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Towards SDG 15.3: The biome context as the appropriate degradation monitoring dimension

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ABSTRACT

Accurate and reliable estimation of terrestrial ecosystem degradation is critical to meeting the challenge of reversing land degradation. Remote sensing data (especially land productivity dynamics) is commonly used to estimate land degradation, and this study uses the TRENDS.EARTH toolbox for the period covering 2000–2018, demonstrating the benefit of tracking the degradation process (SDG 15.3.1) at a biophysical unit. Contributing to the country's SDG 15.3.1 monitoring, anthropogenic degradation was estimated based on RESTREND land productivity, biome-specific land cover trends, and soil organic carbon (SOC) stocks. Underlying degradation was evaluated by reclassifying a 28-year national land cover change dataset to match the UNCCD land cover legend. Analysis results indicate that land productivity changes (especially in stable grasslands, afforested, and cropland areas) mainly influenced the degradation status of the biome (19.9% degraded & 25.6% improvement). Global datasets also suggest that land cover and SOC had a minimal contribution (<2%) to anthropogenic degradation dynamics in the biome between 2000 and 2018. The GIS analysis showed that long-term, the major contributors to the biome's underlying 9% anthropogenic degradation were woody proliferation into the Grassland Biome, urban expansion, and wetland drainage. Contextualising the UNCCD matrix helped interpret the SDG 15.3.1 indicator results, showing significant contestations that need careful consideration to avoid misleading policy guidance. The study also outlines the accompanying implications for degradation assessments.

1. Introduction

Land degradation evaluations relating to Sustainable Development Goal (SDG) 15.3.1 indicator – the proportion of land degraded over the entire landscape (United Nations, 2015), are essential to guide and monitor progress made through land degradation interventions (Easdale et al., 2019; Gonzalez-Roglich et al., 2019; Liniger et al., 2019). Approximately 25% of the global terrestrial ecosystems are degraded and negatively affect over 41% of the global population (United Nations, 2020). Without intervention, 95% of the global terrestrial area could be degraded by 2050, further compromising food production, water security, and other ecosystem functions (Esch et al., 2017). South Africa reported that nearly 10% of the country's landmass was degraded over the baseline period (2000–2015) (UNCCD, 2018a). However, the implication of the above indicators remains unclear at the biophysical scales where the degradation process plays out at biophysical units (Gibbs and Salmon, 2015; von Maltitz et al., 2019).

Within the 2030 Agenda, SDG 15 sets out to protect terrestrial ecosystems and biodiversity (United Nations, 2015). One of the key targets for SDG 15 is goal 15.3, which aims to "*combat desertification, restore degraded land and soil, and foster ways to achieve a land degradation-neutral world*" (United Nations, 2015). The ratified indicator for target 15.3 is referred to as SDG 15.3.1, which aims "*to monitor for the proportion of land that is degraded over the total land area*" under the custodianship of the United Nations Convention to Combat Desertification (UNCCD) (Orr et al., 2017; United Nations, 2015). SDG 15.3.1 has three key sub-indicators for monitoring: land productivity, land cover change, and SOC (United Nations, 2015). The first sub-indicator for SDG 15.3.1, land productivity, refers to the biological capacity of the land to produce; it represents the source of all food, fibre and fuel that sustains humans (Clark et al., 2001). The land productivity sub-indicator is based on the notion that loss of vegetation production in productive lands can

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result in land degradation and vice-versa (Bennett et al., 2012; Graw et al., 2017; Munyati and Ratshibvumo, 2011). As a step towards increasing resilience of land and populations dependent on the land, SDG target 15.3.1 tracks change in SOC (third sub-indicator) under the rationale that loss of SOC is a form of land degradation that contributes to reduced soil quality and fertility, which consequently impacts on biodiversity and food security (Lal et al., 2012; Stavi and Lal, 2015). SOC stocks are influenced mainly by land-use and management choices that affect nutrient input and output rates (Mills and Fey, 2003; Solomon et al., 2000). To maintain global consistency in SDG 15.3.1 evaluation and reporting, the SDG 15.3.1 indicator is tracked based on the Land Degradation Neutrality Framework, which aims at achieving land degradation neutrality by focusing on interactions between biophysical and socio-economic factors (Cowie et al., 2018).

The TRENDS.EARTH toolbox has been made available to support countries in the quest for land degradation neutrality by 2030 (Conservation International, 2018). The toolbox was introduced to extend the availability and use of global data sources to study land degradation at multiple scales using a globally harmonised methodology (Conservation International, 2018; Gonzalez-Roglich et al., 2019; Sims et al., 2019). The novelty of the toolbox is three-fold. Firstly, when combining the sub-indicators, the toolbox uses the precautionary one-out, all-out (1OAO) statistical principle (Conservation International, 2018; Orr et al., 2017). The 1OAO states that degradation occurs when there is a significant decline in one sub-indicator, even if the other two show an improvement (Orr et al., 2017). Assessing land quality status using the UNCCD approach is unique because the 1OAO statistical rule provides a reliable monitoring approach that captures different pathways to degradation addressing the limitations raised in earlier degradation assessments outlined before (Cowie et al., 2018; Gonzalez-Roglich et al., 2019). Combining the three SDG 15.3.1 sub-indicators using the 1OAO rule effectively addresses the inherent limitation of omitting other degradation sources when using one degradation proxy, as Gibbs and Salmon (2015) raised.

Secondly, the toolbox allows for degradation definition based on the geographical context (Conservation International, 2018; Cowie et al., 2018). The applicability of the toolbox in different geographical contexts allows countries to track the SDG 15.3.1 indicator based on their local level understanding of the degradation process and formulate a policy response to counter-balance degradation. By monitoring the SDG 15.3.1 indicator at specific geographical locations, different land degradation scenarios can easily be considered using the land cover degradation matrix, depending on the interaction between local biophysical and social-ecological processes (Penman et al., 2003; Sims et al., 2021). To avoid complicating the evaluation process, caution should be paid not to make them too exhaustive, although, in the interpretation step, the complexities should be highlighted (Sims et al., 2021, 2020). The geographical applicability of the toolbox is evident in Namibia (Mariathasan et al., 2019), southern China (Wang et al., 2020), Russia (Andreeva and Kust, 2020), and Botswana (Akinyemi et al., 2021). Along with the above studies, the quality of datasets needed to estimate the SDG 15.3.1 indicator has received mounting attention (Forkuor et al., 2020; Stoorvogel et al., 2017; Venter et al., 2021) and has been adequately considered when conceiving the toolbox (Daldegan et al., 2018). Various datasets have been introduced globally, with an option for country-specific datasets to be incorporated (Sims et al., 2019). To deal with the data availability and quality issues, the toolbox provides moderate resolution (250–300 m) datasets at a global level, with an additional option to use custom data produced at a national level to field levels (UNCCD, 2018b). Consequently, improved quality datasets are expected to increase the reliability and utility of SDG 15.3.1 (Daldegan et al., 2018).

Thirdly, the TRENDS.EARTH toolbox is the option to differentiate between natural and possible human-driven degradation, which has been identified as one of the key challenges associated with using remotely sensed products for land degradation assessments (Prince, 2019). This differentiation is achieved by removing some climate influences in the biological productive capacity within the assessed area based on the relationship between vegetation indices and rainfall trends (Ponce-Campos et al., 2013; Wessels et al., 2012). Notwithstanding the limitations associated with biomass trend cycles in land degradation assessments, as discussed by Prince (2019) and issues with coarse input data (Bai et al., 2018; Dinku et al., 2018), the climate correction indices provided by the toolbox are thus far the best available option to interrogate human-induced degradation.

While many studies (cited above) contribute to the understanding of the degradation phenomenon, most of these studies have evaluated degradation in a narrow sense (i.e., degradation is assessed in the policy planning domain), which is a repeat of the issues raised by Gibbs and Salmon (2015). In addition to Gibbs and Salmon (2015), Prince (2019), von Maltitz et al. (2019), and Sims et al. (2020) stress the need to take cognisance of contextual realities (i.e. pay caution in contexts with complex ecological profiles such as South Africa) when evaluating degradation. The above authors have enriched our understanding of the need to account for and correctly interpret the vegetation processes that influence the SDG 15.3.1 sub-indicators. Moreover, reflecting on a national Sustainable Land Management Target setting, von Maltitz et al. (2019) recommended the biophysical context as the appropriate assessment unit to overcome the above-cited uncertainties of degradation mentioned evaluations. The administrative scale may be appropriate uniform biophysical contexts such as Botswana (Akinyemi et al., 2021) and possibly Namibia (Mariathasan et al., 2019). However, a blank usage of the administrative scale as an assessment unit may lead to less reliable results as it results in neglecting the differences in biophysical settings within the managerial context (Gibbs and Salmon, 2015; von Maltitz et al., 2019). This is particularly the case in areas with complex biophysical landscapes such as Brazil (Guerra et al., 2020), the Sahel (Dardel et al., 2014; Hein et al., 2011; Kaptué et al., 2015) and South Africa (Mucina and Rutherford, 2006; von Maltitz et al., 2019). Therefore, there remains a paucity of understanding of how biophysical conditions and social-ecological factors influence changes in Land Degradation Neutrality indicators (SDG 15.3.1 sub-indicators). This gap adds uncertainty to degradation evaluations while reducing our understanding of the phenomena and capacity for management planning (Gibbs and Salmon, 2015; Hein et al., 2011; Prince, 2019; Sims et al., 2019; von Maltitz et al., 2019). Therefore, an improved evaluation of the land degradation phenomenon remains necessary.

This study demonstrates the benefit of using the biome scale as a degradation evaluation unit. Therefore, this paper will also report on attaining the voluntary sustainable land management targets. In this paper, the TRENDS.EARTH toolbox is customised and applied to capture anthropogenic-related degradation in a biophysical setting - the South African grassland biome over 18 years.

2. Materials and methods

2.1. Study area

The South African Grassland Biome (380–3307 m.a.s.l) is the second-largest biome (357,000 km^2), following the Savannah (Fig. 1A; Rutherford et al., 2006). South Africa most (approximately 90%) of the biome extent and shares the rest with Lesotho and Swaziland. The Grassland Biome is divisible into the mountainous Drakensberg and Sub-Escarpment Bioregions with a temperate climate, the Mesic Highveld Regional Transition Zone with a tropical climate, and the Dry Highveld region inland (Fig. 1B; Mucina et al., 2006; SANBI, 2018). The interaction between grazing pressure, fire regime, and climate regulates the vegetation structure of the Grassland Biome that is dominated by grass species (Mucina et al., 2006).

The South African Grassland Biome was selected as an illustrative case study for biome-scale human-induced land degradation assessment due to its vulnerability to land degradation (Egoh et al., 2011; Skowno

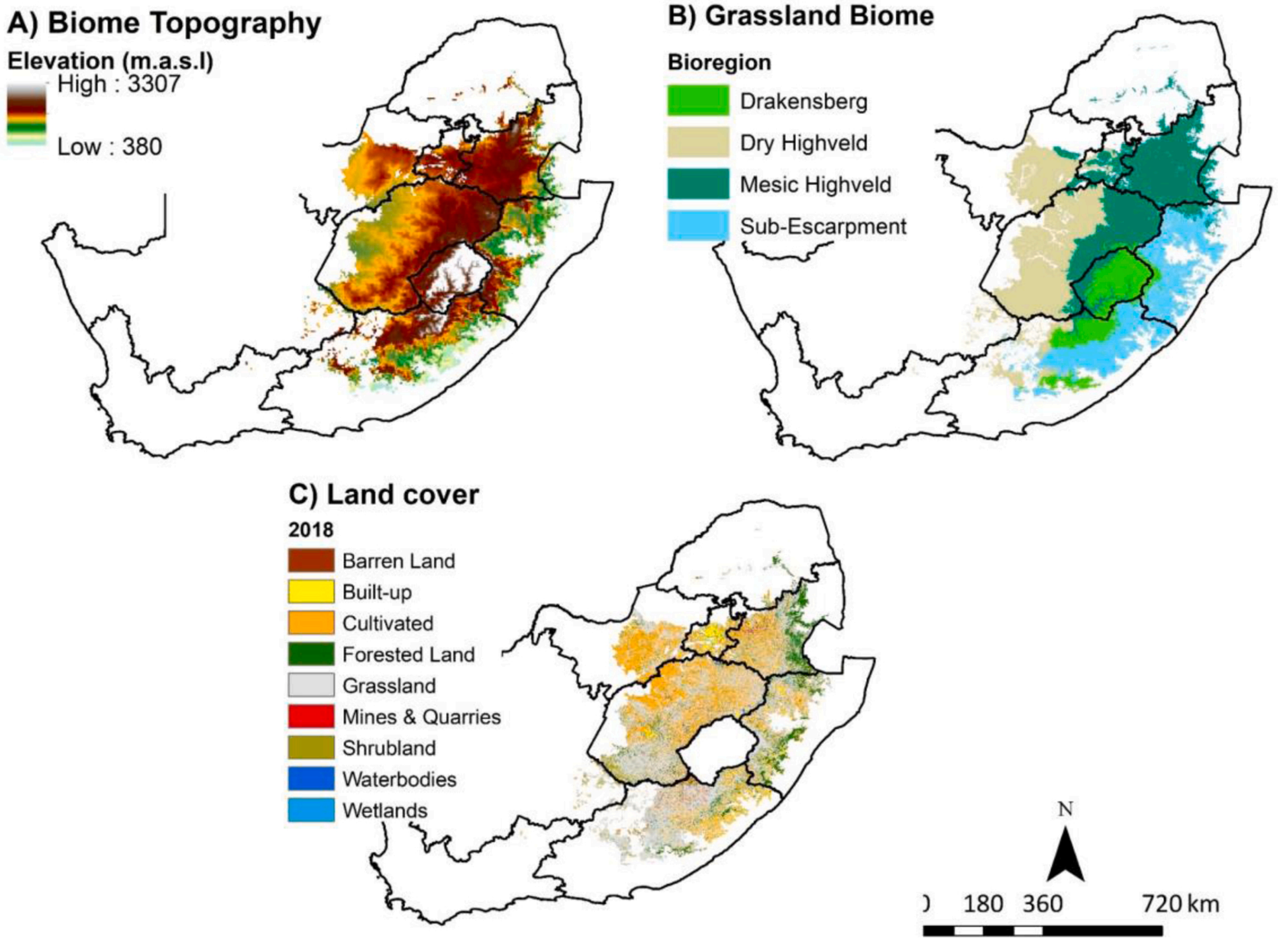

Fig. 1. A Location within the South African landscape and elevation of the Grassland Biome. B Grassland distribution and bioregions were extracted from the South African National Vegetation Map (SANBI, 2012) and the elevation was sourced from the 30 m Shuttle Rader Topographic Mission. C Land cover classes covering the South African Grassland Biome in 2018 produced for Geo Terra Image (20 m; Overall accuracy = 91.32%; 2021).

et al., 2017; Yapi et al., 2018), which has also been highlighted in the national plan for degradation intervention (DEA, 2018). The Grassland Biome in South Africa is among those that have experienced the highest modification (over 30% modification) for food production (Fig. 1B), which facilitates biodiversity loss (Skowno et al., 2019). The recent terrestrial risk assessment (Skowno et al., 2019) indicates that grassland

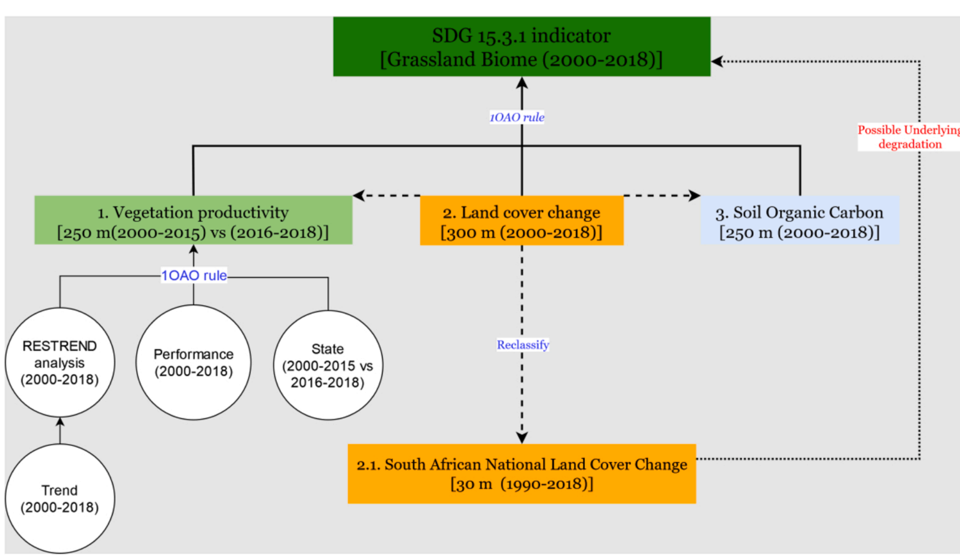

Fig. 2. General overview of the established TRENDS.EARTH framework with an additional national land cover step (2.1).

species face a higher risk of extinction due to fragmentation and climate impacts. In 2014, only 20% of the South African Grassland Biome remained intact, and the conditions continued to deteriorate (Fig. 1C, DEFF, 2021; Geo Terra Image, 2015).

2.2. Computation of the SDG 15.3.1 indicator metrics

This study was conducted using the datasets provided by the TRENDS.EARTH toolbox that runs in the Quantum-GIS software (QGIS Development Team, 2020). For the current assessment, the established TRENDS.EARTH framework was set to estimate and integrate the SDG 15.3.1 sub-indicators for 2000 and 2018 (Fig. 2) (Conservation International, 2018). The assessment is divided into the initial year (2000) and the target year (2018), hereafter referred to as the assessment period. The default global datasets within the toolbox were selected to conduct the degradation assessment because South Africa lacks some custom input datasets (e.g., land productivity and baseline land cover and soil carbon stocks) needed to run the toolbox. The interpretation matrix provided by Sims et al. (2020) was optimised to communicate the degradation phenomena in the South African grassland biome, aided by the high-resolution national dataset. The land cover legend was verified by a reference group of experts working on Nature-Based Solutions for water security space in South Africa [WRC Project K5/2928 (Mantel et al., 2021).

The TRENDS.EARTH toolbox combines the three SDG 15.3.1 sub-indicators following the 1OAO rule to provide the proportion of land degraded over the entire landscape (Orr et al., 2017). The 1OAO principle implies that a pixel with at least one degraded sub-indicators is considered degraded. The result of an 'improved' pixel can be attained when all three sub-indicators improve or at least one other sub-indicator is stable, and the rest are improved during the assessment period, or else the pixel is stable.

2.3. Estimating SDG 15.3.1 sub-indicator 1: Land productivity

TRENDS.EARTH uses a built-in feature to estimate above-ground biomass trajectory based on the 16-day 250 m Moderate Resolution Imaging Spectroradiometer dataset (MOD13Q1). Full details the process for how the toolbox estimates productivity from the NDVI are available in the toolbox manual (UNCCD, 2018b). In brief, the toolbox estimates land productivity using three net primary productivity metrics. The three metrics are (a) the trajectory of degradation - which is obtained by computing Mann-Kendal z-scores from the long-term NDVI time series (2000–2018); (b) land cover performance (2000–2018); and (c) productivity state (baseline: 2000–2015 vs target: 2016–2018) (Sims et al., 2019). The UNCCD global harmonised methodology has been designed to emphasise land productivity trends instead of quantifying the extent of change in land productivity biomass (Conservation International, 2018). Therefore, the land productivity output provides a logical matrix of five categories (i.e. severe decline, moderate decline, stressed, stable and improvement), showing a long-term trajectory for land productivity (Conservation International, 2018; Sims et al., 2019). The toolbox translates the logical matrix following the 1OAO rule into the three degradation states such that (severe decline + moderate decline = potential degradation, stressed + stable = no change/ stable, and improvement = recovery). Additionally, the land productivity sub-indicators were corrected to reduce climate bias and detect potential human-induced impacts (Wessels et al., 2012).

The study area has a large seasonal and inter-annual climate variability and covers semi-arid (rainfall of 300–600 mm yr^{-1}), sub-humid (rainfall of 600–1000 mm yr^{-1}) to humid (1000–2500 mm yr^{-1}) areas ((Mucina et al., 2006), S1). The climate variability within the biome leads to the possibility that the biological productivity trend has the highest correlation to climate as detected in South Africa (Wessels et al., 2012), the Sahel region (Dardel et al., 2014; Fensholt and Rasmussen, 2011; Ibrahim et al., 2015) and in China (Chang et al., 2018; Chen et al., 2018). Climate extremes (mainly rainfall) are removed to detect human-induced degradation since climate correlates the most with biomass productivity (Archer, 2004; Evans and Geerken, 2004).

The TRENDS.EARTH toolbox has an in-built option to monitor possible anthropogenic degradation by correcting for rainfall effects (Conservation International, 2018; Sims et al., 2021). This study adopts the Residual Trend Analysis index (RESTREND), computed on the cloud by the toolbox based on a 3-step ordinary least squares linear regression approach between the NDVI pixel and the Log_eRainfall (2000–2018) (Prince, 2019; Wessels et al., 2012, 2007). RESTREND is an analysis method to assess the relationship between observed NDVI and predicted NDVI using a linear regression relationship of NDVI and the log of annual rainfall or soil moisture to provide NDVI residuals for given precipitation through trend analysis (Wessels et al., 2012). The precipitation dataset used in the RESTREND adjusted land productivity was obtained from the 5 km Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) (Funk et al., 2015). The CHIRPS dataset is based on local rainfall station data with remotely sensed infrared cloud cover data from the quasi-global area (50°S to 50°N) (Funk et al., 2015). As noted by Prince (Prince, 2019), the acceptance of the RESTREND proxy within the Land Degradation Neutrality framework relates to the RESTREND's ability to capture seasonal trends (the growing season in particular) at a pixel level, making the climate-correction indicator a suitable proxy for human-induced productivity degradation in various land cover types. RESTREND use follows the understanding that the photosynthetic capacity of plants relies on rainfall (Wessels et al., 2012). However, this assumption has been challenged since rainwater is not immediately available to plants after a rainfall event which means photosynthetic capacity is more a function of soil moisture instead of actual rainfall; hence the toolbox normalises rainfall similar to the period of vegetation indices (2000–2018 in this study) to reduce the uncertainty of water availability to plants (Prince, 2019; Sims et al., 2019).

2.4. Estimating SDG 15.3.1 sub-indicator 2: Land cover change

Physical degradation (land cover change) was tracked based on the default global land cover dataset (European Spatial Agency, 2017) with a moderate spatial resolution (300 m, 73% accuracy). The default land cover dataset (EuroSpace land cover), with 36 land cover classes defined by the UNCCD. Higher resolution (20–30 m with accuracy > 85%, 47 land cover classes) datasets exist for South Africa from 1990 to 2018 (DEFF, 2021; Geo Terra Image, 2015). But the earlier period (1990 national land cover dataset) goes beyond the baseline year (the year 2000), making it inappropriate for import to the toolbox. This land cover change dataset was used to investigate underlying degradation. (Section 2.2.3). The land cover degradation legend (Table 1, (Penman et al., 2003)) was redefined based on South African literature and validated by South African experts in WRC Project K5/2928 (Mantel et al., 2021) to capture the degradation process of the South African Grassland Biome by modifying the land cover degradation matrix. The definition was based on South African biophysical and socio-economic understanding of whether a change from one land cover to another is positive / recovery or negative / degradation (matrix definition detailed on the WRC report Mantel et al., 2021).

2.5. Estimating SDG 15.3.1 sub-indicator 3: Soil carbon stocks

The toolbox's default option estimates below-ground soil carbon stocks (0–30 cm soil depth) for the baseline period (the year 2000) from the SOILGRIDS dataset (250 m; Overall accuracy $R^2 > 0.6$; Hengl et al., 2017). Change in soil carbon stocks from baseline to target year (2018) is computed by estimating the combined impact of climate (based on climatic zone) and a combination of land-use change and management (based on the land cover change sub-indicator) in each pixel within the assessment area (Conservation International, 2018). Finally, the toolbox

Table 1
A matrix of key changes showing the land degradation definition used for the assessment shows 42 possible transitions and 14 land cover change processes (Mantel et al., 2021). Land cover state transitions are highlighted as degradation (red boxes), stable (grey), or recovery (green). Transitions that could lead to an opposite effect are indicated with white ink.

Baseline land cover	Land cover in the target year (2018)						
	Afforested	Grassland	Cropland	Wetlands	Artificial	Barren land	Water
Afforested	Stable	Woody clearing	Agricultural expansion	Wetland restoration	Urban expansion	Canopy loss	Inundation
Grassland	Afforestation	Stable	Agricultural expansion	Wetland restoration	Urban expansion	Canopy loss	Inundation
Cropland	Afforestation	Vegetation recovery	Stable	Wetland restoration	Urban expansion	Erosion on croplands	Inundation
Wetlands	Afforestation	Wetland drainage	Wetland drainage	Stable	Wetland drainage	Wetland drainage	Damming of wetlands
Artificial	Forestation	Vegetation recovery	Agricultural expansion	Wetland restoration	Stable	Spread of bare land	Inundation
Barren land	Forestation	Vegetation recovery	Agricultural expansion	Wetland restoration	Urban expansion	Stable	Inundation
Water	Forestation	Dry up	Drainage	Wetland restoration	Drainage	Dry up	Stable

aggregates the changes in SOC stocks over the assessment period to detect any false results, and any significant changes (SOC change > 10%) are recorded as improvement or degradation (Conservation International, 2018). Potential false results may arise, for example, when tree-cover establishment in grassland areas leads to an increase in soil carbon stocks, but in terms of degradation, the process itself is degradation (Sims et al., 2019). The default data option in TRENDS.EARTH was chosen to estimate the topsoil SOC stocks that were derived from the SOILGRIDS 250 m project (Hengl et al., 2017).

Higher-resolution (30 m; Accuracy: $R^2 > 0.8$) datasets are available at the continental level (iSDA) (Hengl et al., 2021) and the recently produced estimates for South Africa (Venter et al., 2021). Given their higher spatial scales, both datasets produced better soil carbon estimates than the SOILGRIDS250 (Hengl et al., 2021; Venter et al., 2021), emphasising the necessity of high-resolution data to aid degradation assessments (Sims et al., 2021). Despite the improved accuracy, both datasets could not be used in the present study, as they are not analysis-ready for use in the TRENDS.EARTH toolbox. The dataset remains useful for monitoring (Hengl et al., 2021). Soil carbon stocks by Venter et al. (2021) could not be used in the present study as it excludes some of the critical artificial land cover classes in the Grassland Biome, such as the cropland areas.

2.6. 2-Step validation

2.6.1. Step 1: Satelete- image based validation

A visual interpretation of high-resolution aerial photography covering the assessment period was used to verify the final SDG 15.3.1 indicator. Three known locations with long-term research were identified and used to extract the SDG 15.3.1 using polygons not exceeding 45 km^2. Although long-term research has occurred in these three locations and citizen science-based photographs might exist, in situ repeat photography is rare or does not cover the landscape before the baseline year. Therefore, the verification exercise followed the accuracy assessment of the national datasets that relied on high-resolution satellite imagery (DEFF, 2021). The three polygons were located in 2629BA near Carolina in Mpumalanga Province, falling within the Crocodile River catchment (Pollard and du Toit, 2011), 3128AB near Nqanqaru (formerly Maclear) in the Eastern Cape drained by the Tsitsa catchment (van der Waal et al., 2017), and 2929BD hosting Inanda Dam in KwaZulu-Natal drained by uMgeni Catchment (Jewitt et al., 2020).

2.6.2. Step-1: Possible pre-existing degradation drivers in the South African Grassland Biome

Recognising that degradation is a relative phenomena, and the year is accepted 2000 as an initial for evaluating SDG 15.3.1 is ideal for tracking ongoing degradation (Orr et al., 2017); persistanty degraded areas may be erroneously classified as stable, raising questions about the consideration of pre-existing degradation. This possible error is more relevant for a country where degradation is a long-standing issue as highlighted in a national audit of degradation before the SDGs and popularity of remote sensing techniques, from a mulit-disciplinary viewpioint (Hoffman and Todd, 2000) perspectives. Table 1 was used to calibrate the 30 m 1990–2018 South African Land Cover Change (SANLC) dataset as shown in Table A1 for consistency, to investigate underlying degradation and gain better insight into the human-induced degradation drivers within the biome. The 1990–2018 SANLC dataset is a fine spatial resolution (30 m, overall accuracy >84%) and locally validated product (Geo Terra Image, 2019), making it suitable for comparison as stipulated by Principle 18—"*application of local knowledge and data to validate and interpret monitoring data*" of the Land Degradation Neutrality Framework (Cowie et al., 2018). As the most timely and robust national land cover product, the 1990–2018 SANLC dataset has the most utility in providing an insight into the land cover sub-indicator (Geo Terra Image, 2019). Accuracy was achieved by comparing the degradation matrix of the SDG 15.3.1 indicator with the reclassified SANLC 1990–2018 dataset. The two matrices were based on 1504 sampling points that were extracted from the commonly used verification points for the national detests (DEFF, 2021).

3. Results

3.1. Trends in land productivity

Table 2 highlights possible anthropogenic-related (climate corrected) changes in above-ground biomass productivity for the seven land cover types as a total area (km^2) and the proportion of change over the assessment period. Productivity decline was most prevalent in unchanged grasslands (6.7%), afforested regions (4.5%), and croplands contributed (2.8%). On the other hand, estimates indicate that land productivity improvements in the biome were primarily due to unchanged grasslands (11%), stable afforestation (7.1%) and croplands (6.3%). Other land cover transitions contributed insignificantly to the

Table 2
Net RESTREND land productivity change (sq. km) sub-indicator per land cover class in the Grassland Biome (2000–2015 vs 2016–2018), excluding water bodies. The degraded state (- indicator) combines three categories (stressed, moderate decline and severe decline).

Land cover class	Degraded			Stable	Recovery	No data
	Declining	Moderate decline	Stressed			
Afforested	4,507.2	10,602.9	1,044.8	51,974.1	25,752.0	169.8
Grasslands	9,347.1	14,885.1	136.1	116,986.6	39,638.4	270.0
Croplands	3,052.2	7,006.7	201.5	43,599.0	23,288.0	87.4
Wetlands	45.9	74.0	40.2	419.1	398.9	40.2
Artificial	1,213.0	204.9	91.2	1,417.4	606.2	17.8
Barren land	116.3	33.2	29.7	298.2	224.8	28.8
Total in 2018	18,281.7 (5.1%)	32,806.8 (9.2%)	1,543.5 (0.4%)	214,694.4 (60.2%)	89,908.3 (25.2%)	614.0 (0.5%)

biome productivity degradation (less than 1%).

3.2. Trends in land cover change

EuroSpace dataset estimates show that by 2018, half of the biome (50.3% + 0.3% wetland area) remained, followed by afforested areas (26.1%) and croplands (0.3%) (Table 3). Interims of degradation, most land cover classes within the biome remained unchanged (98% of the biome extent) during the assessment period, with 49.9% grassland, 25.9% afforested, and 20.9% cropland areas (Table 3). Based on Table 3, expansion of desirable but degradation driving processes in the biome (urbanisation on afforested sites, afforestation on native grassland, and grassland to cropland) occupied approximately 1% of the biome 3 705.3 km^2. Reclamation of grassland vegetation from woodland and croplands and increased inundated areas led to some land cover trends (0.5% recovery) in the biome (Table 3).

3.3. Trends in soil carbon stocks

TRENDS.EARTH analysis revealed losses in SOC stocks on 3 066.5 km^2 (or 0.9%) of the biome area (due to loss of afforested areas, and native grassland cover), and improvement from 440.5 km^2 (or 0.1%) (mostly from cropland areas). The UNCCD reporting outputs severe losses (>25% SOC density per transition) from areas without biomass cover (i.e., artificial and bare land). In contrast, biomass introduction onto the barren lead in the biome could increase SOC stocks by up to 74% (Table 4). Afforestation on cropland areas also has positive SOC implications, but this transition has negative socio-economic consequences (Table 4).

3.4. SD.G 15.3.1 indicator and spatial disaggregation

TRENDS.EARTH analysis results showed substantial biome area (15.7%) had ongoing degradation between 2000 and 2018, while less-climate related drivers may have led to improvements in 25.6%. Results also indicate that anthropogenic actions had no detectable influence in a large proportion (54.6%) of the biome area that remained unchanged over the assessment period (Fig. 3A).

The possible human-induced degradation and recovery were spatially distributed across the biome (Fig. 3, Table 6). In the sub-national policy domain, the SDG 15.3.1 indicator for the area covered by the Grassland Biome is summarised in Table 6, showing each province encompassing the biome. The dominance of the greening trend over ongoing degradation suggests zero-net land degradation over the assessment period by the regions that host the biome extent (Table 5). Fig. 3B indicates that the recent gains areas in Mpumalanga and

Table 3
Land cover degradation matrix between initial (2000) and target (2018) for the Grassland Biome, including Swaziland and Lesotho. **Grey** shaded cells depict persistent land cover; degradation is shown in **red**; **green** shows recovery. **White** ink highlights degraded areas that may be desirable in the biome.

Land cover type in 2000	Land cover type in 2018 (km2)						
	Afforested	Grassland	Cropland	Wetlands	Artificial	Barren land	Water
Afforested	93,113.9	1,430.3	529.7	14.5	1,069.7	11.8	13.4
Grassland	632.0	179,534.6	1,611.5	0.9	392.1	5.6	30.3
Cropland	278.0	289.2	75,090.6	0.5	58.6	38.1	8.3
Wetlands	4.1	0.5	0.5	1,001.8	2.2	0.0	2.0
Artificial	0.0	0.0	0.0	0.0	1,985.7	0.0	0.0
Barren land	9.7	3.2	2.3	0.0	39.4	671.7	37.2
Water	13.1	5.5	0.1	0.7	2.9	3.7	2,203.8
Total in 2018	32,090.5 (26.1%)	243,223.7 (50.3%)	77,234.7 (21.5%)	1,018.4 (0.3%)	3,550.6 (1.0%)	730.9 (0.2%)	2,295.1 (0.6%)

Table 4
Soil organic carbon change from baseline (2000) to target (2018) by type of land cover type.

Land cover class	Baseline area (sq. km)	Target area (sq. km)	Change in are (sq. km)	Baseline SOC (tonnes)	Target SOC (tonnes)	Change in SOC (tonnes)	Change in SOC (%)
Afforested	96,169.8	94,037.7	-2132.2	619,031,620.4	602,481,489.6	-16,550,130.8	-2.7
Grasslands	182,176.7	181,257.8	-918.8	1065,993,447.6	1059,315,970.8	-6677,476.8	-0.6
Croplands	75,754.9	77,234.6	1479.7	334,846,395.1	341,589,015.2	6742,620.1	2.0
Wetlands	1009.0	1017.7	8.7	8659,881.7	8731,047.1	71,165.3	0.8
Artificial	1985.7	3547.6	1561.9	11,382,354.0	20,335,395.7	8953,041.7	78.7
Barren land	726.4	727.2	0.8	4360,159.8	4390,318.0	30,158.1	0.7
Total:	*357,822.5*	*357,822.5*	*0.0*	*2044,273,858.8*	*2036,843,236.3*	*-7430,622.4*	*-0.4*

Northern Cape Provinces fall short of offsetting degradation due to persistently degraded.

3.5. Validation based on the physical degradation

3.5.1. Satellite- Image based validation

As observed in the land cover trends, the low spatial resolution of the default TRENDS.EARTH data obscure landscape variations in land conditions (especially for smaller land cover classes) that are visible at high resolution (Fig. 4). Fig. 4-Tile 2929BD shows that productivity losses to newly established reservoirs led to Owing to the 1OAO rule, despite the definition in the land cover matrix. The toolbox detected dense afforested areas in areas with linear relief but yielded different degradation estimates based on the land productivity and land cover trends (Fig. 4). Based on the three verification locations, the degradation assessment using global-level datasets exhibits lower accuracies, reaffirming the need for higher spatial resolution input data and better interpretation of the productivity trends (Fig. 4).

3.5.2. Possible pre-existing physical degradation

Only 28.5% of the physical degradation was consistent between the moderate resolution and the higher spatio-temporal resolution dataset, with the most ommissions (99.4%) detected from stable pixels (Table 4). Extending the initial year to 1990 and the use of finer resolution da resulted in the GIS analysis of the longer-term national dataset (Fig. 3B), revealed nearly 10% underlying degradation during the 28-year period. Table 5 highlights Pre-existing degradation within stable areas in the Grassland Biome for the 1990 and 2018 period derived from the UNCCD land. Based on Table 5, persistently degraded areas namely planted forest (3.1% of the stable area between 1990 and 2018), woody encroachment (0.3%) and ineffective woody clearing (0.2%).

4. Discussion

4.1. Feasibility of using the biophysical domain for SDG 15.3.1 assessment

This study demonstrates how globally consistent remote sensing tools can better evaluate the SDG 15.3.1 indicator over large areas considering the biophysical context suggested by earlier literature (Gibbs and Salmon, 2015; Sims et al., 2020; von Maltitz et al., 2019). The Grassland Biome specific degradation was estimated by customising the SDG 15.3.1 land cover legend to match the land-use processes specific to the biome (Mantel et al., 2021). Contextualisation of the land cover definition follows the inherent uncertainty in the default approach of tracking the SDG 15.3.1 indicator, typically applied in policy planning and decision-making units (Sims et al., 2020; von Maltitz et al., 2019). von Maltitz et al. (2019) note the lack of clear guidelines for interpreting land transition in the context of degradation, leading to possible misrepresentation of land degradation. Sims et al. (2020) responded to von Maltitz et al. (2019) by addressing a range of degradation scenarios to better interpret the degradation finding from the TRENDS.EARTH toolbox. Although biome-specific, the customised land cover definition may still fall short of fully describing the social-ecological context of degradation, which is vital for reliable SDG 15.3.1 reporting from remotely sensed tools (Sims et al., 2020). Moreover, the UNCCD assessment period starting in 2000 may discount underlying degradation in the biome, although it will highlight ongoing degradation. The longer-term and finer resolution national land cover (Geo Terra Image, 2019) was reclassified to match the UNCCD land cover legend to interrogate the underlying degradation Table 7.

The results presented here show a dominance of land productivity dynamics, while physical degradation and soil quality degradation have a minimal impact on the anthropogenic degradation process in the South African Grassland Biome between 2000 and 2018. The proportion of ongoing and underlying degradation identified herein falls within the reported (Skowno et al., 2019) 24% threatened ecosystems. The SDG 15.3.1 results (including pre-existing degradation) suggest a positive trend towards neutrality within in the biome, with lesser contributions from Mpumalanga and the Northern Cape provinces. As noted in earlier literature, woody proliferation (Le Maître et al., 2020; Luvuno et al., 2018; O'Connor et al., 2014; von Maltitz et al., 2019) in the Grassland biome remains a concern despite clearing interventions.

4.1.1. Trends SDG 15.3.1 sub-indicators

The most improvement in the final SDG 15.3.1 indicator for the biome emanated from land productivity increments (98% of all recovery) from unchanged natural grasslands, afforestation (including woody encroachment) and croplands. Despite productivity increments in stable natural grasslands, afforested areas and croplands, the RESTREND results indicate a 15% decline trend dominated by losses from the same land cover classes.

Contextualising the anthropogenic degradation process to the biome-scale helped capture the biome-specific degradation process, following Principle 8 of the Land Degradation Framework (Cowie et al., 2018). Secondly, the contextualisation helped overcome ambiguities in degradation interpretation due to the complex nature of grassland biome transitions and the need to balance degradation neutrality with human needs (Shackleton et al., 2013; Shin et al., 2022; Sims et al., 2020) within the biome. Using a simplified land cover legend and low-resolution datasets when computing the SDG 15.3.1 indicator may overlook a substantial proportion of underlying physical degradation. Underlying degradation was inspected using a higher-resolution nationally derived land cover dataset, which highlighted nearly 10% more physical degradation in the biome that must be considered in SDG 15.3.1 monitoring.

Under a scenario of no change in native grassland cover and stable SOC, spontaneous land productivity increments are expected in areas of low grazing pressure within the South African Grassland Biome (Mucina et al., 2006). Farm management practices could explain the widespread recovery in the Free State due to surging productivity following the recent droughts to increase crop yields and facilitate productivity (DAFF, 2019). DAFF (2019) also notes improving vegetation conditions in KwaZulu-Natal, partly explaining the positive productivity trends. Stable (and expanding) afforestation improves both the land productivity and carbon storage capacity of terrestrial ecosystems due to increments in biomass productivity (Achat et al., 2015; Deng et al., 2014; O'Connor et al., 2014; Preez and Huyssteen, 2021; Zethof et al., 2019).

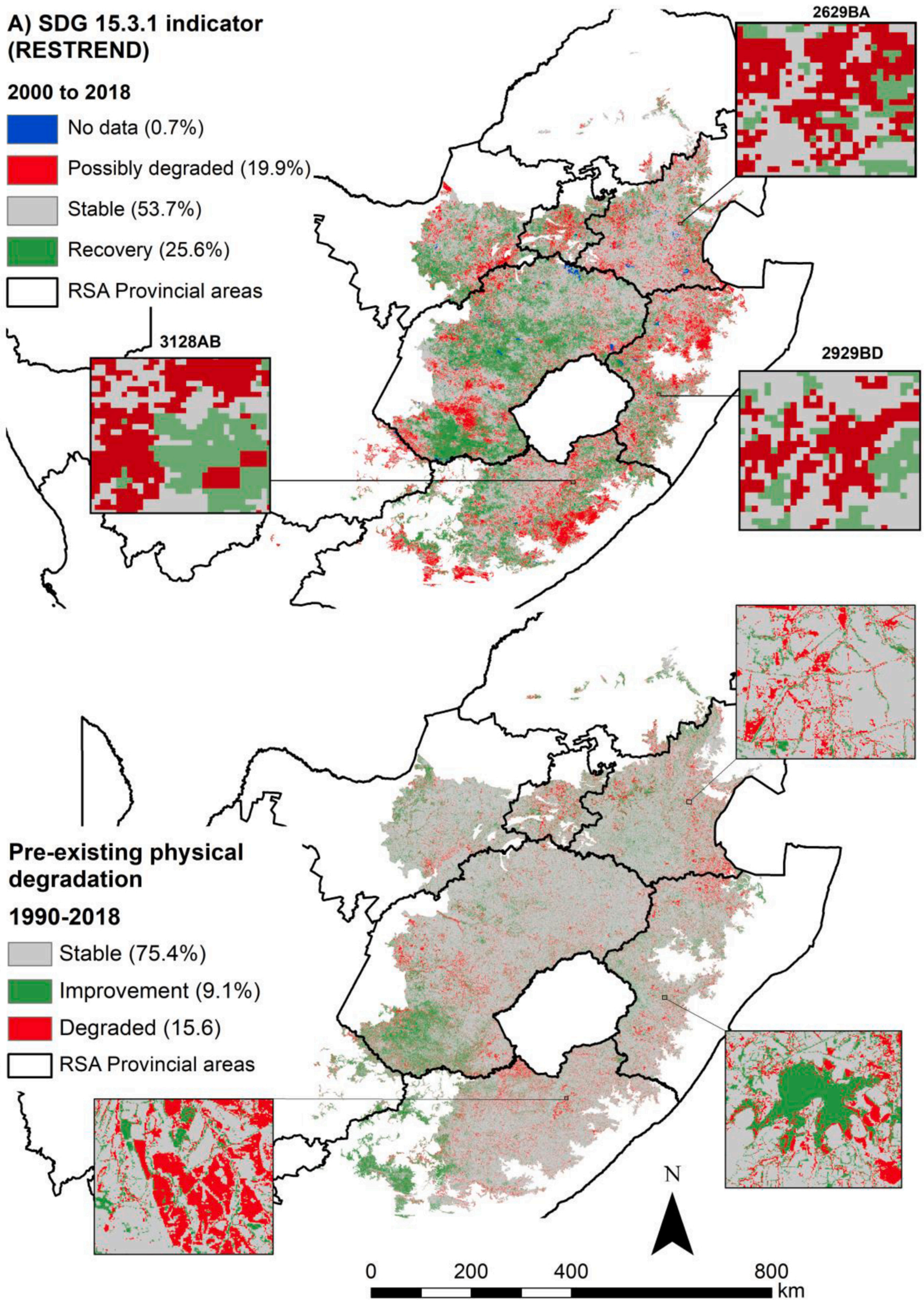

Fig. 3. A The proportion of land degraded over the total Grassland Biome in South Africa between 2000 and 2018 at 300 m resolution, with Lesotho and Swaziland jurisdictions removed. Zoom-in frames top 2629BA in Mpumalanga; left 3128AB in the Eastern Cape; and right 2929BD in KwaZulu-Natal. B Possible pre-existing physical degradation (sub-indicator 2), based on the 30 m 1990–2018 SANLC dataset.

However, grassland afforestation (particularly woody encroachment and the spread of invasive alien plants) adversely affects ecosystem structure and functioning (Le Maître et al., 2020; Luvuno et al., 2018) and is one of the main drivers of grassland degradation.

The downward trend in the ecosystem quality of grassland areas is characterised by a moderate decline signalling a recent negative productivity trend (Easdale et al., 2019). A combination of effects could explain this observation, including the recent droughts (Graw et al., 2017) and the suppression of wildfires within the biome (O'Connor et al., 2014). The negative impact of wildfire losses within the biome is

Table 5
Disaggregation of Grassland Biome SDG 15.3.1 indicator to the provincial level (sq. km), derived by splitting the SDG 15.3.1 raster into provincial polygons.

Province	Grassland area encompassed (%)	Degraded (sq.km)	Stable Area (sq.km)	Recovery Area (sq.km)
Free State	31.40	8,840.5 (2.5%)	64,545.2 (18.0%)	37,840.8 (10.6%)
Eastern Cape	19.14	18,333.9 (5.1%)	31,918.1 (8.9%)	18,117.6 (5.1%)
North West	8.85	3,266.6 (0.9%)	19,589.9 (5.5%)	8,678.5 (2.4%)
KwaZulu-Natal	12.14	7,888.6 (2.2%)	27,133.1 97.6%)	8,207.9 (2.3%)
Mpumalanga	13.85	7,991.4 (2.2%)	34,545.2 (9.7%)	6,550.5 (1.8%)
Gauteng	3.41	2,482.6 (0.7%)	6,544.8 91.8%)	3,054.0 (0.9%)
Northern Cape	1.04	1,180.6 (0.3%)	1,816.0 90.55%)	629.6 (0.2%)
Limpopo	1.01	727.2 (0.2%)	2,518.8 (0.7%)	352.4 (0.1%)
Western Cape	0.03	74.7 (0.0%)	32.9 9 (0.0%)	15.9 (0.0%)
Biome total	90,9	50786,1 (14.1%)	188644,0 (52.7%0	83447,2 (23.4%)

Table 6
Confusion matrix showing accuracy statistics for the final SDG 15.3.1 indicator compared to the long-term land cover change sub-indicator (SANLC 1990–2018).

ESA (2000–2018)	SANLC 1990–2018					Omissions	Comissions
	Degraded	Stable	Improvement	No data	Total		
Degraded	86	2	20	0	108	22.0%	79,6%
Stable	303	319	748	0	1370	99.4%	99,4%
Improvement	2	0	23	0	25	2.9%	2,9%
No data	0	0	0	1	1	100.0%	100,0%
Total	391	321	791	1	1504	28.5%	

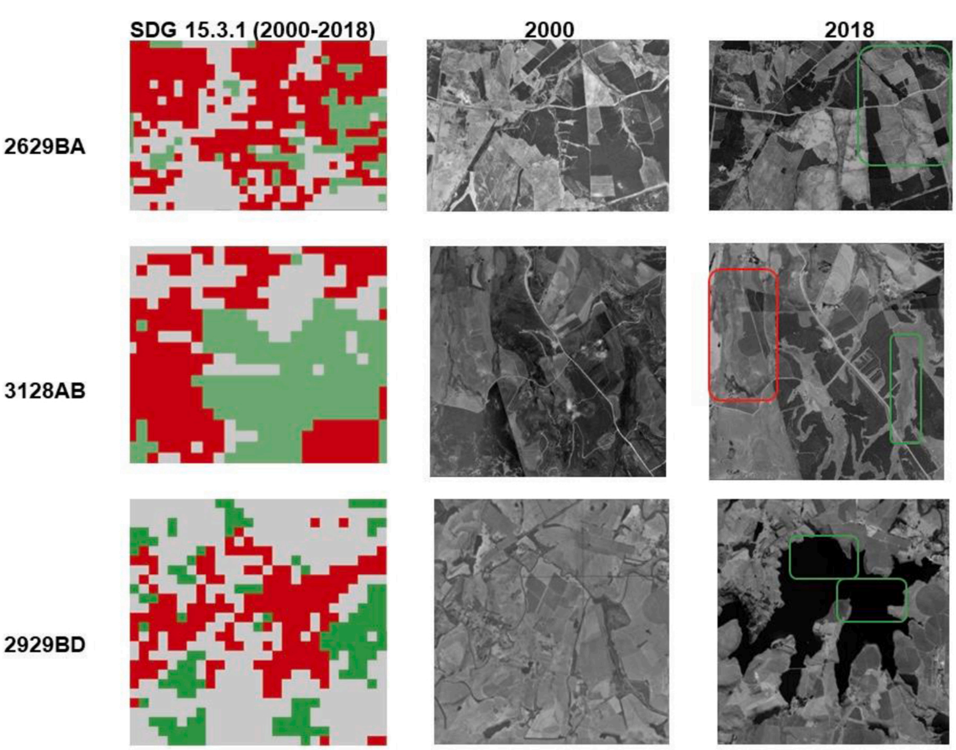

Fig. 4. Visual comparison of the SDG 15.3.1 indicator with high-resolution images Imagery for the baseline year was sourced from the pre-2000 1: 50 000 Flight Plan Query hosted by the Department of Land Reform and Rural Development (http://www.cdngiportal.co.za/cdngiportal/) Google Earth Pro (2018). Polygons in the target year images highlight counterintuitive results of the SDG 15.3.1 indicator and the high-resolution images. The accuracy error was not quantified, hence the images at the initial and target year to aid a visual distinction.

Table 7
Interpretation matrix for the 30 m resolution and long-term (1990–2018) land cover change sub-indicator, highlighting both land cover degradation states (red, green, grey colours) and extent (sq.km) of biophysical/socio-economic drivers of the interpretation matrix (Sims et al., 2020) for the South African Grassland biome, excluding Swaziland and Lesotho.

Land cover modification process	Biophysical/ socio-economic impacts	Possiblly degraded? (Yes/No)
Woody clearing	Naturalness (5,315.2 km^2)	No
	Canopy loss (Can trigger erosion in sensitive soils, and erode natural wood cover) (4,582.8 km^2)	Yes
Wetland restoration	Naturalness (3,167.0 km^2)	No
Natural grassland recovery	Naturalness (35,147.3 km^2)	No
Inundation	Water supply, sanitation & storage of mine by-products (651.4 km^2)	No
Damming of wetlands	Loss of ecosystem functions (191,6 km^2	Yes
Stable/No change	Persistently degraded (11,556.2 km^2)	Yes
	Sustained resilience (233,696.2 km^2)	No
Afforestation	Loss of grazing potential (but natural biome shifts are possible) (11,201.9 km^2)	Yes
	Negative impacts for flow regulation but a desired economic activity (3,882.5 km^2)	Yes (but desired)
	Afforestation on barren areas leads to increments in carbon capture and sequestration (55.3 km^2)	No
Agricultural expansion	Biodiversity loss (374.3 km^2)	Yes
	Restoration & Food production (New croplands in unwanted land cover types) (1,3777 km^2)	No
Erosion on croplands	Loss of food producing ecosystems (149.9 km^2)	Yes
Urban expansion	Human settlements (2,996.0)	Yes (But desired)
	Permanent productivity loss (541.3)	
Spread of bare land	Loss of ecosystem functions (942.3 km^2)	Yes
Water drainage/dry-up	Water shortages (37.1)	Yes
Wetland drainage	Loss of ecosystem functions (4,268.9)	Yes

also supported in this analysis by a succession of Shrubland (bush encroachment), which is classified as a regime shift (Archer et al., 2017; Eldridge et al., 2011; Luvuno et al., 2018). To support the importance of wildfires for grassland maintenance, areas exposed to burning within the Loskop Dam Nature Reserve that falls within the South African Grassland Biome were reported to have experienced slightly higher biodiversity than unburned areas (Bachinger et al., 2016). Despite the importance of wildfires, frequent uncontrolled burning and wildfires during drought periods may reduce grass reproduction, thereby aggravating the Grassland Biome's degradation instead of facilitating recovery (Prince, 2019). Hotspot areas of declining land productivity can be observed in natural grassland areas and the old homeland areas, upholding previous conclusions on the impact of continuous grazing playing out in rural Kwa-Zulu Natal and Eastern Cape (Kotzé et al., 2013; van der Waal and Rowntree, 2018).

The CHIRPS dataset (5 km resolution) is used in this study for climate correction as the best-available dataset recognising its limited accuracy (i.e., 5 km rain correction for a 250 m land productivity pixel), which will impact the validity degradation estimates. An accuracy assessment of the CHIRPS dataset in China revealed that the dataset underestimates rainfall in dry periods due to topographic variation (Bai et al., 2018). The dataset overestimated wet-rainfall season estimates in East Africa, indicating the dataset's limitations in poorly gauged areas (Dinku et al., 2018). The South African Grassland biome and South Africa, in general, has a complex topography (Fig. 1) and is not well gauged (Hughes, 2019), making the CHIRPS limitations observed in China and East Africa relevant for this assessment. Since results indicate land productivity found to be a dominant factor in the anthropogenic degradation status of the South African Grassland biome, uncertainty remains on the accuracy of the climate correction across the biome.

The visual comparison between the SDG 15.3.1 indicator and high-resolution spatial images together with the national land cover revealed inconsistency in some land cover condition of the biome. The discrepancy can be attributed to the over simplified land cover legend (particularly in afforested areas), and TRENDS.EARTH tool's estimation of productivity in waterbodies. The land cover degradation legend was designed flexibly to allow for amendments to fit the different contexts, and the use of seven land cover classes is ideal for simplicity (Running et al., 2017; Sims et al., 2019). However, such simplicity may produce interpretation uncertainty in complex land processes such as commercial afforestation and uncontrolled woody proliferation lumped in one class, hence this study extended the definition in the national dataset to 9 land cover classes (Table A1-A2).

Considering classes based on their socio-economic desirability (e.g. planted forests and orchards, both of which result in similar benefits in biophysical and socio-economic importance despite being water-intensive) could improve the contextualisation (Sims et al., 2021), while keeping the seven land cover classes for ease of reporting. In some cases, a transition may fall under degradation or improvement, but due to the toolbox's aggregation, the same transition may have an opposite effect, which is indicated by white ink Table 1 (e.g., grass recovery due to wildfires in the grassland vegetation could be defined as an improvement but may lead to loss of biomass productivity in areas initially covered by indigenous woody vegetation). On the other hand, the establishment of woody vegetation in croplands could convert to planted forests or uncontrolled woody proliferation (Scorer et al., 2019; Skowno et al., 2017). Better contextualisation was achieved by integrating all woody areas to highlight the negative impact of grassland afforestation following (Sims et al., 2020; von Maltitz et al., 2019). Recalibrating the long-term higher resolution dataset helped uncover possible underlying degradation by woody proliferation in the biome that was overlooked by the default datasets.

As Sims et al. (2020) discussed, the 1AOA principle should be able to correct the counter-intuitive process if the physical degradation process is adequately contextualised, as this paper has done.

The output files for each sub-indicator included an estimate of productivity on areas classified as watetrbodies, which does not exist in reality, considering the biomass relation to productivity. This estimate misled the 1OAO rule as can be seen in the validation, despite the clearly defined physical degradation scenarios for waterbodies (Fig. 4-Tile 2929BD). This underperformance perpetuates the challenge of effectively considering other sources of degradation within an area (Gibbs and Salmon, 2015) (pixel to land cover class level in this case); confronting the SDG 15.3.1 indicator results in accuracy uncertainties. Such uncertainty may present challenges when identifying areas of intervention, as highlighted during the voluntary Sustainable Land Management Target setting in South Africa (DEA, 2018; von Maltitz et al., 2019) and subsequently during large scale monitoring.

4.2. Implications for degradation assessment and SLM policy

The approach presented in this study contributes to the methodology required to represent the degradation phenomenon more realistically at the sub-national level. The study also uses the customised land cover degradation option and the RESTREND index to highlight biome-specific and human-driven degradation in the biome. Following this guidance, previous land degradation assessments (Giuliani et al., 2020; Mariathasan et al., 2019; Wang et al., 2020) used the TRENDS.EARTH toolbox employed the administrative scale for assessing and reporting degradation. While such an approach works in administrative areas with homogeneous bioregions, it may lead to inaccurate degradation reporting in mosaic biomes since degradation occurs in the biophysical context, driven mainly by social-ecological factors (Sims et al., 2020; von Maltitz et al., 2019).

Given the high terrestrial threat levels experienced by the Grassland Biome and the biome's socio-economic importance (Skowno et al., 2019), the South African government has pledged to reverse degradation within the Grassland Biome and sustainably manage over 72 746.1 km^2 grassland area by 2030 (DEA, 2018). In addition, the voluntary National Target Setting for Sustainable Land Management (DEA, 2018) has committed to improving land productivity and SOC in 60 000 km^2 cropland areas by 2030 compared to 2015. The TRENDS.EARTH outputs do not allow for tracking progress land productivity in relation to 2015, but the entire assessment period, implying that South Africa may encounter challenges when reporting on SLM progress. Progress on SLM targets from 2015 can be evaluated using this calibration approach in similar biomes (limited by availability of higher resolution land cover dataset), which will help track progress on the country-specific SLM targets.

Addressing the spatio-temporal resolution issues identified above by developing a higher resolution dataset in the initial SDG 15.3.1 tracking year (2000) is a critical area of future development to set accurate baseline indicators (i.e., 2000–2015). The recommendation of a finer resolution land cover dataset for the initial year, and the use the SANLC 1990–2018 land cover change dataset is founded on the understanding that SDG 15.3.1 is assessed at a pixel-level using the *like-for-like* evaluation (i.e., similar land cover classes—also the intervention level). Such classes are defined in the land cover sub-indicator and have a direct impact on the other two sub-indicators, thereby signifying the need of a finer resolution land cover dataset. Where high-resolution or repeat field images are not available, error estimation of the final SDG 15.3.1 indicator in comparison to the target year image will play a big role in communicating the uncertainty for decision-makers, and methods for such exercises exist in remote sensing literature. Field-based monitoring (which is more expensive) of the anthropogenic degradation remains necessary for progress field to plot level interventions, owing to disparities in spatial resolution from existing remote sensing products. To cut down the expense, citizen science-based monitoring approaches can be optimised, and this will enhance active stakeholder involvement in achieving SDG 15.3.1 indicator (Gann et al., 2019). Additional steps for the SLM policy are identifying priority areas (geographical locations) where the targets will be best met. Focusing on reversing and reducing degradation at local scales especially rural areas may help gain enough traction. Without fully understanding biophysical and social-ecological contexts of degradation, restoration policies may not be adequately formulated. The focus of future research within the realm of degradation will probably be focused on uncovering these dynamics for other biophysical regions, although it will be a challenging but necessary endeavour.

CRediT authorship contribution statement

Conceptualisation, BSX, WM, SKM, ADV, JT, DCLM; Methodology, BSX, WM, SKM, ADV, DCLM, JT; Formal analysis, BSX, BM; Verification, BSX; Investigation: BSX, BM; Resources, SKM, JT; Writing – original draft, BSX; Writing – review & editing, BSX; SKM, ADV, DCLM; Visualization, BSX; Supervision: SKM, JT, ADV; Project administration: SKM, Funding acquisition, SKM, JT, BM, BSX.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.envsci.2022.07.008.

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