKouchak et al. 2015) and for different applications—agriculture (Bijaber et al. 2018; Zeng et al. 2014; Winkler et al. 2017), grasslands (He et al. 2015; Villarreal et al. 2016), savanna ecosystems (Graw et al. 2017; Western et al. 2015). The majority of these applications utilized optical information with coarse spatial resolution (MODIS and AVHRR). Surface moisture

parameters and drought conditions were analysed using different ratios, e.g. NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), VCI (Vegetation Condition Index) as well as SPI (Standard Precipitation Index) (Graw et al. 2017).

Marumbwa et al. (2019, 2020, 2021) conducted several studies to assess the impact of meteorological drought on southern African biomes. To achieve this objective, the authors first analysed spatio-temporal rainfall trends to establish trends at pixel-level and then assessed drought impact on biomes using VCI products. Further, they analysed drought and land cover interactions using land cover data and a novel land cover "village pixel" developed from livestock density data as a proxy for the type of rural community. Based on the 2015–2016 season analysis, the Kruskal–Wallis test showed significant difference in drought impact (mean VCI) among different land cover types. This study provided information to adapt usage to different ecosystems to enable communities to better cope with droughts.

Recent microwave satellite missions for operational soil moisture retrieval are ESA's SMOS (Soil Moisture and Ocean Salinity) and NASA's SMAP (Soil Moisture Active Passive) sensors, which utilize L-Band passive radar data to estimate global soil moisture with coarse spatial resolution (10-25 km) (Entekhabi et al. 2010; Kerr et al. 2012). The most recent global dataset is ESA's Climate Change Initiative (ESA-CCI) soil moisture product at 25 km pixel spacing (Dorigo et al. 2017), for which Khosa et al. (2020) found a correlation greater than 0.6 with in situ measurements for two sites in Kruger National Park. Soil moisture applications with higher spatial resolution have been carried out since the launches of ESA's radar sensors on-board the European Remote Sensing (ERS-1/-2) satellites (e.g. Bourgeau-Chavez et al. 2007; Haider et al. 2004) and ENVISAT ASAR (e.g. Paloscia et al. 2008; Zribi et al. 2005), Canada's commercial RADARSAT (e.g. Glenn and Carr 2004; Leconte et al. 2004), and are continued with the recent Copernicus Sentinel-1 data (e.g. Alexakis et al. 2017; Lievens et al. 2017). The potential of a synergetic combination of Sentinel-1 and Sentinel-2 has been addressed by only a few studies so far (e.g. Gangat et al. 2020; Gao et al. 2017; Urban et al. 2018), indicating that the high repetition rates of the Sentinel-scenes offer good determination rates for surface moisture estimates.

The open SPACES II SALDi-project data cube offers—amongst many other data sets and products (see Chap. 29)—analysis-ready Sentinel-1 radar time series, which allow application of multi-temporal change detection methods for surface moisture retrieval. A sample sequence of six such surface moisture maps derived for December 2020 are shown in Fig. 24.8. The maps begin with dry surface conditions indicated by reddish tones. After December 14, surface moisture generally increases, as indicated by yellow to blue tones. These model results illustrate the heterogeneity of surface conditions (vegetation structure, soil features) and precipitation effects over time and space. The model is briefly explained in Chap. 29.

To validate Sentinel-1 radar-retrieved products, it is essential to consider type and status of vegetation and relate to moisture conditions either through information about precipitation or in situ soil moisture measurements. Therefore, the SALDi-



**Fig. 24.8** Relative surface moisture derived from Copernicus Sentinel-1 radar data for December 2020 for the south-east corner of Kruger National Park (KNP) (black line indicates park-border). The Surface Moisture Index is sensitive to water content of vegetation and the underlying soil surface. It therefore highlights structural differences (e.g. fire scars with in KNP), land-use practices (agricultural patterns in southern territories), and effects of precipitation. The cross indicates the location of SALDi's surface moisture in situ instrument. Times are in UCT

project deployed one SMT100 Time Domain Transmission instrument, which measures volumetric soil moisture, in each of the six project areas. At each site, a total of eight sensors take continuously every 5 min measurements in a depth of 6–10 cm. Figure 24.9 gives geographic information and illustrates the harsh surface conditions.

Figure 24.10 illustrates the temporal behaviour of Sentinel-2 NDVI and the two complex retrievals ESA CCI Soil Moisture and SALDi Sentinel-1 Surface Moisture (SurfMi) product. Precipitation data combined with local knowledge and in situ soil moisture is the key for interpretation: the NDVI-lag in October and November 2020 was caused by a severe fire; thus the smooth surface (see photo in Fig. 24.9) results in specular scattering of the Sentinel-1 signals, keeping SurfMi to Zero (except during rain) although the in situ moisture is increasing. These important insights are needed for a synergistic savanna monitoring tool to map simultaneously vegetation status, realistic surface moisture conditions and even time and location of local precipitation events.



**Fig. 24.9** Left: Map of SALDi's project area Ehlanzeni stretching  $100 \times 100 \text{ km}^2$  south from Skukuza and west from Komatipoort. Green line: southern border of Kruger National Park, black cross: location of SALDi's soil moisture instrument near Lower Sabie. Instrument site after flooding in February 2022 (upper right) and fire in September 2020 (lower right) (Photographs: Tercia Strydom, KNP)

# 24.3.6 Nation-Wide Assessments

The first national survey, conducted by Hoffman et al. (1999) and based on expert interviews at the district level, concluded that about 26% of the surface of South Africa was heavily degraded (own calculations). Fairbanks et al. (2000) calculated on the basis of Landsat satellite images for the years 1994 to 1996, that 80% of the country is covered by "natural" tree and grassland vegetation and only 20% were transformed by humans. Using a similar approach, Schoeman et al. (2013) identified for the year 2005, 16% as being transformed and corrected the value for the year 1994 to 14.5%. For the period from 1981 to 2003, Bai and Dent (2007) identified a degradation process for nearly 30% of the country using NASA/GSFC GIMMS NDVI remote sensing time series.

The first national-scale, remote-sensing based land cover map was produced in the late 1990s using 1994–1995 Landsat 5 data (Fairbanks et al. 2000). Thirty-one classes were mapped manually on hardcopy space maps at approximately 1:250,000 scale. In the early 2000s, a semi-automated land cover classification was produced using Landsat 5/7 imagery based on 2000–2001 data (van den Berg et al. 2008). Both datasets were widely used in research and conservation planning. In 2013, the national government began a programme to regularly produce national-scale land cover maps using a standardized classification scheme.





The company GeoTerra Image, on behalf of the national government, produced a 1990 national land cover map retrospectively (using Landsat 5 data) and a 2014 national land cover map (using 2013-2014 Landsat 8 data) (GeoTerraImage 2015). A process then began to automate the production of a national land cover and bring the capacity to undertake the work into the government (Department of Forestry Fisheries and the Environment). The new system, referred to as the Computer Aided Land Cover (CALC) uses Sentinel-2 data and the same nationally accepted classification scheme as the 2013 map. A 2018 and 2020 CALC based national land cover product has been produced subsequently (available at https:// egis.environment.gov.za/). These land cover maps have allowed for more robust time series analysis of land cover change (Musetsho et al. 2021) and habitat loss (Skowno et al. 2021). Skowno et al. (2021) estimated that 22% of South Africa has been transformed by humans, and 78% is natural or degraded. Natural and degraded areas could not be reliably separated using the NLC 2018 methods. The uncertainties are thus still large due to a missing systematic definition of the term land degradation considering land cover categories and validated assessment.

## 24.3.7 Integrated Modelling

The ARC developed a Land Degradation Index (LDI) to guide the SA government with setting up priorities for remedial action (DEA 2016). This index was generated by exploiting Landsat time-series and integrating water erosion, wind erosion, aridity index, salinity, and soil pH data. The findings showed that: (a) most parts of the country experiences low to moderate degradation, whereas large parts of Northern Cape, Western Cape, Eastern Cape, and North West province experience high degradation levels; (b) parts of Northern Cape experience very high degradation of which the drivers are wind erosion and soil pH; (c) areas of severe degradation and desertification correspond closely with the distribution of communal rangelands, specifically in the steeply sloping environments adjacent to the escarpment in Limpopo, KwaZulu-Natal, and the Eastern Cape provinces (DFFE 2018).

In a case study of the Greater Sekhukhune Municipality, Limpopo Province, Nzuza et al. (2020) focused on various mechanisms to assess and map land degradation using in situ, ancillary, and remote sensing data. The first component was the use of an integrated modelling approach that combines environmental and remote sensing variables (Sentinel-2 bands and vegetation indices) through machine learning techniques. Leaf Area Index (LAI), Soil Adjusted Vegetation Index (SAVI), Normalized Difference Vegetation Index (NDVI), and rainfall were significant variables to predict potential land degradation risk, explaining over 80% of the variation.

The second component (Nzuza et al. 2021) was to evaluate a triangulation approach consisting of remote sensing products, Sustainable Land Management (SLM) practices [using the World Overview Conservation Approaches and Technology (WOCAT) mapping questionnaire (Gonzalez-Roglich et al. 2019)], and a participatory expert assessment. The climatic variability, overgrazing, poor governance, and unsustainable land management practices were cited as major causes of land degradation. Perceived types of land degradation were soil erosion and loss of vegetation cover. The study demonstrated that complementary information from various sources is crucial for monitoring and assessing land degradation (see Fig. 24.11).

# 24.3.8 High-Resolution Validation

Land degradation monitoring relies on precise in situ information. Reference data to be used to estimate parameters linked to degradation status need to follow specific requirements in terms of temporal and spatial precision. In order to map the extent of, e.g., erosion patterns or woody plants, greater spatial resolution is essential. Here, a product is presented, that has been generated in the context of the SPACES II Ecosystem Management Support for Climate Change in Southern Africa (EMSAfrica)-project to support research and management in SANParks' Kruger National Park and serves as a reference data set for validation of EOretrieved surface products (Heckel et al. 2021). The necessary aerial imagery is freely available from the archives of the Chief Directorate, National Geospatial Information (CDNGI), Department of Agriculture, Land Reform and Rural Development (DALRRD). The derivation of the surface models was accomplished by (a) metadata preparation (definition of flight parameters and input of camera specific information), (b) ingestion of data to the bulk processor, (c) selection of tie points (epipolar pairing of stereoscopic imagery), (d) semi-global matching to derive the Digital Surface Model (DSM), (e) surface height removal to retrieve the Digital Terrain Model (DTM), and (f) orthorectification of the initial aerial imagery using the derived DSM. Processing of the extensive data set was carried out using the CATALYST Enterprise software environment. The data sets were modelled with a ground sampling distance of 0.25 m, 1 m, and 5 m and tiled according to CDNGI standards. Free download of the wall-to-wall terrain data coverage (large map in centre of Fig. 24.12) is possible through the Centre for Environmental Data Analysis (CEDA) platform of the British National Centre for Atmospheric Science. For challenges and limitations, see Table 24.1.



**Fig. 24.11** Spatial distribution of land degradation severity based on (**a**) a remote sensing derived map, (**b**) participatory assessment workshop, and (**c**) triangulation approach severity map (Nzuza et al. 2021). Map **c** illustrates how observations and social aspects diversify degradation classification and thus remedial needs



**Fig. 24.12** Centre: First wall-to-wall, 25 cm posting terrain model of Kruger National Park. Numbers indicate the locations of the four subsets 1 (upper left), 2 (lower left), 3 (upper right), 4 (lower right). Each subset contains the orthomosaicked airphotos (top), digital surface model (middle), and digital terrain model (bottom). The subsets illustrate the great detail of cover types and subtle topographies: single trees and larger bushes can clearly be recognized, dry riverbeds and channels are reconstructed including run-off features (Background data: Environmental Systems Research Institute (ESRI), Maxar, GeoEye, Earthstar Geographics, Centre National d'Etudes Spatiales (CNES)/Airbus Defence and Space, United States Department of Agriculture (USDA), United States Geological Survey (USGS), AeroGRID, Institut Geographique National, and the Geo-Information Systems user community)

Table 24.1 Sur	mmary of this chapter findings for new sp	atio-temporal EO monitoring capabilities for land de	gradation in southern Africa
Observable	Key achievements	Key constraints	Emerging technologies
Vegetation development	Increasingly improved spatial and temporal resolution Easy to access data cubes with analysis-ready data Multiple time series techniques and available RESTREND, RUE	Length of available time series Poor compatibility between different sensors Inter-seasonal differences greater than between area differences Overarching effect of rainfall—Stronger signal than the degradation signal CO2 fertilization effect vs. degradation effects Missing in situ information (phenological observations, weather stations, soil moisture, etc.)	Exploitation of full spatio-temporal radar-optical synergies Hybrid modelling techniques merging physical understanding with machine learning approaches Citizen science support
Woody cover trends	Well mapped for expansion of woody plants into grassland Constantly improving woody cover products	High range of uncertainty Possible interference from rainfall effects Radar expertise missing	New spaceborne LiDAR data availability Upcoming radar EO systems (e.g. NASA/ISRO) with longer wavelengths (L- and P-band) and polarimetric capabilities
Bush encroachment	Aerial images, sometimes in combination with very high-resolution satellite imagery, allow discrimination of individual bushes	Enormous efforts for data pre-processing, extremely time-consuming and lack of radiometric comparability Low temporal frequency of aerial imagery, often only available for smaller areas	Upcoming constellations of hundreds of smallsats (miniaturized satellites under 1200 kg) allowing daily coverages at high spatial resolutions around 2–5 m Operational processing opportunities with cloud-based, bulk processing
Invasive species	Reliable discrimination from native species	Mapping accuracy—Spatially, i.e. minimum mapping areas, and thematically, i.e. needs very good spectral library	Hyperspectral data: increasing airborne and drone availabilities and EnMAP satellite—launched April 2022 Radiative transfer model simulations

Drought and soil moisture estimates	Different states of surface moisture can be mapped over large areas at medium spatial resolutions several times per month, additionally provision of uncertainty flags for the user	Influence of vegetation on the ground (do we map moisture of the surface or the canopy) Only relative measurements More in situ references needed Radar expertise missing	Synergistic use of active/passive microwave data plus optical data to better constrain radar products Big data—If all governing parameters can be sampled and included in modelling Fully polarimetric L-band sensors allow better differentiation of backscattering mechanisms (NASA's and the Indian Space Research Organisation's (ISRO) Synthetic Aperture Radar NISAR)
Overall degradation	Development of nation-wide indices Availability of EO data and products Spatial methods (online) courses	Many degradation processes give false positives or negatives Degradation is a multi-phased problem Conflating degradation potential and actual degradation	Nation-wide coordinative actions of process understanding (e.g. Expanded Freshwater and Terrestrial Environmental Observation Network EFTEON) and SANSA's digital earth South Africa (DESA) initiative

# 24.4 Big Data Challenges and Insight into SALDi Process Flow

Remote sensing data as provided by various satellites has proven as a useful tool to monitor the environment and its changing land use and cover through time (e.g. Wulder et al. 2008). It provides the potential of a synoptic view of an explicit spatial extent.

Since the launch of the Sentinel-1 and Sentinel-2 satellites in 2015, the temporal and spatial resolution of freely and open available earth observation data has significantly increased (Gómez et al. 2016). The volume of data is quickly growing especially in the earth observation domain. Multiple scientific projects have produced an exorbitant amount of data in recent years. In the era of big data, information retrieval is increasingly gaining importance. There is an emerging need for developing tools that are able to face the challenge of big data. The methods are expected to be precise and tolerant to noise. The results are expected to be interpretable in order to provide a better understanding of data structures (Giuliani et al. 2019).

One of the areas of research in which great progress has been made in recent years to address the aforementioned big data challenges are earth observation data cubes. Earth Observation Data Cubes (EODC) are known as a promising solution to efficiently and effectively handle big Earth Observation (EO) data generated by satellites and made freely and openly available from different data repositories (Giuliani et al. 2019). So far various EODC implementations throughout the globe are currently operational: (1) Digital Earth Africa and Digital Earth Australia (Dhu et al. 2017), (2) the Swiss Data Cube (Giuliani et al. 2017a, b), (3) the EarthServer (Baumann et al. 2016), (4) the E-sensing platform (Camara et al. 2017), (5) the Copernicus Data and Information Access Services (DIAS) (European Commission 2018), or (6) the Google Earth Engine (Gorelick et al. 2017). These initiatives are paving the way for broadening the use of EO data to larger communities of users, thereby supporting decision-makers with timely information converted into meaningful geophysical variables and ultimately unlocking the information power of EO data (Giuliani et al. 2019).

## 24.4.1 General Big Data Situation

Since the start of continuous satellite observations in 1972, EO data exceeded the petabyte-scale and has been made available to a broad audience by increasingly open access options from different platforms. Big data analysis challenges besides data storage include searching for the data, downloading it, data pre-processing, conducting data analysis, and finally decision-making based on the data analysis. Nevertheless, the full potential of EO data is still not exploited due to the lack of (1) scientific knowledge, (2) difficult to access, (3) lack of expertise, (4) particular structure, and the (5) effort and storage costs. As Laney stated (2001), in the future, there will be no greater barrier to effective data management than the

variety of incompatible data formats, non-aligned data structures, and inconsistent data semantics. Surely, one of the most demanding aspects is the need to develop cross and multidisciplinary applications and integrating heterogeneous data sources (Nativi et al. 2015). Therefore, the *big five* of the big data challenges could be named as (1) volume, (2) variety, (3) velocity, (4) veracity, value, and validity as well as (5) visualization. To address these challenges within the SALDi project, the SALDi data cube was established. Digital Earth Africa and Digital Earth South Africa were established by national entities to address the above challenges on a national level.

# 24.4.2 Necessary Big Data Exploration Methodologies

Conventional technologies in the EO context have limited storage capacity, rigid management tools and are cost expensive. Besides, they often lack scalability, flexibility, and performance which are urgently needed in the context of big data. Therefore, big data management requires new methods and powerful technologies. Local processing of big data will be limited due to the steadily growing amount of data. The solution to overcome these problems is cloud computing, especially in terms of data processing and usage. It can provide the possibility to make large volume of EO data available to a wide range of users, as it provides an environment which is designed for easy EO data handling and visualizing without a need of downloading and pre-processing them beforehand, but with a strong focus on data analyses and decision-making based on large spatio-temporal datasets in an analysis-ready format.

This is especially handy when it comes to time series analysis. As remote sensing satellites revisit a given location on the earth's surface in regular time steps, image sequences of the same areas over time are generated (Ferreira et al. 2020). Time series derived from these sequences can be utilized for analysing land cover change and soil degradation.

To simplify the workflow of time series analysis which have been derived from satellite images, analysis-ready data (ARD) can be produced and organized in multidimensional earth observation data cubes (EODC). ARD can be defined as "satellite data processed to a minimum set of requirements and organized into a form that allows immediate analysis with a minimum of additional user effort and interoperability both through time and with other data sets" (Siqueira et al. 2019). Thus, ARD implicates processing satellite imagery from data acquisition to radiometric calibration, and through additional conversions, to top-of-atmosphere (TOA) reflectance, and finally surface reflectance (Giuliani et al. 2017a, b).

The term data cube refers to a set of image time series associated with spatially aligned pixels (Appel and Pebesma 2019). Each element of an Earth observation (EO) data cube has two spatial dimensions and one temporal dimension, and is associated with a set of values (Giuliani et al. 2019). The SALDi data cube from optical and radar satellite data includes all necessary pre-processing steps and is generated to monitor vegetation dynamics of 5 years for six focus areas within South Africa. Intra- and inter-annual variability in both, a high spatial and

temporal resolution will be accounted for to monitor land degradation. Therefore, spatial high-resolution Earth observation data from 2016 to 2021 from Sentinel-1 (C-Band radar) and Sentinel-2 (optical) are integrated in the SALDi data cube. Additionally, a number of vegetation indices as well as the Bare Soil Index (BSI) are implemented to account for explicit land degradation and vegetation monitoring. A national land cover classification (South African Department of Forestry, Fisheries and Environment) with 72 various land cover classes as well as a digital elevation model in a spatial resolution of 30 m (based on Copernicus DEM with global 30 m resolution (GLO-30) is available. Thus, the SALDi data cube builds a platform which can be utilized for an efficient data analysis of various multi-temporal land surface products (cf. Fig. 24.13).

All current developments in the context of big (EO) data would not have been possible without Free and Open Data policies to facilitate access to data and open source code to efficiently develop software solutions (Ferrari et al. 2018). Open Science is not only a new approach to research but also to educational processes, which seeks to make scientific research more collaborative and transparent. It makes knowledge accessible by using digital technologies and new collaborative tools (European Commission 2016). The open data practice enables scientific research to be reused, redistributed, and reproducible.

# 24.4.3 Available Infrastructures

To ensure the long-lasting availability and permanent access to EO data and results including the ability to continuously develop and adapt data processing chains a so-called EO-Data-Repository was established for the six research sites within the SALDi project. It allows flexible data management and furthermore provides an analysis environment for earth observation data. Through an interactive user interface all partners are empowered to actively participate in data handling.

Therefore, an Earth Observation Data Cube (ODC) was set up for the six research sites within the SALDi project (SALDi data cube). It allows the handling of large data amounts from various data sources and different data types. The SALDi data cube is used for data download, storage, and pre-processing of the Sentinel-1 and Sentinel-2 satellite data which can be used for further remote sensing products and methods. The users can access the data cube through an interactive user interface. The SALDi data cube serves as a central infrastructure for geospatial data and thus forms the interface between remote sensing data-based data provision and method development.

The added value of the SALDi data cube is making earth observation data easily accessible to end-users who do not have in-depth expertise in the evaluation of remote sensing data. The data cube considerably simplifies the access and use of satellite data, since complex and time-consuming steps such as (1) the download, (2) the storage, and (3) the pre-processing are already implemented in the SALDi



Fig. 24.13 The SALDi data cube is a platform for an efficient and user-oriented analysis of land surface dynamics based on multi-temporal earth-observation data and products



Fig. 24.14 Simplified basic remote sensing workflow. The SALDi data cube is capable of easing this workflow by automating the first three to four processing steps

data cube<sup>1</sup> and the user (via an interactive user interface) has direct access to gridded data sets ready for analysis and decision-making (Fig. 24.14).

# 24.4.4 Digital Earth Africa

There are various initiatives in Africa and South Africa that have been established. The Digital Earth Platform provides access to near real-time analysis-ready medium- to high-resolution data and products for various applications derived from the USGS datasets such as Landsat and Copernicus Sentinel-1 and -2 for the entire African continent. The production of analysis-ready data (ARD) derived from Sentinel-1 is currently underway. The South African National Space Agency hosts the programme management office (PMO) for Digital Earth Africa. The PMO will ensure that various users in the continent have access to earth observation data and products that address their needs.

The development of the Digital Earth South Africa (DESA) platform is a collaboration between South African National Space Agency (SANSA) and the South African Radio Astronomy Observatory (SARAO). DESA will provide users with access to very high-resolution analysis-ready data (ARD) and products derived from Satellite Pour l'Observation de la Terre (SPOT) 1–7. It will also provide a common and consistent platform for data and product access, and sharing which will enable users to focus on application-driven algorithms. This reduces the burden of downloading and pre-processing data for the end-users. The ARD is developed according to Committee on Earth Observation Satellites (CEOS) definition. DESA uses the Open Data Cube architecture and utilizes a variety of open source tools such as the Jupyter Notebooks, Python libraries, Open Data Cube Stats, PostgreSQL database, Open Data Cube Explorer, Command Line Tools, and Open Geospatial

<sup>&</sup>lt;sup>1</sup> https://datacube.remote-sensing.org/projects/saldi/.



Fig. 24.15 Overview of the Digital Earth South Africa Platform

Consortium (OGC) web services (Mhangara and Mapurisa 2019). The tools allow users to access and analyse big datasets and products in a cloud environment. The overview of the DESA platform is shown in Fig. 24.15.

### 24.4.5 International Cooperation and Knowledge Exchange

Regional-scale data cubes like the SALDI data cube and the data within this cube are easier to handle—compared to conventional earth observation data—especially for those users who are not explicit remote sensing specialists. To ensure both, a successful international cooperation and efficient knowledge exchange, it is essential that data and processes within the data cube are consistent and well documented.

In addition, to realize the full potential of the ODC products to address local and regional decision-making and policies, it is important to increase research and gather in situ ground data for proper algorithm and product validation. Over time, it is expected that open data products will increase, their accuracy will improve, and data access and usage will become easier and more efficient for everyone.

# 24.5 Moving Forward

Land degradation, as defined by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) Global Assessment of Land Degradation and Restoration (2018) includes both habitat loss and varying degrees of decline or loss of biodiversity and ecosystem function and services, thus encompassing the full range of ecological conditions. Degradation is slight to severe modification of natural ecosystems due to factors like overgrazing, erosion, inappropriate fire regimes, invasive species, etc., but some vestige of the natural ecosystem remains (see also Chap. 3). Hence, EO monitoring tools have to suit very heterogeneous thematic, spatial, and temporal requirements. A single sensor, a single methodology, a "mono"-approach will not suffice. This chapter gave an insight of what can be achieved with state-of-the-art procedures based on the new wealth of space- and airborne observational data. It has to be acknowledged, however, that we are only at the start of data exploration and what we can learn about spatio-temporal dynamics of our precious land surfaces. Table 24.1 is an attempt to summarize achievements, constraints, and emerging technologies as a quick reference for further scientific and programmatic actions.

Figure 24.2 depicts which optical and radar EO products can lead to surface parameters aiding in degradation monitoring. This chapter contains a selection of derivables, such as woody cover and surface moisture, to support monitoring. But the examples also illustrate limitations, if only one data set or one approach is applied or if in situ data is missing. The presented key EO indicators, which are treated as correspondent to relevant degradation processes, consist of poorly validated surface products with respect to savanna vegetation state, structure, dynamics, and surface moisture conditions. They are, e.g., called "woody cover", but they strictly rather represent a "spectral product", not an "information product" (analogue to unsupervised and supervised classification). The most promising methods therefore are based on a better physical understanding of spectral responses, thus enabling a knowledge-based interpretation of annual and inter-annual variations. Understanding spatio-temporal patterns lead to meaningful machine learning (ML) approaches—or vice versa, ML-retrieved results can then be associated with either experience or with discoveries. Having the Copernicus Sentinel-fleet and Landsat time-series for the future decade(s) available and thus an unprecedented wealth of spectral and spatial data sets, multi-temporal characteristics on the pixel-level (statistics, trends, break points, etc.) are assets, which still need to be associated with relevant surface features. Possibly, a new product nomenclature can be drafted, which is closer to spectral characteristics, including radar, and thus to the true nature of EO observations; e.g. radar water clouds and their relevance for structural changes, spectral indices and their significance for pixel-unmixing strategies for complex savanna biomes.

To accomplish break-throughs in the exploitation of EO big data sets, it needs the respective technical infrastructure as described in Sect. 24.4, and it needs experienced natural scientists from the regions. The methods and EO products developed during the SPACES 2 projects were only accomplished based on the strong cooperation that grew between the South African and German team partners and colleagues. Regular conferences, such as SANParks' Savanna Science Network Meeting, where interaction is yearly greatly fostered, have tremendously improved mutual methodological understanding beyond project concepts. Dedicated Summer Schools are a further important asset to develop strong scientific grounds for implementation of the achieved procedures and to educate the next generation of responsible Earth observation experts.

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