Remote sensing for monitoring tropical dryland forests: A review of current research, knowledge gaps and future directions for Southern Africa

Remote sensing for monitoring tropical dryland forests: A review of current research, knowledge gaps and future directions for Southern Africa

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ABSTRACT

Climate change, manifest via rising temperatures, extreme drought, and associated anthropogenic activities, has a negative impact on the health and development of tropical dryland forests. Southern Africa encompasses significant areas of dryland forests that are important to local communities but are facing rapid deforestation and are highly vulnerable to biome degradation from land uses and extreme climate events. Appropriate integration of remote sensing technologies helps to assess and monitor forest ecosystems and provide spatially explicit, operational, and long-term data to assist the sustainable use of tropical environment landscapes. The period from 2010 onwards has seen the rapid development of remote sensing research on tropical forests, which has led to a significant increase in the number of scientific publications. This review aims to analyse and synthesise the evidence published in peer review studies with a focus on optical and radar remote sensing of dryland forests in Southern Africa from 1997-2020. For this study, 137 citation indexed research publications have been analysed with respect to publication timing, study location, spatial and temporal scale of applied remote sensing data, satellite sensors or platforms employed, research topics considered, and overall outcomes of the studies. This enabled us to provide a comprehensive overview of past achievements, current efforts, major research topics studies, EO product gaps/challenges, and to propose ways in which challenges may be overcome. It is hoped that this review will motivate discussion and encourage uptake of new remote sensing tools (e.g., Google Earth Engine (GEE)), data (e.g., the Sentinel satellites), improved vegetation parameters (e.g., red-edge related indices, vegetation optical

depth (VOD)) and methodologies (e.g., data fusion or deep learning, etc.), where these have potential applications in monitoring dryland forests.

Keywords: Remote sensing, Dryland forests, Southern Africa, Forest monitoring, SAR, Optical, Systematic review

1. Introduction

1.1 Tropical Dryland forest

Approximately 40% of the Earth's tropical and subtropical land surface is covered by open or closed forests. Of this, tropical dryland forests (TDFs) account for the largest share at 42%; the remaining 33% is moist forest, and only 25% is rain forest (Murphy et al., 1986; Janzen, 1988). The largest proportion of dryland forests ecosystems are found in Africa, accounting for 60 - 80% of the total biome area (three times the area covered by African rain forest) (Figure 1) (Bodart et al., 2013; Bullock et al., 1995). Dryland forests hold a significant amount of terrestrial organic carbon that may contribute more to climate mitigation and adaptation than previously appreciated (Valentini et al., 2014). Dryland forests also provide diverse ecosystem services, including water regulation and erosion control, the provision of food, fuel, and tourism opportunities (Djoudi et al., 2015; Schröder et al., 2021). On the other hand, dryland forests are subject to prolonged dry seasons and their rate of conversion to secondary forests has historically been higher than other tropical forest types (Pennington et al., 2018). According to the Intergovernmental Panel on Climate Change (IPCC), these changes have impacts on carbon emissions to the atmosphere and forest biodiversity loss that reduce adaptive capacity and resilience to the impact of high temperatures and varying precipitation (IPCC, 2014).

The definition of "dryland forest" remains debatable and controversial, which contributes to the difficulty in accurately assessing and measuring its distribution patterns and status (Blackie et al., 2014). The lack of a clear and comprehensive understanding of general terms including "drylands" and "forests" makes it a challenge to explicitly define dryland forests (Charles-D et al., 2015). Given the fact that dryland forests progressively grade into other vegetation types such as moist tropical forests, woodlands, and savannas, also makes clear definitions complex (Putz et al., 2010). Walter et al. (1971) noted that the accuracy of estimates of all tropical forest areas is constrained by uncertainty in the distribution of open woodlands in dryland areas, which are extensive in Africa, Australia, and Latin America.

In the scientific literature, many different names have been applied to tropical dryland forests, including savanna forests, Sudanian woodland and miombo woodland in Africa, monsoon forest in Asia, neotropical dry forests in South America (Chidumayo, 2013; Linares-Palomino et al., 2011; Suresh et al., 2011). The neotropical dry forests in South America have a plethora of names from “caatinga” in northeast Brazil, to “bosque tropical caducifolio” in Mexico, and “cuabal” in Cuba, which in part hinders comparisons (Mayes et al., 2017; Sánchez-Azofeifa et al., 2005). For example, Dexter et al. (2015) identified dry deciduous forest in India (Suresh et al., 2011), miombo woodland in southern Africa (Chidumayo, 2013), and deciduous dipterocarp forest in continental Asia (Bunyavejchewin et al., 2011) as a form of savanna, and not TDFs, despite the formal classification as TDFs by these studies, and the FAO (FAO, 2001). The Caatinga and Chaco vegetation in Latin America is also considered by some authors as part of the dry forests (Gasparri and Grau, 2009; Pennington and Ratter, 2006), although Olson et al., (2001) classifies these regions as a shrubland ecosystem.

There are several definitions currently available for TDFs, but there is still a lack of consensus in developing a common understanding. Mooney et al. (1995) defined TDFs as forests occurring in the tropical regions characterized by pronounced seasonality in rainfall, where there are several months of severe, or even absolute drought. Sánchez-Azofeifa et al. (2005) broadly defined TDFs as a vegetation type typically dominated by deciduous trees (at least 50% of trees present are drought deciduous), where the mean annual temperature is ≥ 25 °C, total annual precipitation ranges between 700 and 2000 mm, and there are three or more dry months every year (precipitation < 100 mm per month). A widely accepted definition is that of the FAO, which has identified TDFs as a Global Ecological Zone (GEZ), experiencing a tropical climate, with a dry period of 5 to 8 months and annual rainfall ranges from 500 to 1500 mm; GEZ includes the drier type mbo and Sudanian woodlands, savannah (Africa), caatinga and chaco (South America), and dry deciduous dipterocarp forest and woodlands (Asia) (FAO, 2001). For the scope of this present review, we followed the FAO. (2001) definition of TDFs because it recognises forests occurring in the dry tropical climate globally including areas with relatively open canopies such as woodlands, and woody stands, then those based entirely on climate definitions. The growing body of evidence suggests that the current climate does not define the biogeography of TDFs or determine biome distributions (Staver et al., 2011; Sunderland et al., 2015), particularly in the context of future unprecedented climate change (IPCC, 2007). If climates become sufficiently warmer and drier in the tropics, dry forests may expand into areas that are currently dominated by moist tropical forests (Putz et al., 2010).

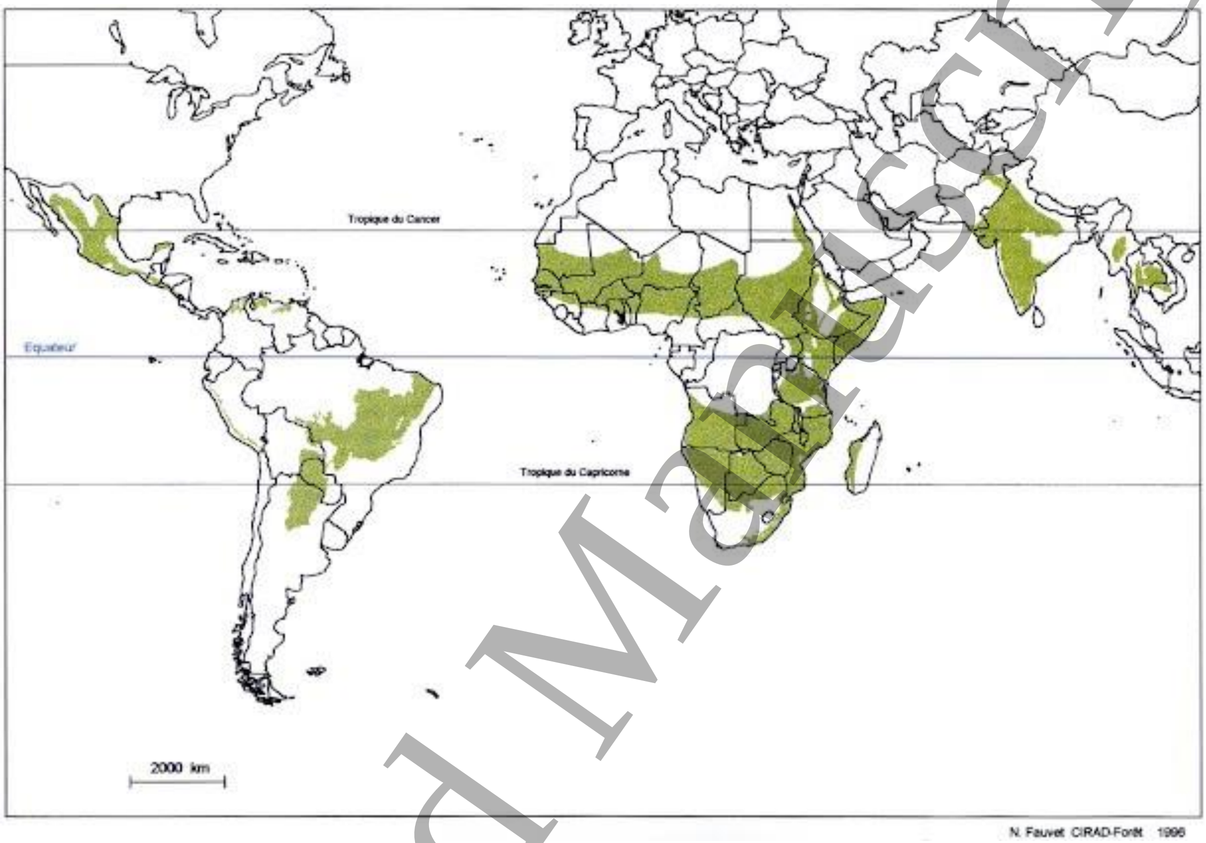


Figure 1. The graphic illustration shows the relative distribution of tropical dry forests.

Source: FAO, (1999). Reproduced with permission.

1.2 Recent research trends on tropical dry forests

1.2.1 Geographical research trends on tropical dry forests

Studies have pointed out that dryland forests generally receive a lower number of scientific publications and are under-represented in research in comparison with tropical moist forests (Miles et al., 2006; Quesada et al., 2009). Global reviews on dryland forests addressed the imbalance in the geographical coverage of dryland forest publications using remote sensing with certain tropical countries such as Latin America receiving the highest publications on dryland forests in comparison to most places in Africa (Blackie et al., 2014; Schröder et al., 2021). To investigate the geographical distribution of tropical dry forest studies, we initially searched for publications in ISI web of knowledge and Scopus on tropical dryland forests from Asia, Africa, America, and Australia. This search was conducted by using the keywords 'Dry Forest', 'Dryland Forest' 'Savan* Woodland', 'Savan* Tree', 'Dryland Vegetation', 'Dry Vegetation' 'Satellite', 'Remote Sensing', 'Optical', 'Radar', 'Image', 'SAR', 'Earth Observation', 'country/continent e.g., Africa'. In the search period from 1997 to 2020, we identified 1662 papers for Africa, 1639 for Australia, 1338 for America, and 1134 for Asia. In Africa, when we narrowed the search to individual countries, the results showed that about 743 publications are from the Republic of South Africa (RSA) while 355 publications were from the Sahel region of Nigeria. We also investigated scientific publications from other Southern African countries with dryland forest and 369 publications were identified, including from Botswana (87), Zimbabwe (69), Mozambique (60), Namibia (68), Zambia (49), Angola (24), Lesotho (6), Swaziland (5). When we combined the scientific publications from the above 8 Southern African countries, the results were 369 publications, indicating that publications on dryland forests for the Republic of South Africa were 2.01 times higher than all 8 Southern African countries combined. These results confirm that much less progress has been made in developing objective methods for assessing the rates of deforestation/conservation and threats to dryland forests ecosystems in most Southern African countries except for the Republic of South Africa.

The dryland forests in other parts of the world like Latin America are increasingly well studied at local, regional, national and continental scale, particularly with regards to carbon/biomass (Chazdon et al., 2016; Marín-Spiotta et al., 2008), fire (Campos-Vargas et al., 2021; White, 2019; Pereira et al., 2014), climate change (Mendivelso et al., 2014; Castro et al., 2018; González-M et al., 2021), floristic and diversity composition (Alvarez-Añorve et al., 2012; Gillespie et al., 2000), ecosystem services (Castillo et al., 2005; Paruelo et al., 2016), Payment for Environmental Services (PES) (Alcañiz and Gutierrez, 2020; Corbera et al., 2009), novel conservation approaches (e.g., sustainable intensification for protected/conservation areas) (Méndez et al., 2007; Reynolds et al., 2016) and has the most comprehensive forest change/deforestation and biophysical aspects including species population changes, with extensive use of remote sensing (do Espírito-Santo et al., 2020; Gasparri and Grau, 2009; Stan and Sanchez-Azofeifa, 2019; Trejo and Dirzo, 2000; Portillo-Quintero et al., 2012). In terms of reviews, many remote sensing reviews are providing valuable information on TDF's biophysical, ecological and socioeconomic at a regional level of Latin America (Castro et al., 2003; Metternicht et al., 2010; Portillo, 2010; Sanchez-Azofeifa et al.,2003; Sánchez-Azofeifa et al., 2005; Sánchez-Azofeifa et al., 2013; Stan and Sanchez-Azofeifa, 2019; Quijas et al. 2019), and Australia (Lawley et al., 2016; Moore et al., 2016; Fensham et al., 2002). Also, reviews of current progress on dryland forests in individual countries can be found in many neotropics countries such as Mexico (Castillo et al., 2005; Curry, 2020), Venezuela (Fajardo et al., 2005; Rodríguez et al., 2008), and Costa Rica (Frankie et al., 2004; Stoner et al., 2004) enabling the identification of knowledge gaps and aiding in the development of a policy-relevant approach to conservation of these forests (Miles et al., 2006).

Latin America is one of the best-represented areas for remote sensing research in dryland forests, for example, Portillo-Quintero and Sánchez-Azofeifa. (2010) utilised remote sensing data at continental America, dryland forests ecoregion, and neotropics countries to show that 66% of tropical dry forest in the region has already been converted and that in some countries the conversion rate is as high as 86% and 95%, respectively. Aide et al. (2012) using Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data estimated that 200,000 km^2 of woody vegetation of Latin American and the

Caribbean region were lost due to deforestation between 2001 and 2010. Nanni et al. (2019) utilised MODIS satellite data at 250 m spatial resolution to assess reforestation at the regional level and reported that the reforestation hotspots cover 167,667.7 km^2 (7.6 %) of Latin America between 2001 and 2014. While there are continental studies in Africa utilising remote sensing on biophysical parameters such as biomass/deforestation (Bouvet et al., 2018; Bodart et al., 2013), as compared to Latin America, these studies may not consider the empirical observations of dryland forests extent/change per region or country level. In addition, most continental studies in Africa rather focus the attention on tropical rainforest in Central Africa (e.g., core Congolese forest) which may under-represent dryland forest (e.g., Aleman et al., 2018). Global applications often report general land use/cover change which results in inaccurate or poor estimates of dryland forest (Smith et al., 2019; Aleman et al., 2018).

Several studies using optical and passive microwave instruments in the African Sahel (Horion et al., 2014; Brandt et al., 2016; Olsson et al., 2005; Tian et al., 2017) has reported that the density/size of woody vegetation stands have increased, with few areas in northern Nigeria reported to experience logging and agricultural expansion into forest reserves. Deforestation in Southern Africa is a major concern, with ca. 1.4 million ha of net forest loss annually, contributing to increased land degradation and the ensuant impacts on the balance of ecosystem function (Lesolle, 2012). A global study by Tian et al. (2017) utilising the optical Normalized Difference Vegetation (NDVI) index and passive microwave VOD across tropical drylands has reported a decreasing trend in woody vegetation in Southern African countries such as Botswana and Zimbabwe. Mitchard and Flintrop. (2013) conducted a coarse-scale analysis of changes in woody vegetation from 1982 to 2006 using NDVI time series from the Global Inventory Modeling and Mapping Studies (GIMMS) dataset and found that significant woody encroachment is occurring in most west African countries, but, in contrast, in Southern Africa, a rapid reduction in woody vegetation (deforestation) is occurring. Bodart et al. (2013) used Landsat satellite imagery between 1990 and 2000 to estimate forest cover and forest cover changes in the African continent and found that 84% of the total deforested area occurred in the dry ecosystems of the Southern African region, with large spatially concentrated areas of forest loss found in Angola, Mozambique, Tanzania, Zambia and Zimbabwe, and isolated hotspots found in Nigeria and the border of the humid forest in Ghana. While such global and continental level studies are useful to highlight and reinforce the need to direct more attention and resources to these threatened/poorly studied ecosystems, research efforts on forest change/deforestation and climate change impacts of dryland forests at the regional level of Southern Africa are much harder to come by (Blackie et al., 2014).

1.2.2 Remote Sensing approaches research trends in tropical dry forests

In recent decades, satellite remote sensing or Earth observation (EO) has proved a valuable tool in forest ecology, owing to its capability to perform systematic, frequent, and synoptic observation of the Earth, resulting in large data volumes and multiple datasets at varying spatial and temporal scales (Donoghue, 2002; Zhu, 2017). There are several sensors including multi-spectral scanners, las184, per scanners (LiDAR), hyper-spectral scanners as well as satellite-borne Synthetic Aperture Radar (SAR), that provide information on the colour and structure of forest environments (Donoghue, 2002). EO has been applied to mapping the distribution, changes in cover, and condition including deforestation, desertification, fire damage, and climate impact (Dogru et al., 2020; Smith et al., 2019). Additionally, these data have been used to estimate biophysical characteristics such as total above ground biomass (AGB), leaf area index (LAI), woody area index, tree diameter, and canopy height which are key inputs into a variety of ecological models, as well as calculations of carbon balance and primary production (Barbosa et al., 2014; Donoghue, 2000). The continuous forest metrics obtained using EO data can be extracted at leaf and crown level to evaluate spectral elements of leaf or species properties and at stand-level and plot-level, or beyond to understand the variation between and among species, and through time (Muraoka et al., 2009). Monitoring of dryland forest cover and forest metrics using EO data also helps to improve our understanding of the ecological drivers behind land cover change dynamics (Chambers et al., 2007; Veldkamp et al., 2001).

Biomass has extensively been estimated based on the spectral reflectance values from two or more wavelengths, and the sensitivity of optical and near-infrared wavelengths to photosynthetic canopy cover has long been used for vegetation analyses (Rouse, 1974; Tucker, 1979). Spectral vegetation indices (VIs), including the NDVI index, are commonly used as a proxy of vegetation cover and have been shown to relate closely to LAI, biomass, and the fraction of photosynthetically active radiation absorbed by vegetation (fAPAR) (Curran, 1980). Several well-known limitations of NDVI for robust estimation of biomass in drylands exist. NDVI is sensitive to green components and insensitive to woody components where the majority of carbon is stored (Tucker, 1979). Also, AGB production is not always uniformly linked to either greenness or plant structure (herbaceous and woody compositions), as moisture content and vegetation species composition have been shown to impact the biomass-NDVI relationship (Asner et al., 2009; Wessels et al., 2006). These observations may help explain reportedly weak relationships between NDVI and tropical forest canopies, particularly for areas with complex and high vegetation amounts as in TDFs (Foody et al., 2001; Sader et al., 1989). For example, Madonsela et al. (2018) investigated the interactions between seasonal NDVI and woody canopy cover in the savanna of the Kruger National Park (NP) to model tree species diversity using a factorial model and found that the interaction between NDVI and woody canopy cover was insignificant. These challenges have led to the development of alternative formulations which include correction factors or constants introduced to account for or minimize, the varying background reflectance (Gitelson et al., 1996; Huete et al., 1999). The Enhanced Vegetation Index (EVI) is a modification of NDVI that provides complementary information about the spatial and temporal variations of vegetation while minimizing many of the contamination problems present in the NDVI, such as those associated with canopy background and atmospheric influences (Huete et al., 2002). Other closely related indices include the Simple Ratio (SR), the Green Normalized Difference Vegetation Index (GNDVI), Soil-Adjusted Vegetation Index (SAVI) amongst others. Xue et al. (2017) provide a detailed review of vegetation indices.

Although vegetation monitoring has been largely based on the multispectral “greenness” indices, which have proven invaluable for monitoring biophysical and biogeochemical parameters, it has been widely reported in the literature that they suffer from several weaknesses in dryland ecosystems (Tian et al., 2016; Shi et al., 2008). Other remote sensing systems such as the passive microwave-based satellite systems capture the biomass signal in the parameter termed vegetation optical depth (VOD) which has been used to monitor changes in vegetation dynamics (Andela et al., 2013; Brandt et al., 2018a; Brandt et al., 2018b). Unlike the optical remote sensing-based vegetation indices that are sensitive to chlorophyll abundance and photosynthetically active biomass of the leaves, the vegetation information (e.g., VOD) deriving from passive microwave instruments is sensitive to the water content in the total aboveground vegetation, including both the canopy (e.g. woody plant foliage) and non-green woody (e.g. plant stems and branches) components due to greater penetration and sensitivity (Liu et al., 2011; Shi et al., 2008). The passive microwave observations VOD is relatively insensitive to signal degradation from solar illumination and atmospheric effects and provide a valuable alternative tool for rapid monitoring of carbon stocks and their changes (Jones et al., 2011). One of the advantages of passive microwave-derived VOD is that it continues to distinguish biomass variations at a relatively high biomass density, as compared to optical-based vegetation indices which are likely to become saturated over dense canopies (Jones et al., 2011; Liu et al., 2015). The main disadvantage of passive microwave observations is the relatively coarse spatial resolution (>10km), as compared to satellite data in the visible and near-infrared parts of the spectrum; however, these data still have highly useful applications at regional and global scales (Liu et al., 2015; Rahmoune et al., 2013; Owe et al., 2001). Some recent global and local studies from Latin America and Africa in the dryland ecosystems found VOD to be more robust against the NDVI drawbacks of saturation effect and continues to distinguish structural differences for vegetation with a near-closed canopy when used as a proxy for vegetation productivity (van Marle et al., 2015; Cui et al., 2015; Liu et al., 2011; Tian et al., 2016). Apart from the VOD and NDVI, an intercomparison between several vegetation indices including other passive microwave-based vegetation indices, such as the Microwave Polarization Difference Index (MPDI) (Becker & Choudhury, 1988), and the Microwave Vegetation Indices (MVIs) (Shi et al., 2008) would be of benefit in monitoring dryland biomes.

Due to the inherent trade-offs between spatial and temporal resolution in EO data, and geographic coverage, vegetation patterns on both spatial and temporal domains have been revealed by various technological advances resulted in the growing availability of remote sensing data and methods (Toth and Jóźków, 2016; Zhou et al., 2020). The application of non-parametric machine learning regression algorithms, such as decision trees, random forests (RF), support vector machines (SVMs), and k-nearest neighbour have become more predominant and demonstrate the ability to outperform widely used parametric approaches, such as polynomial and multiple linear regression variables used with remotely sensed data in a forest environment (Breiman, 2001; Latifi et al., 2010). More recently, deep learning, a branch of machine learning that stems from cognitive and information theories (e.g., convolutional neural network (CNN) founded by Schmidhuber. (2015) has been highlighted as a feasible approach for handling complex data in remote sensing including large-scale image recognition, semantic segmentation, classification, and object detection tasks (Kattenborn et al., 2021; Shafaey et al., 2018). Non-parametric machine and deep learning models are sufficiently versatile to uncover complicated nonlinear relationships and able to extract combinations of the input data that are difficult to describe explicitly by humans, particularly, in areas with high structural variability such as dryland forests (Hastie et al., 2009; Shao et al., 2017). Deep learning has been used by many remote sensing studies to provide in-depth forest investigation from the perspectives of hyperspectral image analysis, interpretation of SAR/ LiDAR images, interpretation of high-resolution satellite images and classification, and multimodal data fusion (e.g., the fusion of Hyperspectral, SAR, LiDAR and optical data (Guirado et al., 2020; Kussul et al., 2017; Liao et al., 2018; Narine et al., 2019; Shao et al., 2017; Trier et al., 2018). Improved techniques in remote sensing such as VOD, and machine and deep learning have been utilised to estimate dryland forest attributes globally and other dryland ecosystems, however, very few of these focused on the local and regional scale of Southern Africa (e.g., Symeonakis et al., 2020). The uncertainties reported in many dryland forests studies (Bastin et al. 2017), could be decreased following further development, application, and comparison of these improved approaches in future works at local, regional, continental studies in Southern Africa and other dryland forest ecosystems. Critically, an increase in the spatial, spectral, and radiometric resolution of satellite sensors, increased availability of EO data and computational resources combined with the machine or deep learning techniques would enhance the potential dryland forest information to be exploited (Ali et al., 2015). For a detailed review of machine learning and deep learning for remote sensing and Sustainable Development Goals, see Zhu et al. (2017) and Holloway and Mengersen (2018).

1.3 Review focus justification

The majority of the residents of Southern Africa are poor and about 75% of them live in rural areas with high reliance on dryland forests (Bond 2010). Additionally, these dryland areas display a high susceptibility to bush encroachment (O'Connor et al., 2014) and economic reliance on tourism (Ferreira 2004) and forest products (Kamwi et al., 2020), which means that both agriculture and tourism development encroach on the dryland forests, resulting in loss of forest biodiversity and land degradation (Eva et al., 2006; Petheram et al., 2006). Across Southern Africa, sustainable management of dryland ecosystems is hindered by complex land tenure due to historical legacy, weak links between policy and woodland use and management, and cultural drivers (Balint and Mashinya, 2006; Dewees, 1994). Also, the dryland ecosystems of Southern Africa are dominated by private land ownership, a high concentration of wildlife and human populations, and agriculture where TDFs occur (Child et al. 2012). This review focuses on Southern Africa because there is a gap in knowledge on carbon storage, biomass, and the long-term trend of forest distribution and degradation in dryland forests. Much of the research on dryland forests in Southern African has concentrated on livelihoods, ecosystem services, energy supply and demand, food security, livelihoods and community forest management, and conservation/development trade-offs (e.g., Chidumayo et al., 2010; Chidumayo and Gumbo 2010; Chidumayo 2019; Djoudi et al., 2015; Dewees 1994; Du Preez 2014; Ryan et al. 2016), leaving forests highly vulnerable to deforestation and degradation (Keenan et al., 2015). The social and economic aspects are important given the large numbers of African people that rely on dry forests for their livelihoods and a range of goods and services. However, the gap in biophysical aspects, threats status, and adaptation to climate change identified for Southern African TDFs at the regional and national level (Blackie et al., 2014; Sunderland et al., 2015), presents an urgent need for an assessment of the effectiveness of the EO scientific foundation on current understanding of TDFs in

Southern Africa; this can aid in the development of policy-relevant approaches and long-term, regional perspective for planning and conservation of the TDFs.

With the prospects of multiple free datasets from optical and SAR sensors being available; combining information from optical sensors on photosynthetic activity (e.g., through various vegetation indices) with SAR-derived information on forest structure and volume brings the benefits of higher spectral resolution, and compensating for the shortcomings of using single data products alone. Based on this hypothesis, this review focuses on examining the studies using optical and SAR sensors, both individually and the combination of the two types of EO data in monitoring tropical forests. While forest distribution, carbon storage, and reducing emissions from deforestation and forest degradation (REDD+) related research exists in African dryland forests, the geographical focus has tended to be confined to several West/Central African countries, whereas Southern Africa is relatively poorly analysed (Lewis et al., 2013; Sunderland et al., 2015). Although numerous reviews have been conducted discussing the application of optical and radar remote sensing, they are either concentrated on mangroves forests (Kuenzer et al., 2011; Wang et al., 2019), rain forests (Dupuis et al., 2020), or ecosystem services (Barbosa et al., 2015). To date, reviews on remote sensing and EO in Southern Africa have focused on research conducted in the Republic of South Africa (Hoffman et al., 2000; Mutanga et al., 2016; Mutanga et al., 2009).

As shown in Figure 2, the climate threats coupled with a growing human population and future anticipated changes in land use are predicted to lead to severe dry forest biome shifts and degradation across the whole of Southern Africa, hence the need to expand the geographical scope of this review from previous work (IPCC, 2014; King, 2014). This paper provides a systematic review of the scientific literatures related to the use of Earth observation data including SAR and optical sensors used to study dryland forests, with a focus on Southern Africa. To achieve this, we present examples from the literature that summarise past achievements, current efforts, and knowledge gaps. The objectives of this review are to (i) to provide a detailed overview of the current approaches and limitations for monitoring dryland forests using optical and radar remote sensing data. (ii) to provide a critical evaluation and synthesis of the literature monitoring dryland forests using remote sensing data and discuss how EO data can contribute to dryland forest monitoring and forest conservation in Southern Africa. (iii) to identify knowledge gaps and make recommendations for research that will enhance monitoring of dryland forests using remote sensing data.

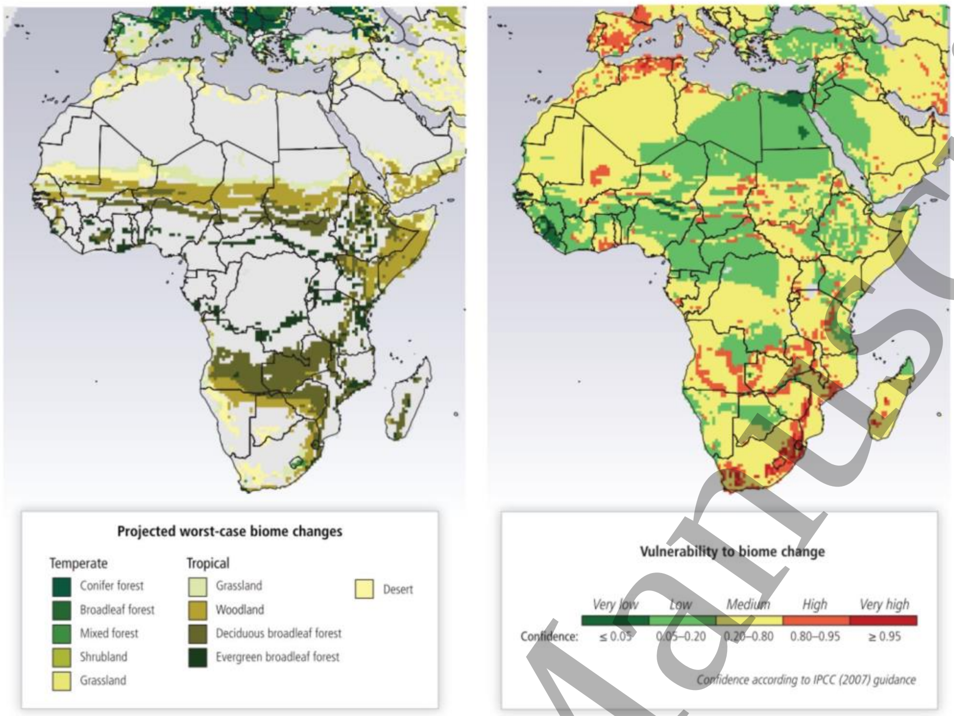


Figure 2. (a) Projected biome change from the periods 1961–1990 to 2071–2100 using the MC1 Dynamic Vegetation Model. (b) Vulnerability of ecosystems to biome shifts based on historical climate (1901–2002) and projected vegetation (2071–2100) (source: IPCC, 2014).

2. Remote sensing applications in dryland forest

2.1 Optical data

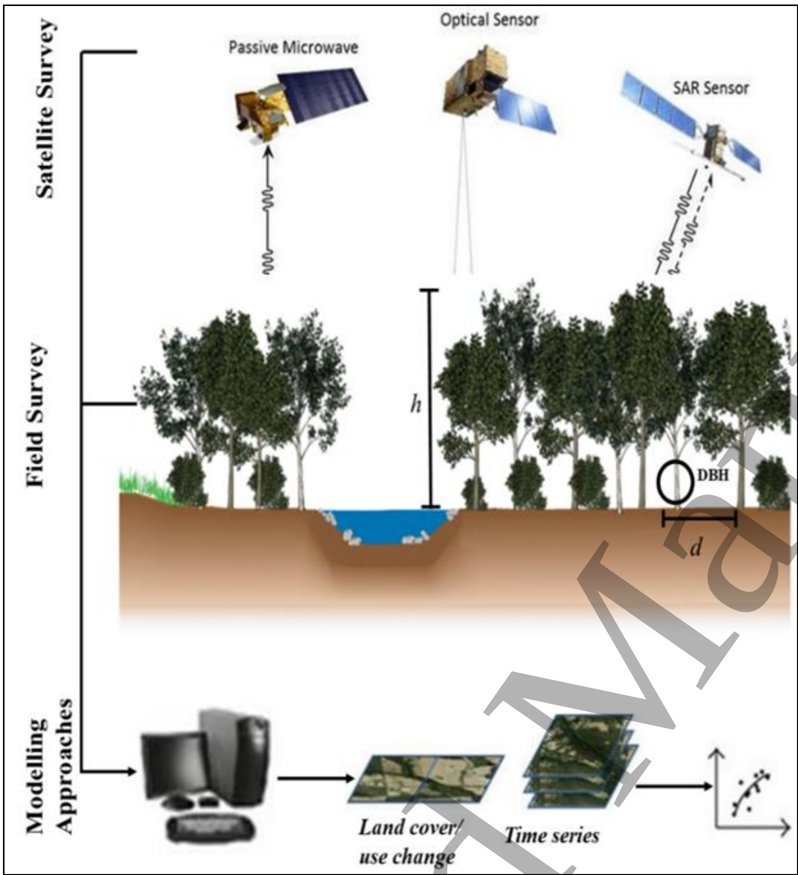
In broad terms, the satellite platforms developed over the past 40 years (since 1972) have carried two broad types of sensor systems; passive optical and active synthetic aperture radar (SAR). Successful change detection and parameter estimation over tropical dryland forests require: (a) correct selection and application of sensor type; (b) coupling with field observation data for calibration and validation, and (c) data integration and appropriate techniques for modelling (Figure 3). Optical sensors have been widely used for land cover and forest resource mapping, providing access to long-term data dating back to the launch of Landsat ERTS (Earth Resources Technology Satellite) satellites in 1972.

Landsat and several other coarse/medium spatial resolution optical sensor missions (National Oceanic and Atmospheric Administration (NOAA) - Advanced Very High-Resolution Radiometer (AVHRR); Indian Remote Sensing Satellites-1C/1D (ISRO-IRS-1C/D); the National Aeronautics and Space Administration (NASA) -Aqua/Terra- MODIS; Sentinel-2) provide well-calibrated, nadir-viewing, near-global systematic coverage which have built up a valuable archive of image data that can be used to analyse ecosystem dynamics (Congalton, 2018; Donoghue, 2000). In 2014, ESA launched the Multispectral Instrument (MSI) onboard Sentinel-2 as part of its Copernicus EO mission. Sentinel-2 MSI uses two identical satellite sensors to measure the Earth's reflected radiance with a revisit time of 5 days and a high spatial resolution of 10 - 20 m pixel size. The length of the Sentinel-2 archive is short (from 2015), compared to the Landsat mission from 1972-present, NOAA-AVHRR 1979-present, Satellite Pour l'Observation de la Terre VEGETATION (SPOT/VGT) (1998-present), IRS-1C/1D (ISRO-IRS-1C/D) (1995-2010), ENVISAT - Medium Resolution Imaging Spectrometer (MERIS) (2002-2010), the NASA - MODIS (2000-present) and the French Space Agency (CNES-Centre national d'études spatiales) high-resolution SPOT satellite constellation (6 m - 20 m pixel size) - SPOT-1 in 1986-1990, SPOT-2 in 1990-2009, SPOT-3 in 1993-2009; SPOT-4 in 1990-2013; SPOT-5 in 2002-present; SPOT-6 in 2012-present; SPOT-7 in 2014-present. The VEGETATION 1 (VGT 1) (1998-2012) and VEGETATION 2 (VGT 2) (2002-2014) instrument on the SPOT 4 and SPOT 5 (SPOT/VGT) satellites provided global daily monitoring of vegetation cover, and it is successor the European PROBA-V satellite (2013-present), with a pixel size of 1 km, 300 m and 100 m are supplied by the VEGETATION image Processing Centre (CTIV) of VITO (Belgium), which can be accessed through the internet site http://free.vgt.vito.be. Although a large number of satellite sensors have been launched that are capable of observing land dynamics, and their pixel size has increased from 80 m of the Landsat-1 to 0.41-1.65 m of the GeoEye-1 satellites (Aguilar et al., 2013), very few sensors provide well-calibrated multispectral, nadir-viewing observations and even fewer systematically capture all global data and provide a long-term archive of data free of charge to the public. Except for AVHRR and Landsat, no other sensor or sensor line offers the chance of long-term monitoring of an area to be monitored back in time to the 1970s, covering about four decades.

There are several non-systematic commercial high-resolution satellites that allow the detection of individual trees or populations. Maxar Technologies Inc. launched 4 very high resolution satellites - WorldView-1 in 2007, WorldView-2 in 2009, WorldView-3 in 2010, and WorldView-4 in 2019 that acquire images with spatial resolution of 0.5, 0.41, and 0.31 m, respectively. From 2009 onward, Planet labs launched a swarm of micro-satellites including PlanetScope (PS), RapidEye (RE), and SkySat (SS) Earth-imaging constellations with multispectral imaging capability with the aim of acquiring daily image capture for any part of the world at a spatial resolution of 3.125 m to 6.5 m (Marta, 2018). In 2011 and 2012, the Space Agency of France (CNES) launched the Pléiades – high resolution optical imaging satellite constellation (Pléiades-1A and Pléiades-1B), with a high spatial resolution of 0.7 – 2.8 m. Other very high resolution commercial space imaging satellites include Earlybird (1997), EROS-A (1998), IKONOS (1999), QuickBird (2001), OrbView (2001), GeoEye (2008) (Maglione, 2016). In Africa, South Africa started satellite developments in the 1990s, with the successful launch of SunSat-1 with a spatial resolution of 15 m in 1999 and SumbandilaSat low orbit satellite with a high spatial resolution of 6.25 m in 2009 (Cho et al., 2012; Mutanga et al., 2016). While the first Nigerian satellite, a microsatellite called NigeriaSat-1, was successfully launched into low earth orbit in 2003, followed by Nigeriasat-2 with a higher spatial resolution of 2.5 – 5 m, built by Surrey Satellite Technology Limited (SSTL) of UK (Agbaje, 2010).

Nevertheless, the use of data acquired by higher spatial resolution optical sensors, particularly at regional and global scales, can be limited by their relatively high cost, huge data volumes, and low frequency of data acquisition compounded further in tropical regions where cloud cover is prevalent (Lehmann et al., 2015; Zhu and Woodcock, 2012). The temporal resolution of sensors has also increased from, for example, 16 days for Landsat to nearly 1 day for the NOAA-AVHRR, NASA-Aqua/Terra-MODIS, SPOT/VGT, and/or ENVISAT-MERIS data, but with a coarse spatial resolution of 250 m to 1 km (Arino et al., 2007; Herold et al., 2008). Although lacking high spatial detail, the daily temporal resolution of such sensors enables frequent estimation of deforestation, detection of disturbances using dense time series data, and enables gaps due to cloud cover to be overcome (Mbow et al., 2015). It is important to mention that the acquisitions of some satellites such as IRS-1C/1D, and

MERIS ceased operations, however, the Sentinel, MODIS, NOAA-AVHRR, SPOT, SPOT-VGT (PROBA-V), and Landsat series continue to operate, with ongoing continuity of data collection ensured with the recent launch of Landsat-9 in September 2021.



Sources of variability	Challenges
Resolution -Spectral -Radiometric -Spatial -Temporal	-Temporal and spatial availability -Imagery quality(clouds) -Financial constraints -Know-how
Ground truthing -Temporal and spatial heterogeneity -Physiognomies	-Accessibility (wildlife, complex forest structures) -Logistics -Time -Financial constraints
Modelling -Allometric Equation -Uncertainty -Model inversion -Classification schemes -Vegetation Indices	-Availability of allometric equation from the destructive survey -Sufficient sampling -generalisation -Know-how

Figure 3. Interaction mechanisms for dryland forest canopies and source of variability and challenges related to each stage of remote sensing monitoring tropical dryland forest extents. Adapted from Barbosa et al., 2014.

2.2 Synthetic Aperture Radar (SAR)

SAR sensors for civilian applications first appeared in 1978 with NASA's SeaSat but have grown in importance as a tool for forest studies. SAR sensors can operate at different frequencies and polarisations; these system parameters provide information on the roughness and scattering properties of forest canopies and data can be captured day and night independent of weather conditions (Durden et al., 1989). Since SAR can penetrate cloud, rain, smoke, and haze, and it is a valuable source of data when atmospheric conditions hamper optical data capture, particularly in the tropical dryland forest such as Southern Africa where the cloud and smoke from forest fires are prominent features (Le Canut et al., 1996). Radar signals are sensitive to moisture, variations, surface roughness, and vegetation structure properties, whereas data from optical systems use characteristics related to reflected solar illumination or surface temperature (for thermal infrared sensors) as a basis for discrimination of the land cover (Kasischke et al., 1997; Mitchard et al., 2009). Cloud cover-free SAR images have great potential in the dryland tropical areas but have been used less often for forest monitoring applications compared to optical imagery, partly because of the scarcity of data (Castro et al., 2003). Since the launch of the Sentinel-1A and B, dense SAR time-series data are now available over tropical forest areas freely and openly, with systematic acquisitions at a 10 m spatial resolution and a 6 - 12 day revisit time (dependent on the location) in all weather conditions.

Over the last 30 years, several satellite-borne SAR has been launched, including the United State Spaceborne Imaging Radar-Synthetic Aperture Radar (SIR-C/X-SAR), European Remote Sensing (ERS-1/-2), ESA's Envisat ASAR (Advanced Synthetic Aperture Radar), Advanced Synthetic Aperture Radar (ASAR), Japanese Earth Resources Satellite (JERS-1), Advanced Land Observation Satellite (ALOS/PALSAR-1/-2), German TerraSAR-X, Italy's Cosmo SkyMed, and the Canadian RADARSAT-1/-2 (Shimada, 2018). Depending on the sensor configuration, a single channel (wavelength/frequency) or multiple channels may be recorded in either single or multiple polarizations. Generally, studies have reported that the longer the wavelength (e.g., P (30–100 cm) and L (15–30 cm)), the further is its penetration into the forest and the greater the importance of scattering beyond the upper canopy (Huang et al., 2015). Besides the greater sensitivity of longer radar wavelengths to forest structure, different studies indicate that cross-polarized backscatter (HV-horizontally transmitted, and vertically received, VH-vertically transmitted and horizontally received) often exhibits greater sensitivity to forest biomass than like-polarized backscatter (co-polarized bands: HH-horizontally transmitted and horizontally received, VV-vertically transmitted and vertically received) (Kasischke et al., 1997).

2.3 Limitations of optical and radar, and benefits of combining sensors

Despite the different generations and types of satellite sensors, no one sensor currently meets fully the requirements of a comprehensive forest resource assessment EO system. The selection of an appropriate source of data requires first the identification of the ecological question being asked, identification of the limitations and advantages of each sensor. The varying temporal, spatial, spectral, and radiometric resolutions unique to the individual sensor system, result in different advantages and disadvantages to the monitoring of dryland ecosystems (Lu, 2006). Optical data are limited in the monitoring of this forest type. For example (1) cloud and smoke severely limit the use of optical products (Le Canut et al., 1996); (2) Dramatic seasonal changes in the dryland forests conditions including droughts and leaf shedding make it unsuitable for systematic all-season monitoring of this forest type (Boggs, 2010). One of the reasons for this is associated with the seasonality of the tropical vegetation: during the wet season, cloud-free satellite imagery is difficult to acquire, while during the dry season when the imagery is more available, the leaf-off configuration of the forest causes misclassification with savanna shrubland or grassland; (3 Optical data is sensitive at the early stages of growth but as forest canopies close, reflected radiation is no longer sensitive to biomass as the reflectance signal saturates at higher biomass values (Lu, 2006); (4) Passive optical sensors only detect the surface top layer, meaning that forest canopy obscures the understory, and similarly grasses/crops obscure soil; (5) Changes in the spectral properties of the soil and atmosphere can also hinder the inference of forest cover properties (Santos et al., 2002; Wang et al., 1998).

Similarly, there are a number of challenges to analysing and interpreting radar images for tropical forest applications, which include: (1) Difficulty in interpreting radar backscatter, including, for example, speckle, which is unwanted random noise inherent in all SAR images, which may increase measurement uncertainty and make interpretation difficult (Klogo et al., 2013); (2) Topography is a major limitation in mountainous regions due to geometric and radiometric effects such as radar shadowing caused by foreshortening and layover when the satellite is not able to illuminate the whole ground surface (Mitchard et al., 2009); (3) SAR observations often lack a long-term and dense time series because they demand a relatively high energy provision on satellite platforms. Until recently, satellite-based SAR data for multi-temporal assessments over large areas were constrained by low spatial and temporal coverage at medium resolution, although this now may be overcome with acquisitions from the recently launched C-band Sentinel-1 and L-band ALOS-2 satellite missions (Reiche et al., 2016).

Rather than using EO data from a single satellite sensor, the synergy of remotely sensed data from multiple sensors, particularly SAR systems with those acquired by optical sensors, has been shown to be beneficial for forest resource assessment (Lehmann et al., 2015). Because optical data is capable of measuring the reflectance of the topmost layer of the forest canopy and SAR data deliver useful within-canopy biophysical parameters without being affected by cloud cover and weather conditions, one dataset may compensate for the shortcomings of the other (Reiche et al., 2016). Previous research indicated that integration of optical and radar can improve land and forest cover characterisation (Symeonakis et al., 2018). For example, the fusion of optical and radar sensor data has the potential to improve AGB estimation because it may compensate for the mixed pixels and data saturation problems in a tropical forest area. In addition to the spectral synergy afforded, the cloud penetrating capability of microwave radar sensors allows areas that have missing optical data to be included in analyses, particularly if multi-temporal methods are being employed (Reiche et al., 2016).

3. Methodology

This review focused on scientific papers studying tropical dryland forests and made use of remote sensing data to monitor and estimate changes in dryland forests. Airborne remote sensing studies were excluded from this review process, since the review's major focus lies on satellite Earth observation of dryland forests and because the acquisition of airborne sensors have low area coverage and high cost per unit area of ground coverage (e.g., the airborne hyperspectral images), making them spatially and temporally limited in most African countries. The systematic search approach taken to querying the literature was carried out by making use of selective keyword searches in the form of structured queries using field tags and Boolean operators through the Web of Science (http://apps.webofknowledge.com) and Scopus (http://www.scopus.com) databases. At each query, terms, and keywords such as '*Dryland forests'*, '*Savan**', '*Woodland*', '*Tree*', '*Vegetation*', '*Satellite*', '*Remote Sensing*', '*Optical*', '*Radar*', 'Image', '*SAR*', and '*Earth Observation*' were used to produce an extensive list of articles, where * is a wildcard search. The results were further refined with keywords such as '*Forest change'*, '*Degradation*', '*Deforestation*', '*Trend*', '*Biodiversity*', 'P*henology*', '*Biomass*', '*Structural parameter'*, and also keywords representing the countries in Southern Africa, such as '*Botswana'*, '*Namibia*', '*Mozambique*', '*South Africa*', to provide a comparison in terms of the numbers of studies undertaken across the region. Within the context of this review, all research articles were categorized into eight categories, including: 'Land-use/land-cover', 'Forest cover/types', 'Biomass', 'Forest structure', 'Biodiversity/habitats', 'Phenology', 'Plant traits', and 'Disturbances'. Articles with a publication date between 1997 and 2020 were considered, capturing a period of two decades within the review, based on a broad set of inclusion criteria:

1. The paper should address dryland forests and remote sensing as either main or secondary subjects.
2. The selection terms and keywords should exist as a whole in at least one of the fields: title, keywords, and abstract.
3. The paper should be published in a peer-reviewed scientific journal.
4. The paper should be written in the English language.

During our data extraction process and literature search, we aimed to find studies meeting the criteria for peer-reviewed publications, available through the chosen indexed bibliographic databases. For this reason, our literature search did not include general non-scientific reports, books, grey literature, thesis documents or dissertations, extended abstracts, or presentations. The initial steps of the search process returned 1,478 published articles. Additional publications were added to the total set of studies by identifying relevant literature found in the reference lists of these selected papers that conform to the inclusion criteria. The review methodology was guided by the Guidelines for Systematic Review and Evidence Synthesis in Environmental Management (Collaboration for Environmental Evidence, 2013). A systematic review and meta-analysis were undertaken and framed based on the PICO (population, intervention, comparison, outcomes) model (McKenzie et al., 2019) and reported using PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) flow diagram (Moher et al., 2009). The 1,478 articles were reduced to 870 articles as we selected for inclusion in the review only the studies that had a full text available in English, papers published in peer-reviewed journals, and removing all repetitions across databases. Initially, the titles and abstracts were screened to assess eligibility by searching for predefined keywords and terms of the abstract or summary, identifying terms 'dry or dryland forests' and the country or countries where the research took place. In this way, studies not conducted in Southern Africa or dryland forests were filtered out, which reduced papers from 870 to 599 papers. The screening was followed by a full-text assessment that reduced the papers to 270 by excluding studies that, for example, mentioned the term 'dryland forest' once in the abstract but did not investigate dryland forests, as outlined in the PRISMA flow diagram in Figure 4. The search was subsequently refined by assigning the papers to each of the study aims they addressed and to each category for the variables identified in the search protocol, reviewing the methodologies of each publication, excluding them from further analysis if they did not meet the inclusion criteria on review. These steps reduced the total number of entries to 137 scientific publications. The selected literature was reviewed systematically, searching for specific information regarding the publication temporal development, study location, remote sensing sensor/platform used, spatial and temporal coverage, remote sensing product (e.g., biophysical indices) used, and application areas of the study (e.g., land cover, forest biomass). The parameters used to extract relevant information from the remaining 137 identified scientific publications are in Table 1. Figure 4 is a PRISMA schematic representation of the methodology used and the derivation of the final number of articles selected.

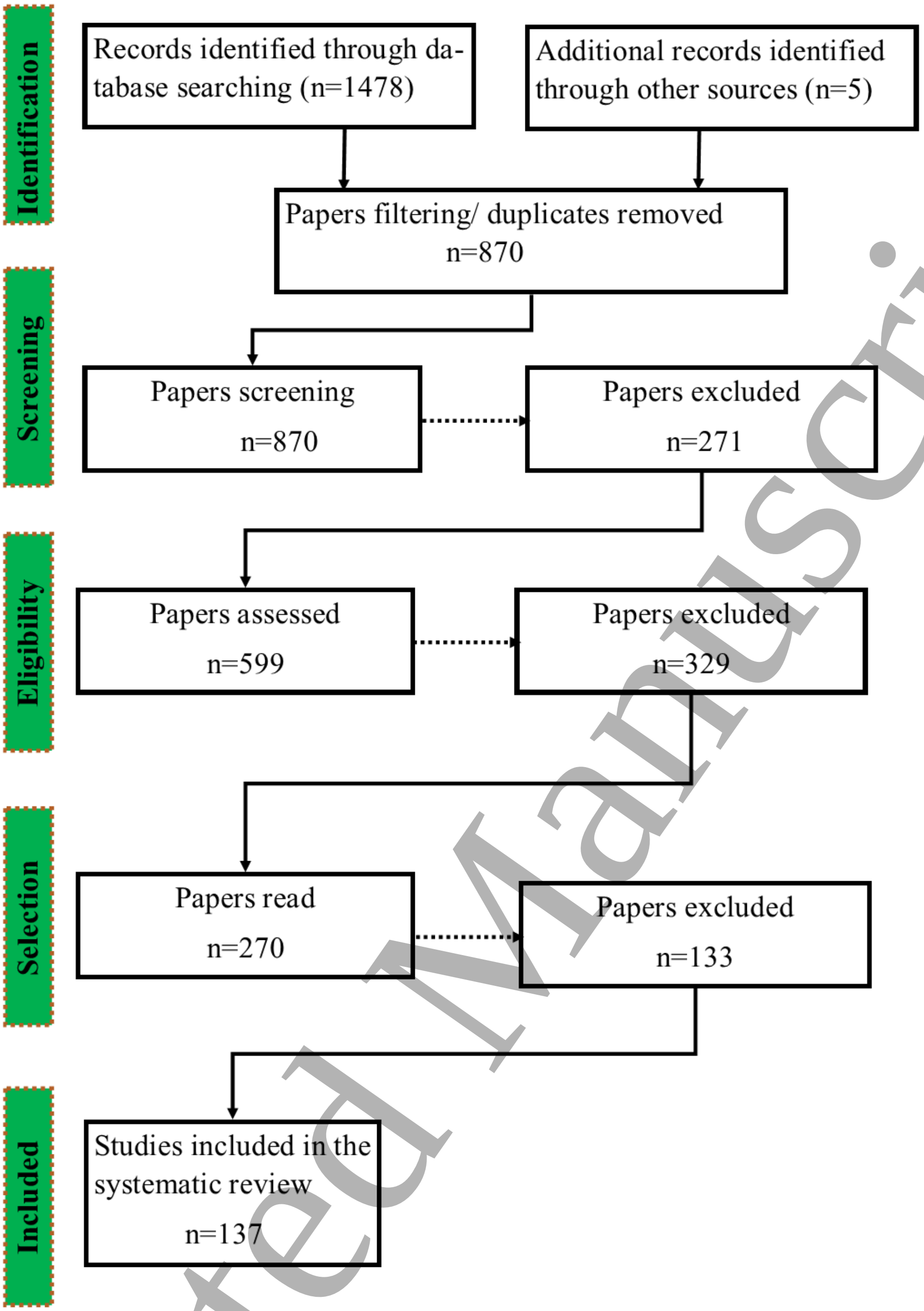


Figure 4. PRISMA follow diagram (Moher et al., 2009) showing the flow of information through the different phases of the systematic review.

Table 1. Parameters used to extract relevant information for this review

General information

Paper Id
1st author's institution
Research institute city
Publication year
Publishing Journal
Journal category
No of Citation
Study type
Site specific information
Location of the study area
Study country
Forest management area
Predominant forest type
Information on remote sensing data
Sensor Type
Instrument name
Image resolution
Time period observed
Temporal resolution of EO data
Database used
Information on research
Research topic considered: Forest cover/type, disturbance, phenology, biodiversity/habitats, plant traits, land cover/land use
Parameters examined in the study
Examined object scale
Applied methodology
Information on validation and accuracy of results
Database used

4. Results

4.1 Temporal development of publications and author affiliations

After the literature search, we found that the cumulative number of published research papers integrating remote sensing data in dryland forests of Southern Africa grew exponentially from 2 in 1997 to 155 in 2020. The temporal development of the 137 investigated research articles is illustrated in Figure 5. The graphic shows that the number of studies has increased significantly over the last 23 years, with the majority of the studies published from 2013. More than 105 (80%) of articles were published from 2009 to 2020 and only 4 (3%) of articles were published before 2000. The growth in number is also related to the increased availability of remote sensing platforms, sensors, data, for example, Landsat 8 in 2013 and Sentinel satellite in 2014, respectively.

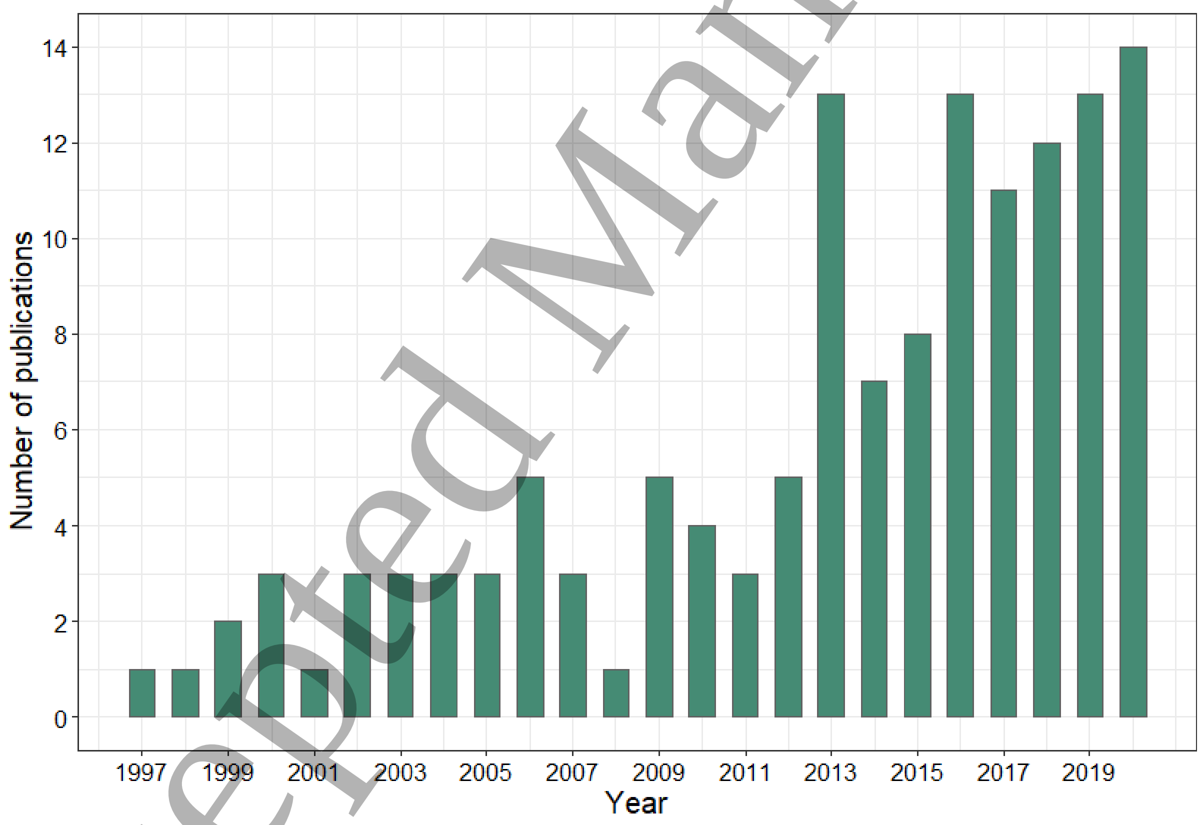


Figure 5. Number of papers included in the review integrating remote sensing and dryland forests in Southern Africa published annually between 1997 and 2020.

In the review, we have only considered studies within Southern Africa; however, the majority of first authors, 83 (61%) of 137 investigated papers, are mainly scientists from international research institutions outside of the focus region, mainly the USA, UK, Portugal, Germany, and The Netherlands (Figure 6). Conversely, the majority of first author institutions from Africa, 37 (27%) of published papers, were from RSA research institutions. The state funded research institutions in Southern Africa shown in Figure 6 include South African Council for Scientific and Industrial Research (CSIR), South African National Space Agency (SANSA), Water Resource Commission of South Africa, South Africa Agricultural Research Council, Range and Forage Institute, Botswanan Harry Oppenheimer Okavango Research Centre, Desert Research Foundation of Namibia, and Namibia Ministry of Environment and Tourism. Considering the 137 studies conducted, about 120 (90%) of the first authors are affiliated with either International and RSA institutions, but no first authors were from Zambia, Lesotho, or Angola.

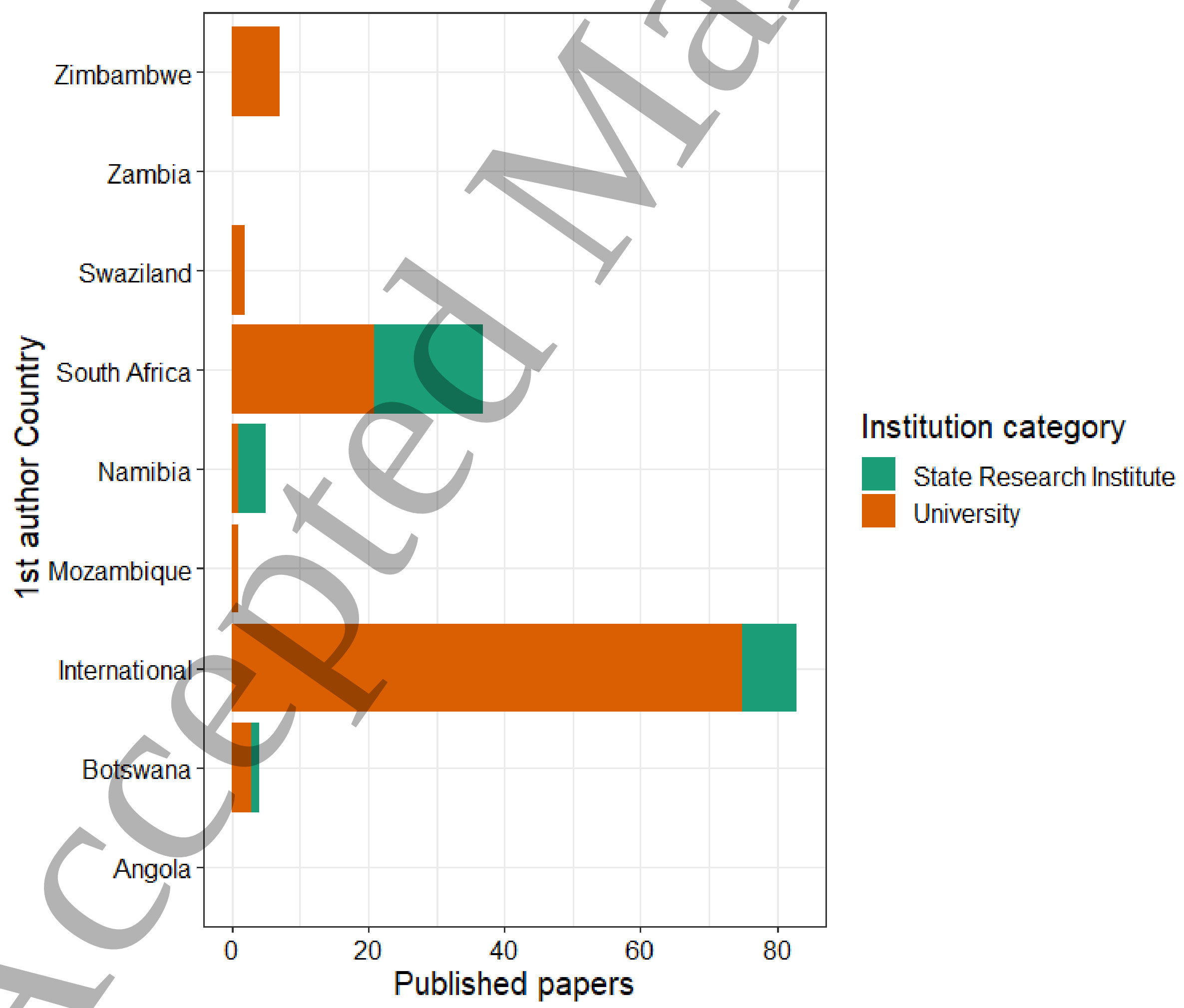


Figure 6. Number of papers by research institutions.

4.2 Spatial coverage, spatial extent, and investigated protected areas

Looking at the spatial scale of the study areas, we distinguished between studies done at a local community level in a single country, termed local scale, and studies done at more than one local community or province termed regional scale. We also considered studies done at the national level and the whole of Southern Africa. If a study covered more than three countries, it was counted as an analysis of Southern Africa. The spatial extent of the studies in the review is shown in Figure 7. The majority 88 (64%) of the investigated studies focused on a local scale, despite the need for regional scale information on dryland forest distribution. From Figure 7, out of 137 investigated research papers, 20 (15%) and 13 (9%) research papers covered regional and national scales, respectively. Only 10 (7%) out of 137 research papers dealt with transboundary protected areas, while 6 (4%) of research papers were covering Southern African, considering the region as a whole, using mainly multispectral data of large spatial resolution of 1km to 8km (MODIS, SPOT, and AVHRR) to generate information on phenology, and vegetation condition (fire or drought), as shown in Figure 7.

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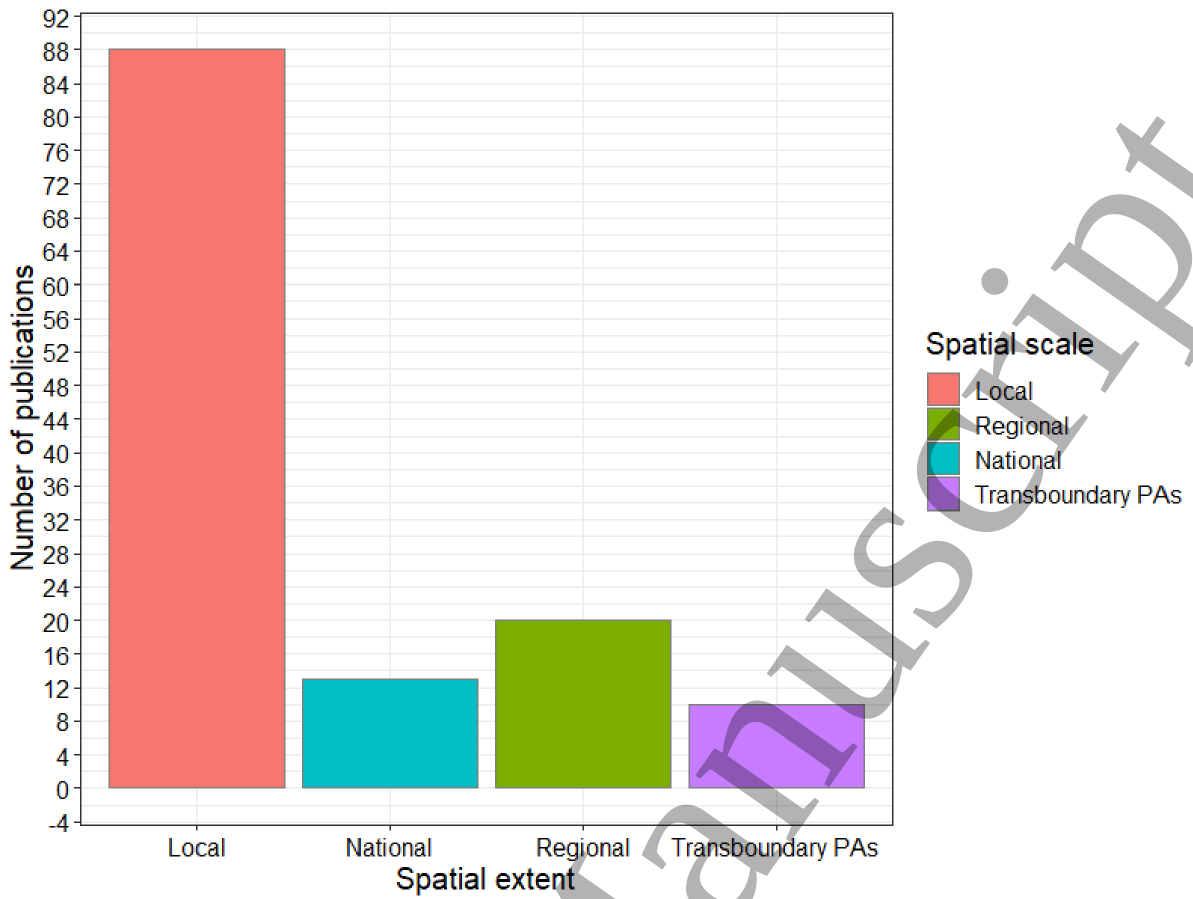

596 Figure 7. Spatial extent of investigated studies.

597 From Figure 8, it is evident that considerable gaps in geographical focus of research on tropical
598 dryland forests mapping still exist in Southern Africa. With respect to spatial coverage of the research,
599 most studies, 50 (36%) of research papers were carried out in RSA, followed by Namibia and
600 Botswana, with 22 (16%) and 18 (13%) of research papers, respectively. Swaziland, Angola, and
601 Lesotho were the least frequently investigated, each with < 10 papers. Angolan dryland forests are
602 even less well studied with 4 (6%) of research papers, despite being found extensively in that country.
603 Figure 8 also shows the location of the most frequently studied protected areas. By far, the most
604 studied was the Kruger National Park (NP) in RSA, involving research by local and foreign
605 researchers from as far afield as the USA, the UK, and beyond. With this interest in the Kruger NP,
606 there is, unfortunately, a lack of attention on other conservation areas and parks in Southern Africa.
607 Kruger NP was the only subject of more than one-third, 23 (37%) of the 61 of all reviewed papers on
608 protected areas. The second most frequently studied protected areas are the Etosha NP in Namibia

with 6 (8%) of papers, Chobe NP with 4 (7%) of papers, and Kwando, Kavango and Zambezi transboundary NP with 8 (13%) of papers). Malipati Safari Area, South Luangwa NP, Gorongosa NP, and Central Kalahari Game Reserve were each studied 3 (5%) and 2 (3%) times.

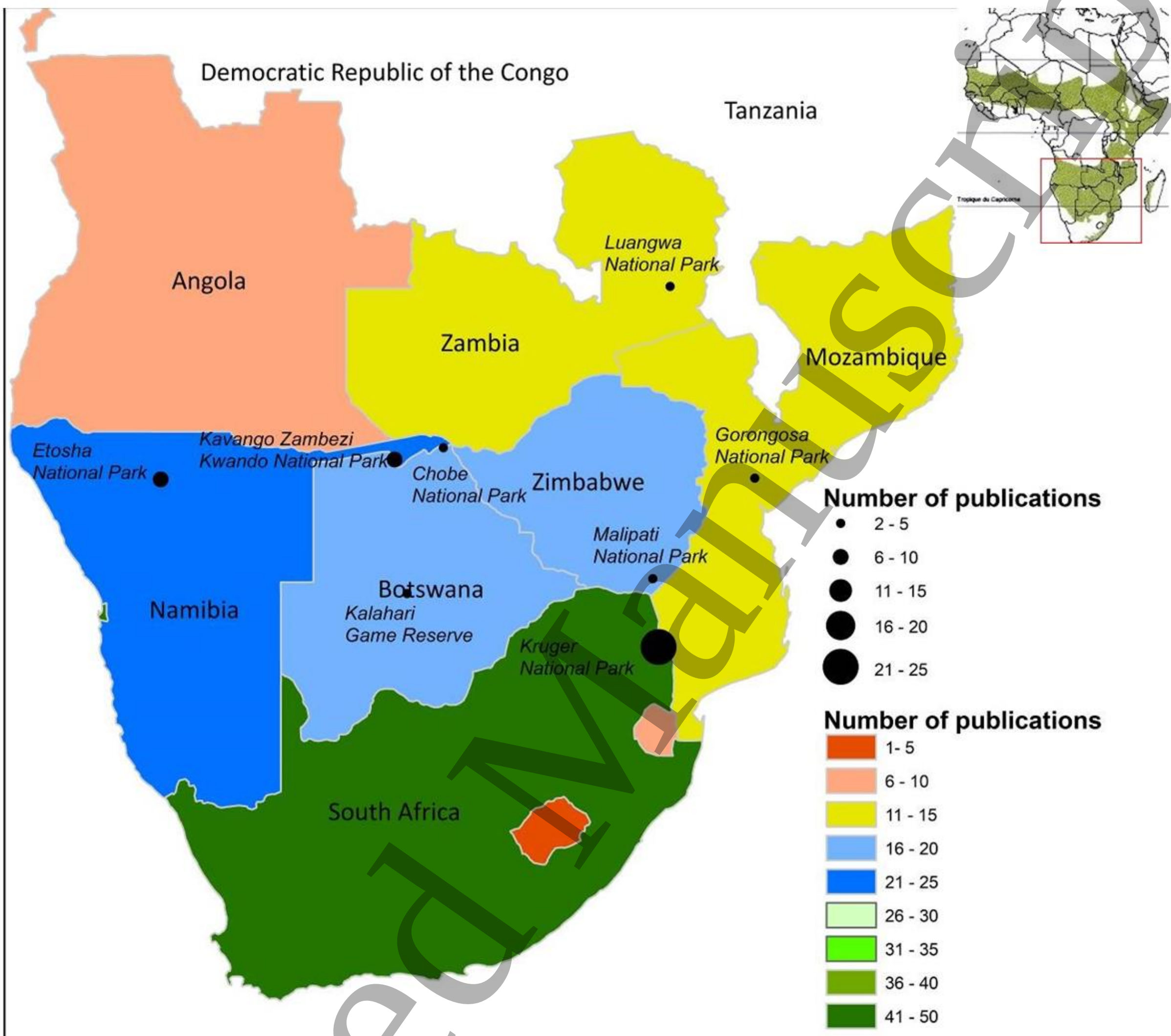

Figure 8. Number of studies per country and National Park in Southern Africa. (Note: The data are not scaled to the proportion of dryland forest area of countries, and National Parks with fewer or no publications are not shown. Source: FAO, (1999). Reproduced with permission).

To identify land surface changes and the drivers behind these, as well as short- and long-term trends, it is essential that EO temporal coverage has sufficiently frequent revisit periods and resolutions. Nonetheless, this is not an easy task since the availability of remote sensing data for long-term monitoring is constrained by sensor characteristics (e.g., revisit time) and environmental factors (e.g., cloud cover). Looking at the temporal resolution of the EO datasets used, we distinguished between data acquired at a single point in time on a monthly basis, termed mono-temporal analyses, and on a single annual basis, termed mono-annual analyses. We also considered multi-temporal and multi-annual to separate monthly and yearly analyses studies. From Figure 9 it is seen that the majority of published material has focused on a single temporal period. The majority of studies involved mapping over two or more years (multi-temporal/multi-annual) comparing images at two or more different times, with a bi-temporal approach based on discrete classification (e.g., Chiteculo et al., 2018; Coetzer-Hanack et al., 2016; Matavire et al., 2015). Although the bi-temporal approach is mathematically simple and does not require large data storage, it is less useful compared to the time series approach that can provide a more comprehensive understanding of the complexity of the Earth's land surface dynamics. Very few studies feature time series analysis, which is required to perform continuous long-term monitoring of changes in a tropical forest ecosystem. The majority of articles on time series analysed multi-annual data, which masks within-year variations, as compared to the detail provided at a monthly temporal scale (e.g., Akinyemi et al., 2019; Venter et al., 2020; Verlinden et al., 2006a; Wessels et al., 2006). Only 22 (16%) out of the 137 studies analysed more than 15 years and only 11 (8%) studies covered more than 20 years using monthly time series (e.g., Bunting et al., 2018; Schultz et al., 2018).

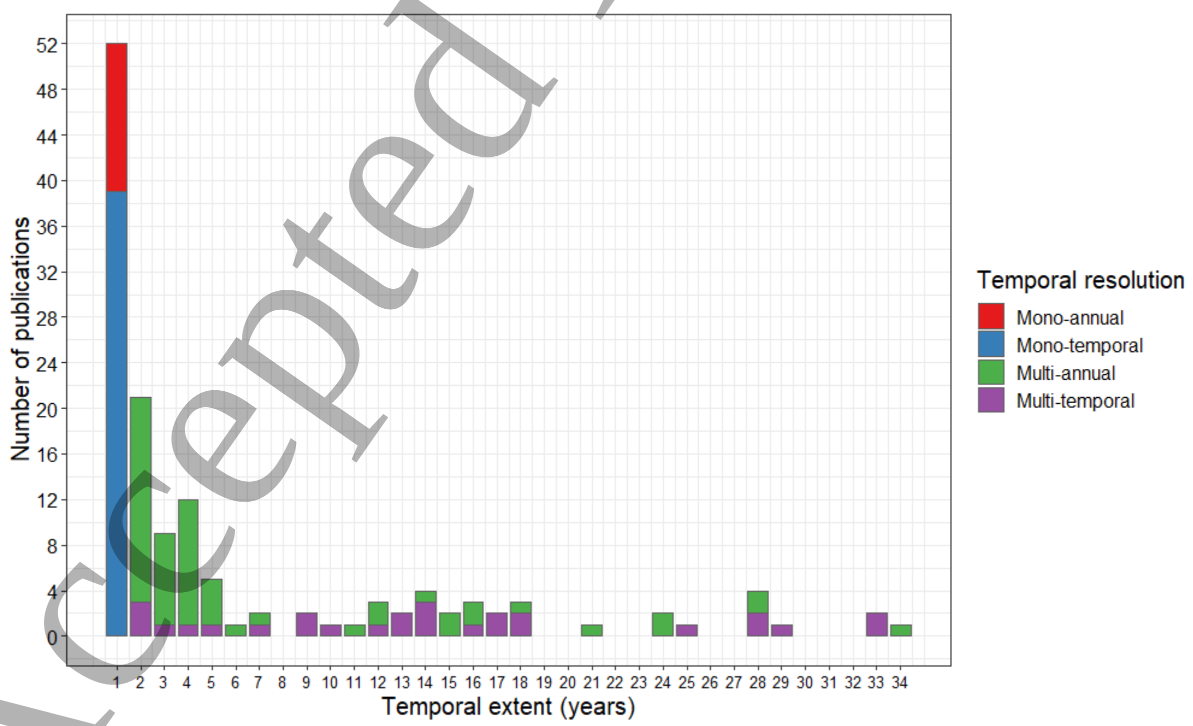

Figure 9. Temporal duration of studies included in the review integrating remote sensing and dryland forests in Southern Africa between 1997 and 2020.

4.3 Research Topics

We have classified the large number of research topics into eight broad categories that cover the diversity of research into dryland forests. The eight categories, and the number of studies belonging to each of them, are shown in Figure 10.

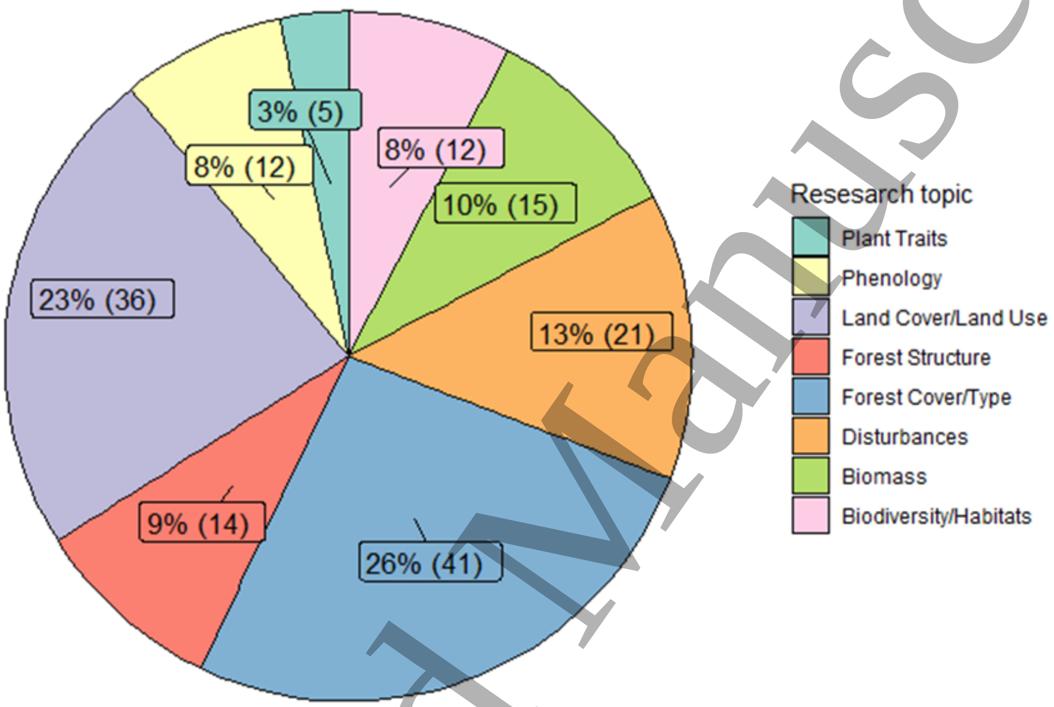

Figure 10. Research topic categories of reviewed articles between 1997 and 2020. Note that some studies cover different topics, which may result in multiple entries.

4.3.1 Land cover/land use

Land-cover change is one of the most researched areas using EO in Southern Africa, with 36 (23%) publications making it the second most common topic. We considered land-use/cover describing land surface classification, typically represented in thematic maps of different dryland vegetation. Land-use/cover changes with a specific focus on other dryland vegetation such as rangelands, grassland, coastal vegetation, or plantation forests without covering dryland forests were excluded. The majority of publications on land-use/land-cover used optical data. For example, Landsat data have been used by more than 90% of publications, except Daskin et al. (2016) and Hüttich et al. (2011) which used RapidEye and MODIS data. Only one publication used a combination of Radar and optical data (Symeonakis et al., 2018). Sentinel data have not been utilised for land cover and land use study in the reviewed papers, probably due to the relatively recent availability of these data. Looking at scale, the majority of papers on land-cover change focused on the local scale in Southern Africa, but there is still a general lack of synthesis of land-use /cover change assessment at the regional, national or subcontinental scale (Figure 7).

4.3.2 Forest cover/type

The majority of publications, 46 (31%) of studies cover the topic "Forest cover/type". The forest cover/type comprises the generation of a forest/non-forest mask (Dlamini, 2017; Heckel et al., 2020), forest cover change estimation (Erkkilä et al., 1999; Ringrose et al., 2002), forest type discrimination between dryland forests (McCarthy et al., 2005), forest health assessment (Herrero et al., 2020), woody cover (Boggs, 2010; Ibrahim et al., 2018), and tree species classification (Adelabu et al., 2013; Hüttich et al., 2009). The majority of forest type/cover mapping was undertaken with optical multi-spectral data including Landsat, MODIS, and AVHRR and a few studies used high-resolution data such as RapidEye, GeoEye, and WorldView. On the other hand, a few studies on forest cover/type mapping used a combination of multispectral and spaceborne SAR data (X-band, C-band, and L-band) such as Landsat and JERS-1 (Bucini et al., 2009), Landsat and ALOS PALSAR (Higginbottom et al., 2018; Naidoo et al., 2016) and Sentinel-1 and -2 (Heckel et al., 2020) (Figure 11).

A few studies on forest cover/type mapping relied on field data (Bucini et al., 2009; Ibrahim et al., 2018; Schultz et al., 2018) or forest inventory plots (Heckel et al., 2020). Most studies did not include detailed field measurements (species composition, density, frequency, dominance, and basal area, percentage soil cover, total height) and had very few field samples (Gessner et al., 2013). Other studies relied on high resolution EO data (Dlamini, 2017; Higginbottom et al., 2018), and published maps (Westinga et al., 2020) as reference data to validate their results. The majority of studies did not perform any form of accuracy assessment or validation of quantitative estimates (e.g., Campo-Bescós et al., 2013; Harris et al., 2014). Forest cover and species mapping is essential for many forestry-related tasks and play a key role in sustainable forest management; the importance of these topics can be seen in the fact that they are addressed across all countries in Southern Africa, with the majority of studies conducted in RSA, followed by Namibia and Botswana (Figure 12).

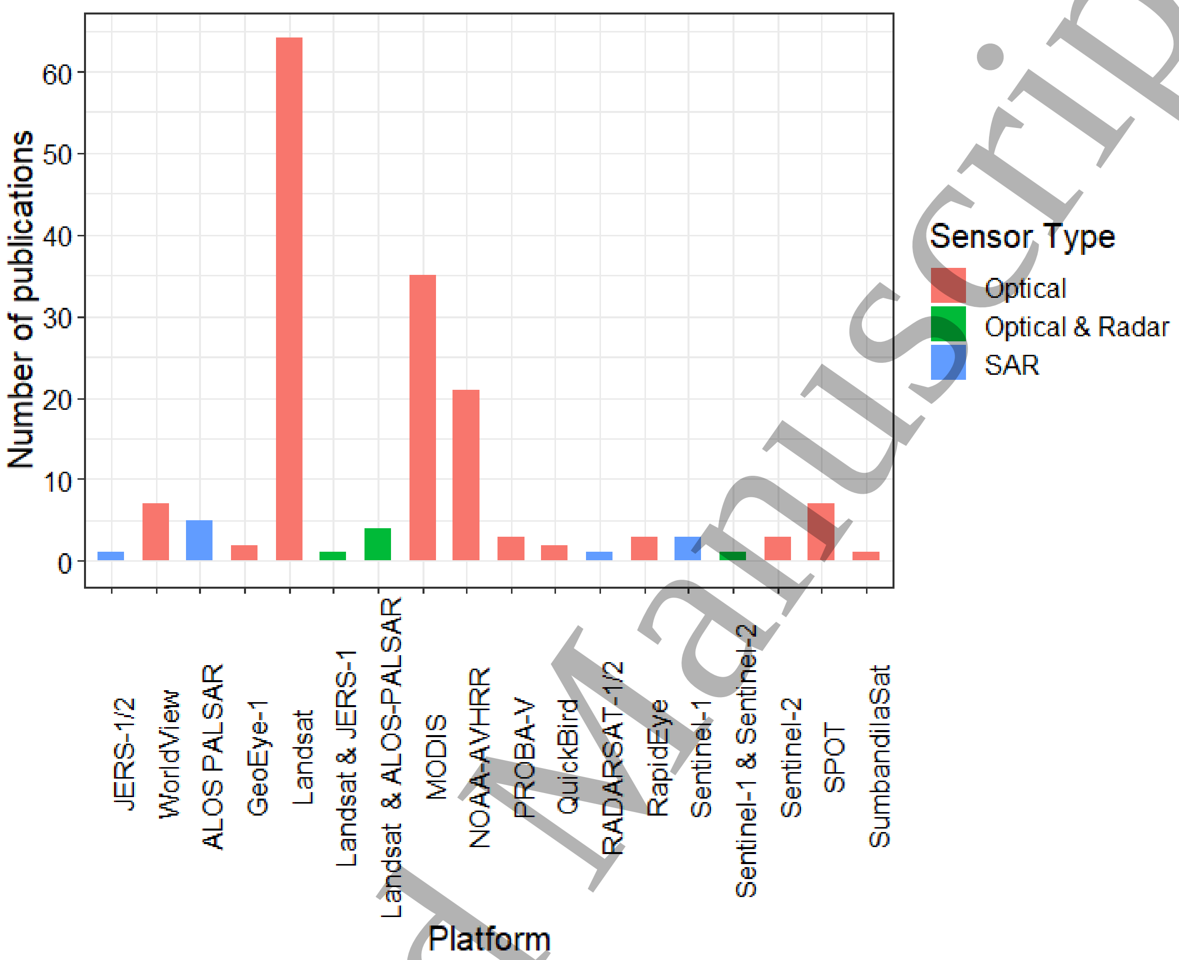

Figure 11. Number of studies based upon platform and sensor type. Note that studies investigating forest change with multiple platforms were counted multiple times.

4.3.3 Forest biomass and structures

Fifteen research papers (10%) studied forest biomass, and fourteen publications (10%) assessed “forest structure”. Studies on biomass included the estimation of AGB (Dube et al., 2018; Mutanga et al., 2006), and changes in carbon stock (Gara et al., 2017). Some of the publications used National Forest Inventory (NFI) data (Halperin et al., 2016; Verbesselt et al., 2007), and field-based samples (Mareya et al., 2018; Tsalyuk et al., 2017) to estimate biomass in Southern Africa.

Forest structure in the review includes research on stand structure (Mathieu et al., 2013), canopy cover (Erkkilä et al., 1999; Huemmrich et al., 2005), canopy gaps (Cho et al., 2015), and stand density (Adjorlolo et al., 2013). The majority of studies on “forest structure” in Southern Africa dealt with canopy cover (e.g., Adjorlolo et al., 2014; Yang et al., 2000). Very few studies considered vertical forest structure including tree height and tree crown diameter (e.g., Verlinden et al., 2006b). Mareya et al. (2018) utilised freely available high resolution Google satellite imagery in combination with object-based image analysis (OBIA) to estimate tree crown areas in miombo forests and found the overall accuracy to be low and unsuitable when high accuracy is required. Some of the “forest structure” publications are also assigned to the research topic “biomass”, which discusses the relevance of forest structure for biomass (Meyer et al., 2014). Forest structure is also a very important parameter when it comes to habitat suitability, species diversity, biodiversity estimation, and conversation studies and thus some publications cover both topics (e.g., Akinyemi et al., 2019).

The methods applied in the biomass and forest structure publications are diverse. Most studies employed some sort of regression analysis between in-situ field data and EO data, with the most popular methods being random forests, support vector machines, kriging, linear and generalised linear models (Berger et al., 2019; Carreiras et al., 2013; Halperin et al., 2016; Mutanga et al., 2006; Wingate et al., 2018). Williams et al. (2013) utilised the simple ensemble model to analyse biomass dynamics and found that biomass distributions can diagnose disturbance processes in miombo woodlands. Most studies utilised NDVI index in dryland forest mapping to correlate with biomass (Gizachew et al., 2016; Wessels et al., 2006), but very few studies considered other vegetation indices such as red-edge (RE)-computed indices (e.g., Dube et al., 2018; Gara et al., 2016). For the most part, optical sensors were used to derive forest biomass and structures, only four papers utilised radar data, and one paper used a combination of radar and optical data to estimate biomass (Wingate et al., 2018). More research is needed to explore the improvement of forest AGB and forest structure estimation through multi-sensor (optical and radar) data fusion.

4.3.4 Climate change and disturbances

Here we refer to dryland forests stress monitoring (e.g., damage due to fire, climate/weather-related hazards including drought events, floods, extreme temperatures as part of climate change and disturbances. Twenty-one papers (13%) investigated disturbances to forest cover. Among the different forms of disturbance, fire damage was the most commonly studied (Mayr et al., 2018; Pricope et al., 2012; Roy et al., 2019; Silva et al., 2003). In the context of threats of climate change, other disturbances included drought (Lawal et al., 2019; Marumbwa et al., 2021; Urban et al., 2018) and floods (Pricope et al., 2015). A regional studies Lawal et al. (2019) used gridded climate data from the Climate Research Unit and GMMS NDVI to characterise the impact of drought to vegetation in southern Africa from 1981 to 2005; They found that the responses of vegetation varied according to season and biome, and showed that droughts had extensive impacts over the central parts of South Africa and Namibia, and the southern border of Botswana and the western parts of Zambia. In this review, we only considered studies that investigated climate change in terms of temperature/drought in dryland forests where satellite data are a primary or secondary source of data. Although there are a number of studies on climate change modelling in Southern Africa, the results show that there is a striking lack of studies investigating climate change into dryland forest change and stress monitoring.

The sensors used to detect disturbances differs, with most studies using MODIS (Alleaume et al., 2005; Archibald et al., 2009; Chongo et al., 2007; Giglio et al., 2009), two publications used SPOT-VGT (Silva et al., 2003; Verbesselt et al., 2006), and one Landsat and Sentinel-2 (Roy et al., 2019). Only two publications utilised SAR data. Mathieu et al. (2019) investigated SAR Sentinel-1A C-band images for detecting surface fires in the Kruger NP, while Williams et al. (2013) used ALOS PALSAR to analyse known disturbance agents in tropical woodlands in Mozambique. The research by Urban et al. (2018) used Sentinel-1 SAR time series NDVI from Sentinel-2 and Landsat-8 to derive surface moisture for drought monitoring in the Kruger NP between 2015 and 2017. A combination/fusion of SAR and Optical data for detecting disturbances is not tested by any study. Only one study used field data as input data for validation (Alleaume et al., 2005), while two studies used forest inventory data (Verbesselt et al., 2006; Verlinden et al., 2006a).

4.3.5 Biodiversity, plant traits, and phenology

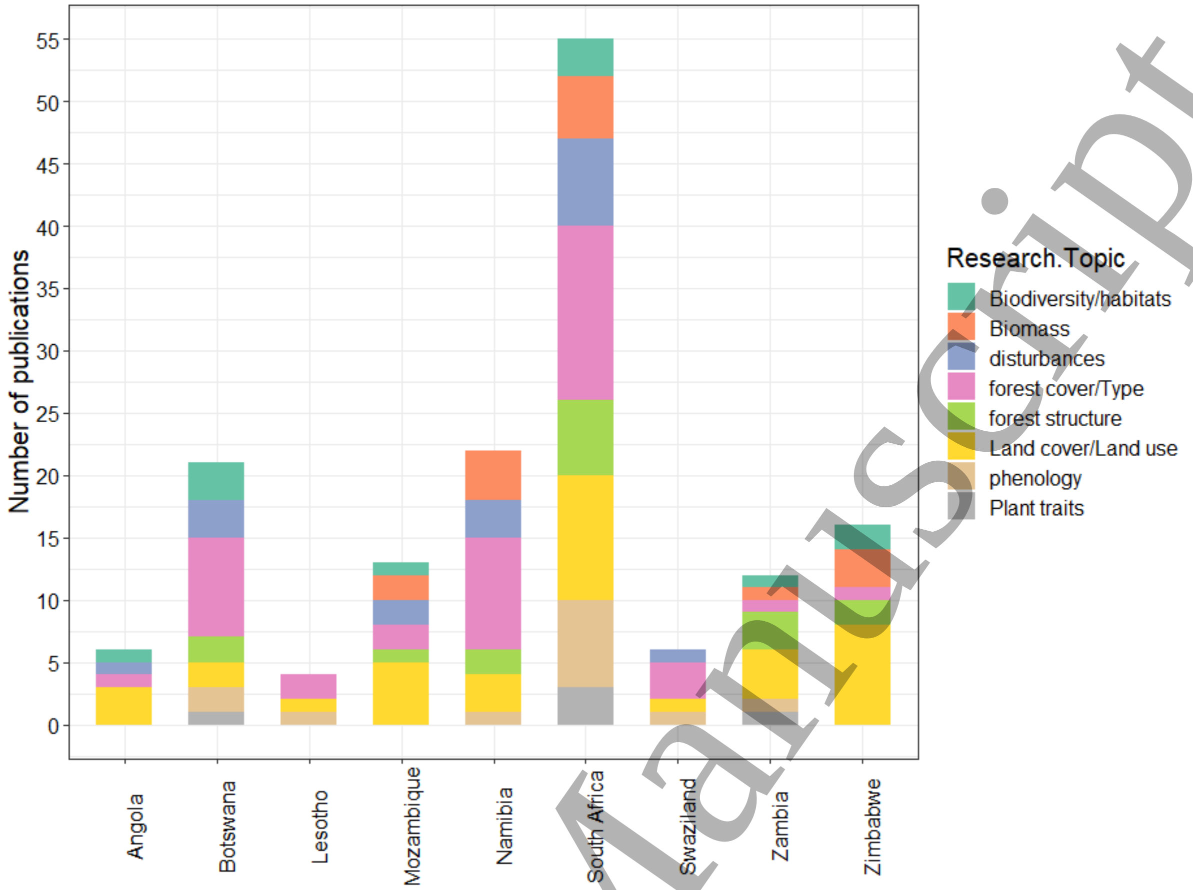

Figure 12. Research topic by country. Note that the order of the mentioned topics has changed when compared to Figure 10 as some studies were conducted in several countries.

Twelve (8%) of the reviewed publications dealt with research questions in the context of forest biodiversity. Almost half of the papers on forest biodiversity examined plant species diversity (Adjorlolo et al., 2014; Chapungu et al., 2020; Mapfumo et al., 2016). Others looked at animal species and habitat suitability (e.g., Cáceres et al. (2015) for birds, Ducheyne et al. (2009) for tsetse flies, impala (Van Bommel et al., 2006), and elephants (Marston et al., 2020). Forest biodiversity is often related to structural canopy parameters. Most studies, nine (75%) of twelve used Landsat to derive parameters such as plant canopy height, species occurrence, richness, and diversity. Three (25%) of the studies used MODIS data (e.g., Fullman et al. (2014) used MODIS at 250 m pixel resolution and a Moving Standard Deviation Index (MSDI) to detect elephant-modified vegetation along the Chobe riverfront in Botswana; Akinyemi et al. (2019) utilised 1 km spatial resolution of SPOT - VGT and

PROBA-V annual time series of 18 years to understand species diversity and richness assessment based on the Vegetation Degradation Index in Palapye Botswana.; Adjorlolo et al. (2014) investigated the utility of SPOT-5 multispectral data to assess tree equivalents and total leaf mass to model grazing and browsing capacity in KwaZul-Natal province in RSA.

Five papers (3%) dealt with different plant characteristics, known as plant functional traits. These include canopy chlorophyll content (Cho et al., 2012), leaf nitrogen concentration (Cho et al., 2013), and vegetation water content (Verbesselt et al., 2006), and LAI (Scholes et al., 2004). Plant functional traits including vegetation biophysical and biochemical properties (e.g., pigment levels, nitrogen content) are often related to patterns of biodiversity. Huemmrich et al. (2005) explored monthly MODIS data at 1 km spatial resolution over two years to estimate LAI and FAPAR and found that ground-measured LAI values correspond well with MODIS LAI, and showed a discrepancy with FAPAR. Cho et al. (2012) utilised variogram analysis and the red edge shift from SumbandilaSat and SPOT 5 to estimate canopy chlorophyll content in Dukuduku forest in Southern Africa and found that SumbandilaSat provides additional information for quantifying stress in vegetation as compared to SPOT image data. All studies on plant traits were undertaken at the local scale.

Looking at research categories per country, biodiversity/habitat publications were mainly undertaken in Botswana and RSA (Figure 12). All studies in the context of forest biodiversity and plant traits covered only mono-temporal and multi-annual classifications. Only two studies utilised multi-annual time series (Akinyemi et al., 2019; Verbesselt et al., 2006), and one study used MODIS multi-temporal time series over two years (Huemmrich et al., 2005). All of these studies focused on a coarse resolution of 1 km.

Phenology is also strongly linked to plant traits, but analysis puts more emphasis on the seasonal variations including growing season (green-up date) (Archibald et al., 2007; Whitecross et al., 2017), end of the season, and length of the season (Davis et al., 2017). To date, phenological research in Southern African dryland forests is limited, and more than half of the published papers on phenology focused only on examples from RSA. In the few studies that have analysed phenology, most studies dealt with estimating leaf flush and early-greening dates (Chidumayo, 2001; Higgins et al., 2011). For example, Archibald et al. (2007) developed an intricate algorithm that used MODIS NDVI products and field-based parameter estimates to predict green-up dates for grass and tree components at a site in the Kruger NP in RSA. Jolly et al. (2004) compared a water balance model to a 3-year NDVI time series and found the deviation between the onset of leaf flush predicted by the model and empirical data was between 10 and 40 days.

5. Discussion

5.1 Temporal extent

In this article, we have synthesized the current research with EO on dryland forests, with a particular focus on Southern Africa. Although the volume of scientific literature has demonstrated a sharp increase, the use of remote sensing is still limited, and up until 2013, the number of publications on this topic was relatively small. Substantial research on the dryland forests of Southern African is mainly based on single-date observations, and comparing classified images at two or more different times. Maps that relate successive land cover change between two dates typically lack information regarding underlying processes and do not enable insights on the nature of the transformations present, such as the rate or persistence of change (Lambin et al., 2003). Time series analysis on dryland forests, which enables tracking changes is scarce, only 22 (16%) out of 137 studies feature time series lengths that exceed 15 years and only 11 (8%) studies that cover more than 20 years. Longer time series of remote sensing data afford the ability to assess the dynamics of forest structures, biodiversity, degradation, disturbance from climatic extremes, and change in phenology, in which a gap still exists.

5.2 Spatial scale

Another finding that stands out from our analyses is that there are very few studies at the national and regional levels. Despite new sensor and EO data availability, it is clear that a systematic and consistent regional monitoring of dryland forests is not yet fully exploited and is still in its infancy in Southern Africa. In fact, the majority of publications 88 (64%) concentrated their research efforts on local scale investigations (Figure 7). Desanker et al. (2001) and Geist (2002) also emphasised that Southern Africa is limited to local-scale studies, thereby lacking a simultaneous analysis of the impacts of these changes at a larger scale. To fully assess regional and long-term implications for tropical dryland forest change studies, analyses on large(r) scales are needed, ideally with higher spatial resolutions and longer temporal duration.

5.3 Accuracy assessment

Through evaluation of the literature, we identified that the assessment of accuracy for thematic/classified maps and statistical data to be another important issue, with only 54 (39%) of the studies appearing to have performed some form of accuracy assessment. Our results show there is limited information on sources of error and uncertainty levels of the estimates provided by most studies. We found that most forest and vegetation-related scientific outputs in Southern Africa are not yet strongly linked to field measurements and forest inventory data. Among the reviewed studies, very few studies utilized field test sites/ ground-based independent datasets for accuracy assessment, while other studies estimated uncertainties using other procedures e.g., using a sample of finer spatial resolution remote sensing data, or did not report the map uncertainty. Some studies employed root-mean-square error to assess model accuracy (RMSE) (e.g., Adjorlolo and Mutanga, 2013; Higginbottom et al., 2018), while many studies used an error matrix to assess map uncertainties, which was employed for instance (e.g., Adelabu et al., 2013; Hüttich et al., 2011). However, some studies used sample points below the desirable target number of validation points per class (e.g., Cabral et al., 2011), while studies briefly mentioned that a confusion matrix was calculated but did not report how many sample points were used for validation (e.g., Chagumaira et al., 2016). Congalton. (1988) suggests planning to collect a minimum of 50 samples for each map class for maps of less than 1 million acres in size with less than 12 classes. It has been empirically confirmed that a good balance between statistical validity and practicality for larger area maps or more complex maps can be achieved with about 75 to 100 sample sites per class (Congalton & Green, 2009).

Globally, owing to TDFs low commercial importance in comparison to other tropical forests such as moist forest, they are often not assessed by field surveys, or surveyed regularly by governments (Keenan et al., 2015). Independent validation data for dryland forest estimations are rarely available because acquiring appropriate field survey data is a time-consuming and expensive task. In Southern

Africa, these areas are often remote and dangerous to visit in the field, due to the hazard posed by wildlife and if present, unexploded landmines, almost impracticable to obtain independent validation data for large(r) area studies, especially for many protected areas. Despite challenges to obtain ground-based observation, effective integration of these data and remote sensing methods will be key to accurately mapping and monitoring dryland forest across a range of spatial scales and in reporting the accuracy of models. However, the applicability of remotely measured geospatial data is reliant on quality, and translating remote sensing data into accurate and meaningful information is often a challenge prone to errors (Congalton et al., 2009; Donoghue, 2002). In this context, it is critical to ensure the validity of these data and their suitability for each particular application, particularly where coarse spatial maps can be misleading. In addition, characterising dryland forest for large areas of Africa cannot entirely rely on global and pantropical monitoring studies for dry forest estimation because global forest monitoring generally underestimates, and in some instances overestimates, dryland biomes (Bastin et al., 2017).

5.4 Research topics and geographical focus

The classification of studies into eight broad subject categories revealed forest cover/types 41 (26%) and land cover/land use 36 (23%) to be the most commonly researched topics. Topics receiving less attention included phenology, plant traits, biodiversity/habitats, and disturbances with regards to climate change (Figure 10). With regards to disturbances, fire damage was the most commonly studied but there is a missing body of literature on the climate change impact on the composition, biodiversity, and ecological health of dry forest ecosystems in most countries of Southern Africa. We also found an interesting, non-uniform spatial distribution of dryland vegetation and forest studies using spaceborne remote sensing, particularly when considering disparities among countries and across protected areas. The distribution of research categories by country reveals that RSA is, by far the most studied nation across all categories in Southern Africa (Figure 8). It should be noted that care should be taken here not to assume that the number of studies equates to research quality, which remains difficult to articulate from a review of this nature. However, the dryland forests of Mozambique, Lesotho, Swaziland, and Zambia are noticeably very poorly studied. Studies on the dryland forests of Angola are even less frequent, receiving relatively little global attention, and the few studies conducted on its forests were mostly conducted by researchers from Portuguese Universities (Catarino et al., 2020; Leite et al., 2018). The focus of publications tended to be biased towards conservation and national parks, particularly as a large proportion of studies were undertaken in the Kruger NP, leaving many other private and international protected areas relatively understudied. Transboundary conservation areas, such as Kavango-Zambezi (KAZA), have received relatively little attention but merit further research in terms of the vast dryland forests extent, biodiversity, species abundance and diversity, and the potential for this area to form important corridor areas for wildlife animals. There is a further concern as a result of such gaps because some of the dryland forests, and species to which they are home, notably in countries like Angola and Zambia, are listed on the IUCN red list and would almost certainly merit Alliance for Zero Extinction (ACE) ranking (Cumming, 2008). Furthermore, future efforts to estimate important variables such as forest cover and biomass need not be restricted by country boundaries. Future studies, based on medium-fine resolution EO and validated with field data, will provide information to improve our understanding of African dryland vegetation and its management.

5.5 Vegetation indices, optical, SAR, and fusion of optical and SAR sensors

The most commonly used vegetation index was the NDVI, with more than half of the studies, 84 (54%) of papers utilising this index, but only 13 (8%) of papers used EVI index and SAVI index. Other vegetation indices such as the GNDVI index and Sentinel red-edge related indices and passive microwave observations such as Vegetation Optical Depth were not utilised in studies considered in this review. One major problem commonly encountered in the less studied ecosystems, such as dryland forests, is that of generalizing or transferring knowledge and methods derived from remotely sensed imagery over both space and time (Foody et al., 2003). For example, commonly used vegetation indices and classification schemes are in general mainly been calibrated on other, better-studied ecosystems, such as temperate or rain forests, and this has led to poor accuracy results when extrapolated, to for example, tropical dryland forests. This phenomenon justifies the importance of utilizing a range of vegetation indices when studying dryland forests using EO data. Imagery from optical sensors is most commonly used, out of all sensor types, providing the data used in 90% of papers reviewed, followed by SAR data with 6%. The fusion of optical and radar data was rarely used, with only 4% of publications exploring this. The most frequently used platforms are Landsat, followed by MODIS and AVHRR. Imagery taken by the Sentinel-1/2 satellites only makes up a small portion of the remote sensing data on dryland forests. For example, Sentinel-2 was only used by 2% of investigated studies, but this may reflect the relatively short period (since 2015) when these data have been available.

5.6 Remote sensing platforms and cloud-based computing

Most of the EO data used in the publications reviewed were downloaded, and are available at no cost from a number of online portals, including the Oak Ridge National Laboratory (ORNL), the United States Geological Survey (USGS) Distributed Active Archive System (DAAC) and Earth Explorer (EE) tool. The lack of remote sensing research centers in most Southern African research institutions may contribute to limit the number of African Scientists engaged in monitoring forests resources. For example, most studies in RSA made use of remote sensing data through the University of the Witwatersrand, Satellite Application Centre (SAC), the South African National Space Agency (SANSA), and the Council of Science and Industrial Research (CSIR). The development of remote sensing capacity at local universities has inevitably contributed to RSA universities and research institutions conducting the majority of studies in Southern Africa (Figure 6). To improve EO data access, and the skills to handle and interpret this across Southern Africa, there is a need to increase the number of local institutions that distribute the remote sensing data, and who have the capacity to access and use innovative web-based platforms such as the Google Earth Engine (GEE) and Amazon Web Services to overcome some of the logistical and financial constraints of this type of research.

Southern African countries face considerable technical challenges with remote sensing, particularly in respect to REDD+-related research on dryland forests monitoring. Freely available tools, for example, the cloud-based geospatial analysis platform Google Earth Engine (GEE), make it easier to access powerful computing resources for processing and analysing pre-processed large-scale datasets

(Shelestov et al., 2017). However, only nine papers (6%) out of 137 used GEE to access or analyse remote sensing data. The “near real-time” remote sensing data offered by GEE is of particular interest for monitoring changes and automating the analysis of time-series, when detecting and tracking trends in surface reflectance properties. With increasing spatio-temporal coverage of satellite data and computational platforms that reduce the need for costly local infrastructure (e.g., GEE), there is an opportunity to overcome the limitations previously enforced by large volumes of data and the scale of analysis, whereby our knowledge of dryland forest dynamics can be improved in the upcoming years.

6. Conclusion

This review summarizes research progress towards the use and integration of remote sensing data within the context of monitoring dryland forests in Southern Africa, using a systematic review methodology that focused on 137 most relevant research articles. We have reviewed the temporal and spatial coverage of these studies, their application area, and the remote sensing platforms and sensors used. Based on the results, the following conclusions can be drawn. There are a broad range of topics covered by research on dryland forests, from which land-use/land-cover and forest cover and disturbances from the fire were the most frequently studied. However, there is still a relative lack of studies assessing dryland forest structure, phenology, biodiversity/habitats, plant traits, and disturbance from climatic extremes, suggesting additional research is required. The majority of studies relied on single-date or annual data and bi-temporal discrete classification; only a very few studies employed time series analysis.

We consider some of the limitations of the research reviewed, which indicates a need for more frequent use of field and inventory data, a greater use of validation/accuracy assessments, and testing other vegetation indices beyond NDVI and EVI such as the Vegetation Optical Depth and Sentinel-2 red-edge related indices. In addition, further improvements should focus on for extensive combination and fusion of SAR and optical data in order to have a temporally and spatially consistent data set necessary for several applications in dryland forests. Given the state of decline of woody vegetation condition in Southern Africa, long-term monitoring of monthly time series of EO data at regional and transboundary scale clearly hold potential to capture dryland forests dynamics and to understand their current status and future trends. A significant move from EO predictions that are extremely site-dependent to large(r) ecoregional level monitoring approach that integrates a range of remotely-sensed data of sufficiently high spatial and temporal resolution with field measurements and using machine/deep learning models could provide a sound basis for assessing dryland forest-related changes and dynamics. Information inferred from these kinds of models would be extremely useful for the current knowledge, management and conservation of the dryland forests as well as for understanding their responses to disturbance (natural or anthropogenic) and climatic change at regional to sub-continental level. Finally, there is significant geographical heterogeneity in study coverage; whilst there is substantial research on the forests in the Kruger NP and across RSA, the same cannot be said for other areas of Southern Africa. The EO interventions not only assess deforestation rate, but also support other forest related REDD+ activities such as sustainable forest management which reduce forest degradation and enhance forest carbon stocks at a range of scales, transcending both provincial and national boundaries e.g., Kavango-Zambezi Transfrontier Conservation Area (KAZA TFCA). Nevertheless, REDD+-related research on dryland forests in most Southern African countries and protected areas has been limited, with clear gaps across Angola, Mozambique, Zambia, and Zimbabwe. Finally, Africa has the potential to emulate other continents, such as Latin America, that have made notable progress in employing freely available remote sensing data to monitor tropical dryland forest area change and biomass on a large scale.

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Conflicts of interest

The authors declare no conflict of interest.

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