# The habitat and feeding ecology of black rhinoceros (*Diceros bicornis michaeli*) in the Ngorongoro Conservation Area

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# Abstract

Habitat loss, due to destruction, fragmentation, or degradation, is the second major threat to black rhino populations after poaching. It negatively impacts food quality and availability and consequently, decreases the carrying capacity of an area. Studies on habitat preferences are vital to improve habitat quality and ensure appropriate conservation management and reintroductions. Browse availability affects black rhino distribution and unsuitable browse can prevent populations from reaching optimum numbers. In the Ngorongoro Conservation Area (NCA), browse availability and quality remains uncertain posing challenges in determining the potential carrying capacity. It is hypothesized that the NCA’s rhino habitat has declined since the 1960s. Land cover changes in several habitats frequented by rhinos have rendered them unsuitable to sustain a growing population. Here, a map of the main vegetation types in the NCA for 2019 was developed and the land cover changes between 1985 and 2020 were identified. The results show a replacement of forest with bushland in the highlands surrounding the Crater. In the Serengeti plains there was a decrease in grassland cover and an increase in shrubland suggesting woody encroachment.

Additionally, the area between the Olmoti and Ngorongoro Craters was identified as ideal rhino habitat for a future population as it contains preferred plant species that are unaffected by seasons and is not severely impacted by human factors. However, it is also important to note that monitoring through direct observation in such a dense habitat would be incredibly challenging. Ideally, the rhinos in this area would be fitted with trackers, so anti-poaching patrols could locate them easily with minimal disruption to the animals while ensuring the safety of the rangers. The area surrounding Oldupai Gorge remained mostly unsuitable and human presence would also raise security concerns. Contrastingly, the forage characteristics associated with rhino presence identified the area as a potential site for reintroductions. This apparent discrepancy underscores the importance of integrating remote sensing techniques with detailed fieldwork. Overall, these findings provide valuable insights into identifying unoccupied habitat for black rhinos and highlight the need for enhanced conservation efforts to safeguard populations amidst changing environmental and anthropogenic pressures.

# Dedication

This thesis is dedicated to all the rangers that risk their lives every day to ensure the safety of our wildlife.

# Acknowledgements

Thank you to all my supervisory team: Dr Martin Jones who took me on to begin with and supported me through the project; Dr Elias Symeonakis who guided me with the remote sensing part of the project; to Dr Bradley Cain for all the rhino knowledge; Prof Richard Preziosi and Dr Jennifer Rowntree for the support during the initial years of the PhD.

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## Table of Contents

# Chapter 1 – Introduction

## 1.1 General information about the black rhino

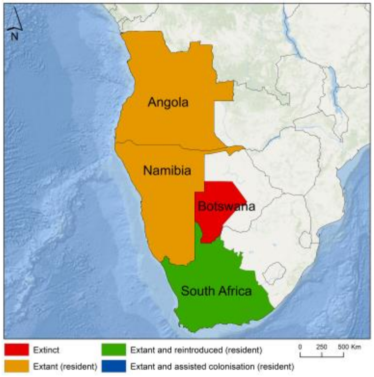
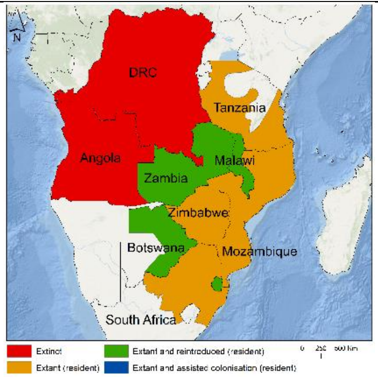
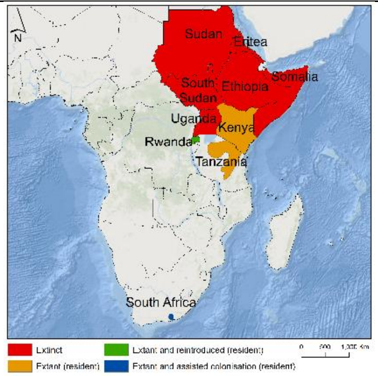
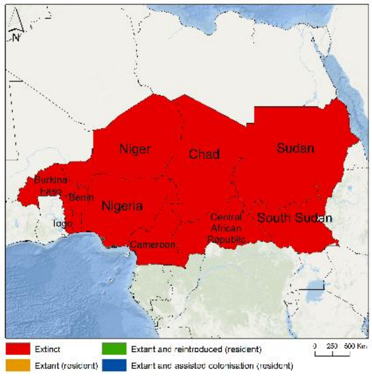
### 1.1.1 History, distribution, and status

In the early 1960s, there were estimated to be approximately 100,000 black rhino (*Diceros bicornis*) across Africa (Emslie, 2020). Illegal hunting, due to an increased demand for rhino horn, and habitat loss lead to a dramatic 98% population decline, resulting in only 2500 individuals by 1992 (Emslie and Brooks, 1999; Emslie et al., 2016).

Rhino poaching emerged as a pressing issue during the 1960s and early 1970s. A brief reduction in poaching activities from the mid-1990s to 2007 led to the perception that the problem had been effectively addressed (‘t Sas-Rolfes, 2011). Between 2000 and 2007 only 120 rhino were poached in South Africa (Huebschle, 2016). Nevertheless, poaching intensified until 2015, fuelled by a surge in illegal demand for rhino horn, but since slowdown in certain areas (‘t Sas-Rolfes, 2011; Rubino and Pienaar, 2017; Emslie, 2020). The black rhino was listed as a *Critically Endangered* species in 1996 and it remains so even though there had been small increase to 5630 rhinos across 14 countries by 2018 (Knight, 2019; Emslie, 2020).

There are currently four recognised subspecies of black rhino: South-western Black Rhino *D. b. bicornis (*N=2390) in Namibia, South Africa and possibly Angola; South-eastern Black Rhino *D. b. minor* (N=2196), South Africa, Zimbabwe, Tanzania, Zambia, Botswana, Eswatini, Malawi and possibly Mozambique; and Eastern Black Rhino *D. b. michaeli* (N=1044) in Kenya, Tanzania and Rwanda (Emslie, 2020). The fourth recognised subspecies that once occupied the savannas of central-west Africa, the Western Black Rhino (*D. b. longipes*), is now considered extinct and its last known location was in northern Cameroon (Emslie, 2020).

Table 1.1. Black rhino numbers and distribution across the four subspecies for 2020.

| Subspecies | Historic range | Current range | Map |
|---|---|---|---|
| *D. b. bicornis* (N=2390) | Namibia, southern Angola, western Botswana, and southwestern and southeastern South Africa | Namibia, South Africa and possibly Angola |  |
| *D. b. minor* (N=2196) | Southern Tanzania Zambia, Malawi Zimbabwe, Mozambique northern South Africa; probably DRC, Angola, eastern Botswana, Eswatini. | South Africa, Zimbabwe, southern Tanzania, Botswana, Malawi, Eswatini and Zambia |  |
| *D. b. michaeli* (N=1044) | South Sudan, Ethiopia, and Somalia, through Kenya into northern-central Tanzania and Rwanda | Kenya, Tanzania, Rwanda and one subpopulation in South Africa |  |
| *D. b. longipes* (extinct) | Benin, Burkina Faso, Cameroon, Central African Republic, Chad, Niger, Nigeria, South Sudan, Sudan, Togo. | |  |

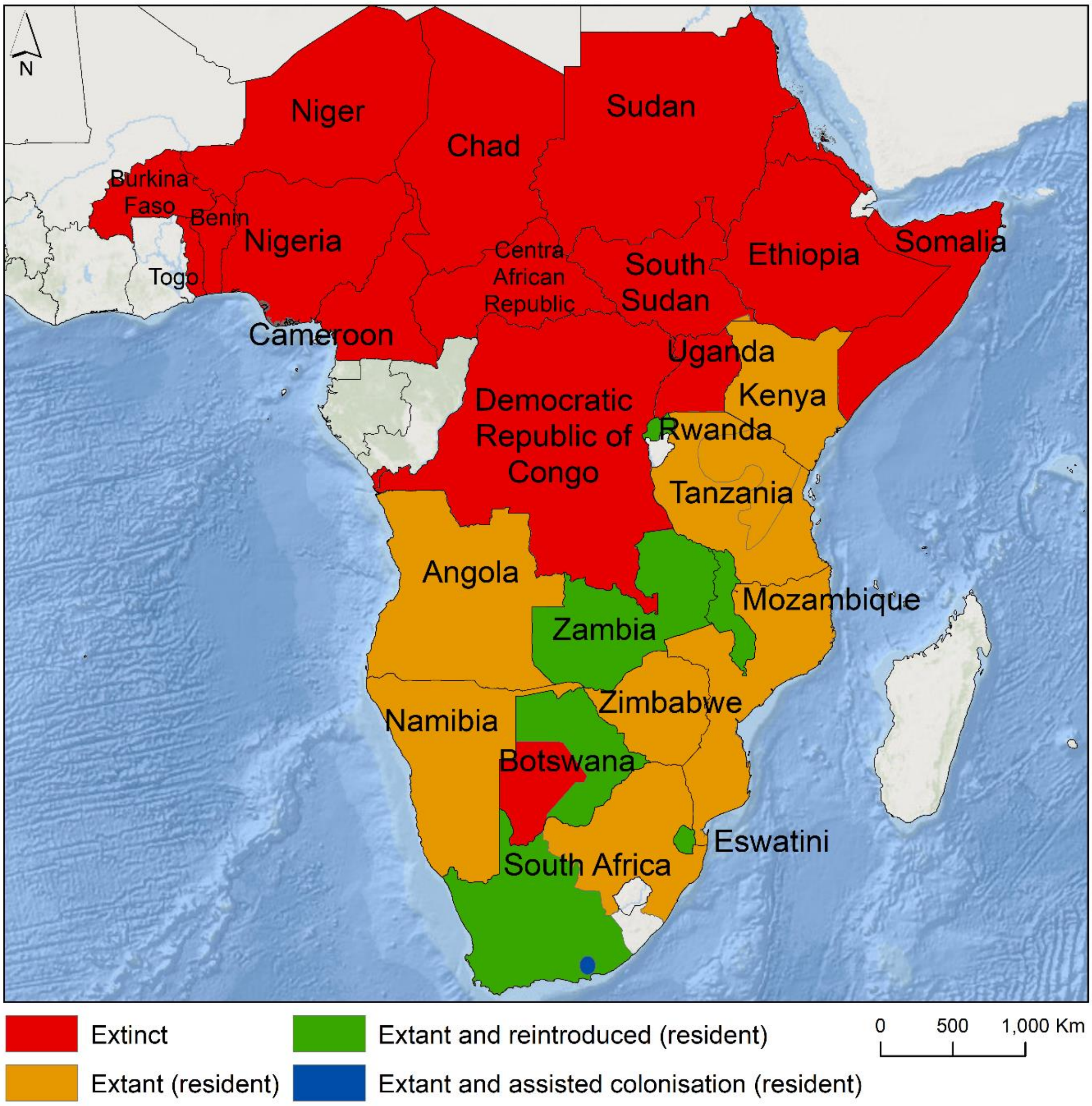


Figure 1.1. Distribution of the black rhino populations (IUCN 2020).

### 1.1.2 Threats

#### *1.1.2.1 Illegal hunting*

Currently, the main threat to black rhino is illegal hunting (poaching) due to high demand for rhino horn (Emslie et al., 2016, 2019). Roughly 95% of rhino horn accessible in the unlawful business sectors in Southeast Asia is sourced from illicit poaching in Africa (Emslie, 2020). The demand for rhino horn originated from various traditional beliefs, particularly in some Asian countries, where it is falsely believed to possess medicinal properties and is considered a status symbol (Emslie, 2020). Historically, rhino horn was used to make decorations for ceremonial daggers (jambiyas), worn in some Middle East nations (in the 70s and 80s), and, from 2007 onwards, to supply South East Asian markets (Emslie, 2020). Despite the expansion of rhino populations across Africa, poaching has slowed overall growth, and a few populations have even declined (Emslie, 2020). Black rhino poaching peaked in 2015 and has been declining since but it is unknown if this is due to success against poaching or fewer rhinos remaining (Emslie, 2020).

#### *1.1.2.1 Habitat loss and change*

Habitat loss is the second major threat to black rhino populations after poaching (Emslie and Brooks, 1999). Habitat loss, due to destruction, fragmentation, or degradation, negatively impacts food quality and availability and the suitability of nursery and shelter areas, and consequently, decreases the carrying capacity of an area. Fewer resources may increase intra and interspecific competition which can drive black rhinos to expand their home ranges to fulfil their nutritional needs (Hitchins, 1969; Makacha et al., 1979; Mills et al., 2006). Due to their territorial behaviour, black rhinos can become stressed and aggressive without enough space and, when forced to remain in high density areas, population growth can slow down. Populations in these high-density areas, are then more susceptible to loss of genetic diversity, inbreeding, disease and more accessible to poachers (Brett, 2001; Fyumagwa et al., 2007).

Habitat loss is linked directly or indirectly to human activity, namely clearing for settlements or agriculture and searching for thatching materials and fuel wood (Masao et al., 2015; Hamza K. Kija et al., 2020; TAWIRI and NCAA, 2020). Additionally, habitat loss can be caused by invasive species, fire and unsustainable animal populations, which are also directly affected by management policies particularly in enclosed protected areas (Augustine and McNaughton, 2006; Holdo et al., 2009; Wigley et al., 2014). For instance, the Mandusi swamp in the Ngorongoro Crater in Tanzania, was regularly used by black rhinos for shelter and browsing, but nowadays, rhinos only visit these places sporadically (Klingel and Klingel, 1966; Goddard, 1968; Amiyo, 2006; Mills et al., 2006; Gadiye et al., 2016). The presence of elephants contributed greatly to this shift in behaviour - firstly, rhinos tend to avoid elephants to prevent competition for resources and secondly, the elephants damaged the vegetation contributing to a decrease in preferable browse, specifically, leguminous plants (Amiyo, 2006; Mills et al., 2006; Landman et al., 2013).

Studies on habitat preferences are vital to improve habitat quality and ensure appropriate management of protected areas (Reid et al., 2007; Omari, 2009; Hazarika and Saikia, 2012). The ultimate goal is to reach the minimum 5% annual growth in rhino populations by optimizing Maximum Productivity Carrying Capacity (MPCC, Emslie, 2020). Browse availability affects black rhino distribution and unsuitable browse can prevent populations from reaching optimum numbers (Goddard, 1968; Lush et al., 2015). As the habitat changes, the rhino diets are also expected to shift; as such, the need for updated site-specific feeding ecology studies is paramount. These studies can also be used to predict rhino distribution and so help to identify suitable habitat which may not yet be occupied (Buk and Knight, 2012; Lush et al., 2015). Until now the primary model for rhino conservation is the use of fenced sanctuaries which have 'known' Ecological Carrying Capacities (ECCs). With populations rising, particularly in Kenya, there is an emerging shift from fenced sanctuaries to intensive protection zones (IPZs) which are unfenced areas within protected areas (Okita-Ouma et al., 2007).

### 1.1.3 Black rhino ecology

#### *1.1.3.1 Habitat suitability*

Habitat suitability is a major contributor for rapid population growth and a contributor to the ECC (Muya and Oguge, 2000). In order to sustain a viable rhino population, populations must be managed bellow the ECC to maximize breeding performance, decrease death rates and ensure browse availability (Kanini, 2009). This is particularly important in small populations which are more vulnerable to environmental changes (Heywood et al., 1995).

Black Rhinos occur in a wide variety of habitats, namely marsh areas, forests or deserts, however the highest densities of black rhinos occur in savannah areas and bushvelds, mainly due to the higher quantity of nutrient-rich woody species .

The habitat type affects the size of rhino home ranges (Hitchins, 1969). Rhinos that occur in the bushveld have smaller home ranges due a higher concentration of woody species, than in savannah areas (Hitchins, 1969). Nonetheless, thick bush is not necessarily better for feeding (Emslie and Adcock, 1994). An area rich in unpalatable woody species has little value for black rhinos and is usually used for protection and shelter rather than feeding (Kotze and Zacharias, 1993). Studies on habitat preferences are vital to support suitable management to enhance habitat quality (Kanini, 2009; Hazarika and Saikia, 2012). These studies can also be used to model habitat preferences and help suitable habitat which may not yet be occupied (Lush et al., 2015).

In recent years, remote sensing has emerged as a valuable tool for studying vegetation and assessing habitat suitability for species like the black rhino (Adole et al., 2016; Woodcock et al., 2008; Wulder et al., 2012). Remote sensing methods are quick, cost-effective, and provide the opportunity to study both accessible and inaccessible areas, as well as to obtain historical data on vegetation cover and land use changes (Broich et al., 2011; Woodcock et al., 2008; Wulder et al., 2012). Satellite Earth Observation (EO) data has been increasingly used to map and monitor vegetation cover and its characteristics, providing insights into habitat quality over time (Adole et al., 2016; Woodcock et al., 2008; Wulder et al., 2012).

For black rhinos, monitoring the quality and quantity of preferable browse is particularly crucial, as there is emerging evidence of a decrease in both, leading to a reduction in suitable habitats (Amiyo, 2006; Makacha et al., 1979; Niboye, 2010). Remote sensing techniques allow researchers to overcome challenges like varying degrees of vegetation cover, high background soil signal, and spectral similarities between land cover types that are prevalent in savannah environments (Müller et al., 2015; Tsalyuk et al., 2017; Zhang et al., 2019). This is particularly crucial in environments where field data collection is limited by logistical challenges and costs.

The use of remote sensing data allows for the detailed assessment of land cover changes and the identification of areas where the availability of suitable browse is declining. These provide critical information for understanding spatial and temporal patterns in habitat suitability, helping to predict areas where intra- and interspecific competition may increase (Makacha et al., 1979). Overall, the integration of remote sensing technologies facilitates monitoring of habitat quality and contributes to more informed management decisions aimed at conserving the black rhino population in dynamic and changing environments.

#### *1.1.3.2 Diet*

Black rhino foraging behaviour affects distribution and habitat preference (Goddard, 1968; Buk, 2004; Lush et al., 2015; Ngoti, 2017). Black rhinos are selective browsers (Emslie and Adcock, 1994; Ganqa et al., 2005; Buk and Knight, 2010) that can eat up to

220 species of plants within their home range (Leader-Williams, 1985). Despite this variety, a large portion of their diets relies on 3 or 4 plant species, making their diets less diverse than the species available, underlining a strong preference for certain species (Emslie and Adcock, 1994; Ganqa et al., 2005; Buk and Knight, 2010). Plant nutritional value could explain these choices, with preference for high protein and water content and low phenol and non-aromatic species (Muya and Oguge, 2000; Ganqa et al., 2005; Buk and Knight, 2010). Contrastingly, other studies show no significant nutritional difference between browsed species and there is even evidence of black rhinos eating species classified as toxic (Goddard, 1968; Ausland et al., 2000; van Lieverloo et al., 2009). These latter studies suggest that black rhinos feed on what is available, rather than nutritional composition, to avoid searching costs (Muya and Oguge, 2000; van Lieverloo et al., 2009; Buk and Knight, 2010).

#### *1.1.3.3 Social Structure*

The social structure of black rhinos is characterized by a combination of solitary and somewhat social behaviours that can vary based on factors such as habitat, food availability, and individual needs(Mukinya, 1973). They are generally solitary animals, with the only strong social bond being between a cow and calf (Goddard, 1966; Hitchins, 1969; Schenkel and Schenkel-Hulliger, 1969; Mukinya, 1973; Frame, 1980). Adult males are mostly solitary, have specific home-ranges between 2 to 130 km$^2$ depending on season and availability of browse and water (Mukinya, 1973; Frame, 1980). Adult bulls are also known to have a consort relationship with oestrous cows (Schenkel and Schenkel-Hulliger, 1969). Subadults and young adults frequently form loose associations with older individuals and their home-ranges intersect (Klingel and Klingel, 1966; Goddard, 1967; Schenkel and Schenkel-Hulliger, 1969).

Female black rhinos exhibit more social behaviour, occasionally forming loose groupings with other females and their offspring (Mukinya, 1973). These associations are not strictly organized, and individual rhinos within these groups may change over time as they move through overlapping home ranges (Goddard, 1966, 1967; Mukinya, 1973). Cows tend to have larger home-ranges than adult bulls, especially when accompanied by calves, which can overlap with other cows or certain bulls (Reid et al., 2007).

#### *1.1.3.4 Breeding system*

Black rhinos have a polygynous breeding system wherein dominant males establish and defend territories that contain optimal resources for mating, such as rich browsing areas and water sources (Garnier et al., 2001; Nhleko et al., 2017). Dominance among males is established through aggressive displays and physical confrontations, ensuring access to mating opportunities with multiple females within their territories (Owen-Smith, 1992).

While black rhino mating is not strictly confined to a specific season, it is usually influenced by environmental factors, such as rainfall and food availability, impacting the condition and receptiveness of females for breeding. Female black rhinos reach sexual maturity between 5 to 7 years of age, while males attain maturity between 7 to 10 years (Owen-Smith, 1992; Gedir et al., 2018).

The gestation period for black rhinos lasts approximately 15 to 16 months and newborn calves weigh around 35-40 kg (Owen-Smith, 1992). Inter-calving intervals range between 2.5 to 5 years contingent on factors such as resource availability and the female's health (Patton et al., 2008; Gedir et al., 2018).

### 1.1.4 Rhino populations in East Africa

The Eastern black rhino (*Diceros bicornis michaeli*) population in East Africa has faced severe challenges, largely attributed to habitat loss, poaching, and human-wildlife conflicts. Historically distributed across the region, black rhino numbers declined by over 90% due to extensive poaching and habitat degradation (IUCN Red List, 2021). Conservation efforts to reverse this decline have been extensive, involving collaborations between governments, conservation organizations, and local communities. Despite progress, illicit wildlife trade continues driven by Asian markets' demand for rhino horns, while human settlements and agriculture expansion encroach upon rhino habitats, heightening human-wildlife conflicts (D. Maige, NCAA, 2023*, pers. comm*.). Recently, protected areas have exhibited population stabilization and growth in East Africa due to anti-poaching measures, translocation efforts, habitat restoration, and community involvement (du Toit, 2006; Emslie, 2020).

Kenya holds over 80% of the world's Eastern black rhinos - 960 as of 2023 (Kohi and Lobora, 2019, ICT Authority). Kenya's current Action Plan has the long-term aspiration of cultivating a meta-population of at least 2,000 black rhinos within the next 14 years held within secure and suitable habitats (ICT Authority, 2023). The 2,000-animal threshold is acknowledged as the minimum meta-population size imperative for the species' sustained existence in Kenya (du Toit, 2006).

Since 2001, rhino conservation initiatives in Kenya have increasingly prioritized population growth through biological management, resulting in an increase in rhino numbers and the achievement of the targeted 5% net growth per annum for several years in some areas (Anon, 2003, 2012; Okita-Ouma et al., 2007; Amin et al., 2017). This success has led to the need to identify additional areas to accommodate surplus rhinos and under the 2007–2011 and 2012–2016 Rhino Action Plans Intensive Protection Zones (IPZs) within National Parks have been developed together with the extension of existing sanctuaries whenever feasible (Okita-Ouma et al., 2007; Anon, 2012; Emslie et al., 2019). The underlying premise of these interventions lies in the assumption that adequate security measures for rhinos would lead to reduced poaching rates with stringent law enforcement serving as a deterrent (Khayale et al., 2020). This approach should be complemented by active biological monitoring aimed at assessing the meta-population's status and implementing management strategies for population growth, ensuring that rhino habitats do not exceed ecological carrying capacities (Khayale et al., 2020).

#### *1.1.4.1 Rhino populations in Tanzania*

Tanzania has been working on rhino conservation efforts to protect and recover its black rhino population and it currently holds slightly over 10% of the world’s Eastern black rhinos  (Kohi and Lobora, 2019). The Government, in collaboration with conservation organizations and local communities, has implemented anti-poaching measures, increased law enforcement efforts, and established protected areas to safeguard black rhinos (Mills et al., 2003; Kohi and Lobora, 2019). These efforts aim to mitigate the threats faced by black rhinos and promote their recovery. Between the 1970s and 1992 Tanzania rhino numbers declined 98.4% from over 10,000 to less than 100 individuals due to high levels of poaching (Kohi and Lobora, 2019). In the Serengeti National Park, the rhino population was nearly completely eradicated, decreasing from approximately 700 individuals in the 1970s, to just a handful by the 1980s (O’Connor, 2010). At that date, Tanzania’s remaining black rhinos existed in three isolated small populations in the Serengeti, the Ngorongoro Crater and Selous Game Reserve, although the later was comprised of a different subspecies (Makacha et al., 1982; Sinclair and Arcese, 1995).

The lack of connectivity between these areas presumably suppressed the genetic diversity of the rhinos (Makacha et al., 1982; Emslie and Brooks, 1999).

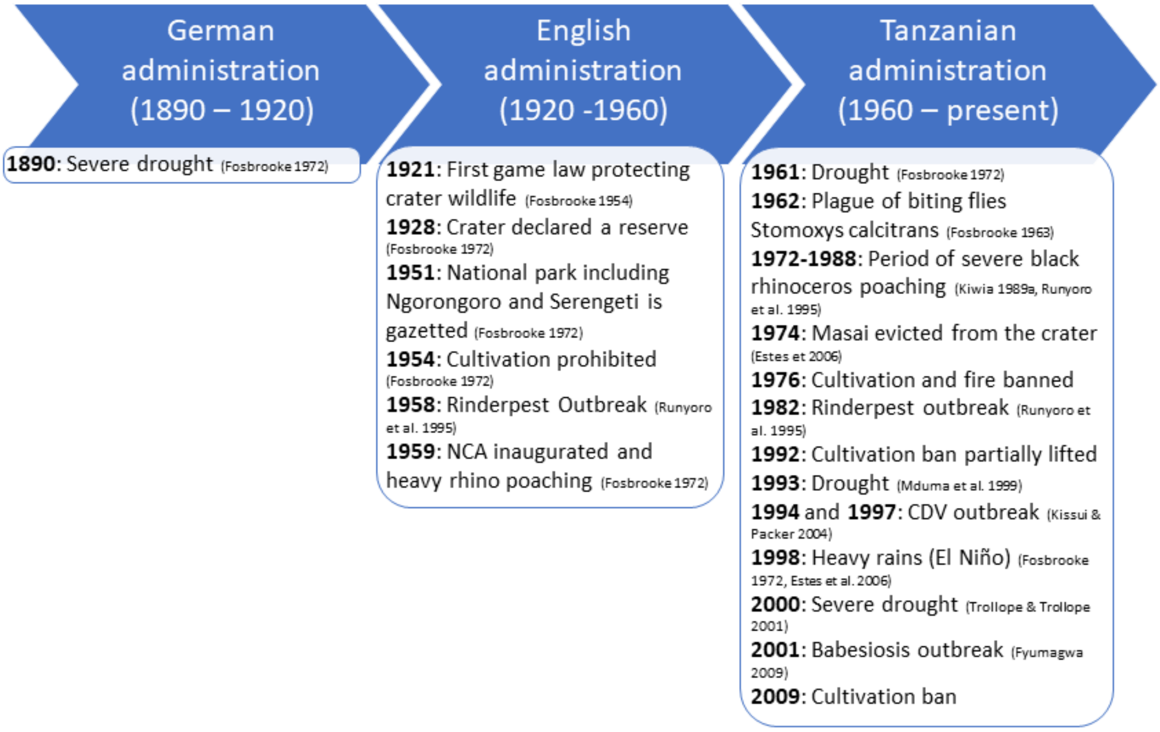
There are currently five subpopulations of rhinos in Tanzania, located the Serengeti and Mkomazi National Parks, the Ngorongoro Conservation Area (NCA) and  Maswa and Grumeti Game Reserves (Kohi and Lobora, 2019). Following increased protection and monitoring as well as translocations from other countries, Tanzania’s rhino population was estimated to be 161 individuals by the end of 2018 (Kohi and Lobora, 2019). However, Tanzania can potentially host the highest rhino population in Africa due to extensive suitable habitat and secure protected areas (Kohi and Lobora, 2019). Limited or no dispersal between subpopulations, makes metapopulation management key to the recovery of the species in Tanzania (Kohi and Lobora, 2019). The NCA rhinos are a key source population and are therefore central to the future conservation efforts. They are also a major attraction for tourists (the only site where they are regularly seen by visitors) and tourism contributes USD 2 billion to Tanzania’s economy (17% of the country’s GDP, PwC 2023). The NCA rhinos are, therefore, key for tourism and are a ‘flagship’ for the successful conservation for the whole NCA and the well-being of its people.

## 1.2 Ngorongoro Conservation Area

### 1.2.1 Background

The Ngorongoro Conservation Area was initially created as part of the Serengeti National Park created by the British in 1951 but was separated off in 1959 when the Ngorongoro Conservation Area Authority (NCAA) was established (Gadiye et al., 2016, FIgure 1.2). The NCA became a Man and Biosphere Reserve in 1971 and was recognized as an UNESCO World Heritage Site in 1979, emphasizing its global significance in terms of both natural features and cultural aspects, and highlighting its crucial role in biodiversity conservation (Harris et al., 2020). The NCA is renowned for supporting significant populations of black rhinoceros, African elephants (*Loxodonta africana*) and a wide range of other herbivores and large predators (Homewood et al., 2001). It supports one of the world's largest mammal migrations, which includes 1.5 million wildebeest (*Connochaetes taurinus*), 260,000 of plains zebra (*Equus quagga*), and 470,000 Thomson's gazelle (*Eudorcas thomsonii*)(Sinclair and Arcese, 1995; Lembo et al., 2011; Larsen et al., 2020).

An important feature of the NCA is that it has been managed as a multiple land-use area since 1959, a designation intended to maintain coexistence between indigenous residents and wildlife (Goldstein, 2004). It accommodates a large human population with various ethnic groups and cultural traditions, including Hadzabe hunter-gatherers, Datooga, and Maasai pastoralists (McCabe, 2003). Currently, there is a program underway to relocate the indigenous residents outside of the NCA (A. Kisingo, MWEKA, 2023, *pers. comm.*).



**1890**: Severe drought (Fosbrooke 1972)

**1921**: First game law protecting crater wildlife (Fosbrooke 1954)
**1928**: Crater declared a reserve (Fosbrooke 1972)
**1951**: National park including Ngorongoro and Serengeti is gazetted (Fosbrooke 1972)
**1954**: Cultivation prohibited (Fosbrooke 1972)
**1958**: Rinderpest Outbreak (Runyoro et al. 1995)
**1959**: NCA inaugurated and heavy rhino poaching (Fosbrooke 1972)

**1961**: Drought (Fosbrooke 1972)
**1962**: Plague of biting flies Stomoxys calcitrans (Fosbrooke 1963)
**1972-1988**: Period of severe black rhinoceros poaching (Kiwia 1989a, Runyoro et al. 1995)
**1974**: Masai evicted from the crater (Estes et 2006)
**1976**: Cultivation and fire banned
**1982**: Rinderpest outbreak (Runyoro et al. 1995)
**1992**: Cultivation ban partially lifted
**1993**: Drought (Mduma et al. 1999)
**1994** and **1997**: CDV outbreak (Kissui & Packer 2004)
**1998**: Heavy rains (El Niño) (Fosbrooke 1972, Estes et al. 2006)
**2000**: Severe drought (Trollope & Trollope 2001)
**2001**: Babesiosis outbreak (Fyumagwa 2009)
**2009**: Cultivation ban

Figure 1.2. Relevant events under the several NCA administrations.

### 1.2.2 Vegetation cover in the NCA

The NCA is comprised of more than 1.5 million ha of savannah habitat (Masao et al., 2015) and is included in the Greater Serengeti Ecosystem (GSE), within which the ‘great African wildebeest migrations’ takes place (Swanson, 2007). The Northern Highlands Forest Reserve (NHFR) and the remaining highlands cover 20% and 27% of the NCA respectively, the Ngorongoro Crater (NC), 3 % and the bushland and grassland plains 50% (Swanson, 2007). The suitable grazing areas are essential for wildlife but also for the pastoralists livestock (cattle, sheep and goats) which either reside within, or are passing through the NCA (Swanson, 2007). The NCA has an open border policy that allows grazing livestock for resident and non-resident Maasai, however, the NHFR and the Crater floor are restricted areas (Swanson, 2007). Changes in management policies over the years may have contributed to the woody encroachment and spread of invasive plant species. The latter are often unpalatable species, (e.g. Gutenbergia cordifolia and Bidens shimperi) and have negatively affected rangeland quality, reducing food availability for wildlife and livestock (Estes et al., 2006; Mills et al., 2003; Trollope, 1980). Controlled burning has been attempted after the drought in 2000 but it remains unclear whether it was successful (Oates and Rees, 2013). Currently, the only consistent methods of invasive plant control are mowing (Gutenbergia cordifolia and Bidens shimperi) before the dry season begins and manual removal of plants (Lippia javanica, Macha 2023 pers. comm).

The NCA vegetation varies with altitude, soil pH, water availability and salinity and ranges between highland plains, savannah woodland, forest and savannah grasslands (Herlocker and Dirschl, 1972). The north-west, bordering the Serengeti National Park, comprises savannah grassland plains and some woodland areas. In the Ngorongoro Crater (NC), the vegetation is mostly of short/medium grasslands, wetlands, and a soda lake, Lake Magadi. Next to the lake, there is the Lerai forest, which is thought to be slowly disappearing (Mills, 2006). The Lerai forest was dominated by mature Vachellia xanthophloea trees, however their demise has not been accompanied by replacement by young trees (Amiyo, 2006). A combination of factors, such has high herbivore pressure, high salinity, water availability and encroachment of invasive species could explain the Lerai forest dieback (Amiyo, 2006; Anderson and Herlocker, 1973; Mills et al., 2003).

The highlands area, which serves as shelter for wildlife, is dominated by woodland, forest and bushland, (Swanson, 2007). Vachellia lahai, Albizia gummifera, Cassipourea malosana, Croton spp., and Nuxia congesta are the most common species of tree this area. Due to the higher altitude, higher rainfall and variable temperature of the Crater rim, the vegetation is often described as 'montane' (Swanson, 2007). The highlands outside of the Highlands Reserve are essential for the Maasai, as they use them to collect wood and natural remedies and graze their livestock (Swanson, 2007). These areas also supply most of the water resources for the local communities and tourists although in recent years there have been concerns about water shortages (Mills et al., 2006; Swanson, 2007).

Remote sensing technologies have become increasingly important for monitoring vegetation cover and its changes over larger areas like the NCA. While traditional methods, such as ground-based surveys and aerial photographs, provide valuable insights into vegetation dynamics, they are often time-consuming, expensive, and limited in scope (Adole et al., 2016; Woodcock et al., 2008; Wulder et al., 2012).

Mapping savannah landscapes presents unique challenges due to the mixed composition of grasslands, woody plants, and bare soil, which can result in spectral similarities and confusion in classification (Symeonakis et al., 2018). To address these challenges, multi-sensor approaches combining optical data with Synthetic Aperture Radar (SAR), such as Sentinel-1, are increasingly being used (Borges et al., 2020). SAR data are particularly advantageous in areas like the NCA, where cloud cover can obscure optical images; they remain unaffected by atmospheric conditions and can effectively differentiate between woody and herbaceous vegetation (Venter et al., 2018). In addition, the development of machine learning techniques such as Random Forests (RF) and Support Vector Machines (SVMs) have enhanced the accuracy of vegetation classification in the savannah landscape (Breiman, 2001; Schneibel et al., 2017). These methods enable the development of detailed vegetation maps, essential for identifying areas experiencing environmental changes, such as woody encroachment or invasive species spread, which could impact the habitat quality for both wildlife and livestock.

Given the pressing need to quantify the extent of land cover changes, Earth observation approaches allow for the detection of gradual changes (e.g. shrub encroachment and grassland decline), as well as abrupt shifts, (e.g. land clearing, (Verbesselt et al., 2010b, 2010a). The use of EO data not only helps to identify vulnerable areas but also supports effective management strategies in a complex, multi-use area such as the NCA (Harris et al., 2020).

### 1.2.3 Rhinos in the NCA

Historically, the population of black rhino in the NCA has been described as the densest in Africa (Homewood and Rodgers, 1991) and the largest in northern Tanzania (Oates and Rees, 2013). In 1966, the Crater (actually a caldera) and Oldupai Gorge supported 108 and 69 rhinos respectively (Goddard, 1967). At one point, their abundance was so high that they were almost considered a nuisance (Oates and Rees, 2013). Poaching, during the 1970s and 80s, reduced the NCA population to just 13 individuals by 1993 (Kiwia, 1989; Moehlman et al., 1996; Oates and Rees, 2013); by 2004 the population had increased to an estimated 19 individuals (Kohi and Lobora, 2019), comprising 3 breeding males and 6 breeding females plus senescent individuals, sub-adults and calves (Mills et al., 2006). Following an assessment by TAWIRI (Kohi and Lobora, 2019) the NCA rhino population has been identified as the largest population (55 confirmed, 11 probable in the Crater) in Tanzania and critical to the conservation of the species in the country (Kohi and Lobora, 2019).

According to Goddard (1967), the black rhino in the NCA comprised of a sedentary, isolated population confined to the crater and the Oldupai area. Moehlman et al. (1996) viewed the NCA population as an isolated relic, although others, such as Frame (1980) and Kiwia (1989), suggested a mixture of resident and transient individuals. Klingel and Klingel (1966) suggested that some rhinos migrated out of the crater, likely due to harsh conditions during the dry season. Runyoro et al. (1995) noted fluctuations in rhino numbers, ranging from zero to 52 before 1974, followed by a significant decline to an average of 13 in 1992. Kiwia (1989) highlighted instances where NCAA staff recorded zero rhinos during ground counts, despite their known presence. These zero counts were likely due to the insensitivity of the census method to detect rhinoceros occurring at relatively low densities (Oates and Rees, 2013). Adult mortality between 1993 and 2003 was estimated at 8%, while neonatal mortality was alarmingly high, ranging between 25% and 45% (Mills et al., 2006).

### *1.2.3.1 Rhino habitat in the NCA*

Despite being a relatively small area (8,283 km2) the NCA comprises of a wide range of habitats that are apparently suitable for black rhino (Goddard, 1968; Mills et al., 2003; Swanson, 2007). However, the available browse quantity and dynamics for black rhinos in the NCA remain uncertain, posing challenges in determining the potential carrying capacity (Mills et al., 2003). It is hypothesized that the NCA's carrying capacity has declined since the 1960s (Goddard, 1967, 1968; Mills et al., 2003). The structural changes in several habitats frequented by rhinos have rendered them unsuitable to sustain a population (Makacha et al., 1979; Amiyo, 2006; Niboye, 2010a) .

Unsuitable habitats and limited browse may promote intra and interspecific competition for resources and emigration of rhinos out of the Crater and NCA (Makacha et al., 1979). For instance, in the 1960s the Lerai forest and the Mandusi swamp were regularly used by black rhinos for shelter and browsing, but nowadays, rhinos only rarely visit these places (Klingel and Klingel, 1966; Goddard, 1968; Amiyo, 2006; Mills et al., 2006; Gadiye et al., 2016). The presence of elephants contributed greatly to this shift in behaviour (Mills et al., 2003; Amiyo, 2006; Landman et al., 2013). Rhinos tend to avoid elephants to prevent competition for resources and secondly, the elephants damaged the vegetation contributing to a decrease in preferable browse, specifically, leguminous plants (Amiyo, 2006; Mills, 2006; Landman et al., 2013). Inadequate habitat/browse can also explain why the rhinos in the NCA were recorded eating wildebeest droppings, an unusual behaviour for an herbivore and that suggests nutrient deficiencies (Klingel and Klingel, 1966; Goddard, 1968). Additionally, the rhino home ranges also increased compared to early studies (Mills, 2006). This increase can be due to unsuitable habitat, as the rhinos will need to cover larger areas to reach their nutritional requirements (Mills, 2006).

### Ngorongoro Crater

Most of the NCA rhino population frequent the Crater, which is predominantly grasslands, marshes and the Lerai forest (Goddard, 1968; Herlocker and Dirschl, 1972). The grassland habitat features medium-height grass, ranging from 0.6 to 1.5 meters tall, and the dominant species, listed in order of significance, include *Cynodon dactylon, Digitaria scalarum, Andropogon greenwayi,* and *Digitaria milanjiana*. *Cenchrus mezianus* and *Setaria pallide-fusca* occur occasionally in this habitat (Goddard, 1968). Sparse patches of herbs are scattered across the grassland, with *Solanum incanum, Cyathula orthacantha*, and Pluchea monocephala (Goddard, 1968; Herlocker and Dirschl, 1972). Large areas of the Crater floor have experienced a decline in palatable forbs and a spread of tall unpalatable grasses (Mills et al., 2003).

The marshes in the NCA, the Mandusi and Gorigor swamps, are dominated by *Aeschynomene schimperi*, but less common species, namely *Leersia hexandra*, *Panicum repens, Diplachne fusca*, are also present (Goddard and Herlocker). Along the swamp's periphery, *Sporobolus spicatus, Cyperus laevigatus, Cyperus dives, Cyperus immensus* also occur (Goddard, 1968; Herlocker and Dirschl, 1972). These swamps appear to have decreased in area and lost much of the shrub cover, likely due to herbivore pressure (Mills et al., 2003).

The Lerai forest is an *Vachellia xanthophloea* woodland that used to support a thriving rhino population due to its browse availability and consistent access to water sources (Goddard, 1967). The earliest records of change date back to the 1960s when the dieback of the Lerai forest was first suggested but very little research has been done since (Amiyo, 2006; Mills et al., 2006). Large mature trees in the overstorey have disappeared, leading to an observable opening of the crown layer. Factors contributing to this decline include heightened water levels infiltrating the forest due to lake level rises and elephant damage (Goddard, 1968). Consequently, increased sunlight penetration prompts the rapid colonization of the understorey by *Pluchea ovalis, Achyranthes aspera, Abutilon longicuspe* and *Justicia betonica* forming a dense bush layer measuring 1.8-2.4 metres on the forest floor. This dense growth inhibits the regeneration of *Vachellia*, resulting in very sparse regeneration within the forest (Goddard, 1968). *Rauvolfia caffra* trees and *Cyperus immensus* reeds grow in the wetter locations (Herlocker and Dirschl, 1972).

### Crater rim

The Crater rim has non-palatable bush species (*Lippia javanica*, *Lantana ukambensis* and *Clausena ansinata*) which have encroached prime rhino habitat that previously comprised of *Vachellia lahai* and palatable shrubs and forbs (Mills et al., 2003). The eastern side of the caldera is dominated by *Lippia javanica* and medium-height grassland ranging 0.6 to 1.5 meters of *Themeda triandra*, *Sporobolus jimbriatus*, and *Setaria sphacelate* (Goddard, 1968). In the northeastern and northern walls of the Crater, there is an extensive area of *Vachellialahai* woodland with scattered *Vachellia abyssinica* which extends partly onto the caldera floor (Herlocker and Dirschl, 1972). The understory typically comprises *Lippia-Lantana-Solanum* over a layer of *Cynodon dactylon* grass (Herlocker and Dirschl, 1972). However, in various locations across the northern wall and crater floor, the *Vachellia lahai* high woodland has deteriorated into bush and grass communities (Herlocker and Dirschl, 1972). This decline is attributed to multiple factors, namely the demise of large trees due to aging, fire, and elephant damage, followed by the suppression of *Vachellia lahai* regeneration prompted by recurring grass fires (Herlocker and Dirschl, 1972).

### Moist evergreen forest

The moist evergreen forest vegetation can be divided into lower and upper montane forest zones. There is not a precise boundary between these zones due to the gradual shifts in the composition of this diverse and intricately structured forest (Herlocker and Dirschl, 1972). The expansive stands of the lower montane forest zone form an uneven semicircular band on the western slopes of the Olmoti crater. Adjacent to this band lie *Vachellia lahai* high woodland, situated approximately at 2,600 meters, while above it is the *Gymnanthemum-Crotalaria* bush. Smaller clusters of this forest can be spotted within Mount Makarut's eastern-facing canyons. Additionally, scattered remnants and solitary trees are dispersed amid the extensive area of *Gymnanthemum-Crotalaria* bush across Olmoti, as well as the eastern and northeastern slopes of Empakaai Crater. Dominant species within this zone include *Croton macrostachyus, Albizia gumrnifera, Calodendrum capense, Olea welwitschii, Olea europaea subsp. cuspidata*, and *Olea hochstetteri* (Herlocker and Dirschl, 1972). In undisturbed sections of the forest, the intertwining crowns of numerous tree species form a dense canopy, allowing minimal light penetration from above (Herlocker and Dirschl, 1972).

Tree species characteristic of the upper montane forest zone include *Lasiosiphon glaucus* and *Hagenia abyssinica* together with several species normally found at lower elevations (Herlocker and Dirschl, 1972).

### Dry evergreen forest

The dry evergreen forest consists of isolated clusters of *Juniperus procera* within steep canyons at elevations ranging from 2,450 to 2,900 meters, the most extensive example being in canyons which nearly reach the peaks of Makarut and Empakaai. On Makarut, *Juniperus procera* stands predominantly maintain a pure composition, while elsewhere they are mixed with diverse broadleaved species like *Nuxia congesta* and *Olea europaea subsp. cuspidata* (Herlocker and Dirschl, 1972).

### *Gymnanthemum-Crotalaria* bushland

Bushland occurs on the west and southwest slopes of Olmoti, along with the eastern slopes of Empakaai; it is dominated by *Gymnanthemum auriculiferum*, *Crotalaria agatiflora*, *Pavonia urens irakuensis*, and *Clutia abyssinica*. Scattered areas and individual tree relics of moist evergreen forest, namely *Nuxia congesta, Lasiosiphon glaucus* and *Bersama abyssinica* are also present at higher elevations. A mosaic of *Gymnanthemum-Crotalaria* bush occurs in the area which indicates an intermediate stage in secondary succession to moist evergreen forest after severe disturbance (Herlocker and Dirschl, 1972).

### The Oldupai region

In the Oldupai region there is a transition towards a typical thornbush habitat (Goddard, 1968). The Oldupai Gorge itself is covered in *Acacia-Commiphora* scrub, mixed with extensive growths of wild sisal *Sanseveria ehrenbergii, Euphorbia tirucalli, Salvadora persica*, and *Barleria eranthemoides* (Goddard, 1967; Herlocker and Dirschl, 1972). The remainder of the region comprises open areas dominated by short grassland and trees suc as *Vachellia tortilis, Commiphora madagascariensis* and *Senegalia mellifera* (Goddard, 1967; Herlocker and Dirschl, 1972). In the 1960s, there was a population of rhinos inhabiting the gorge without readily available free water sources which forced them to have larger home ranges (Goddard, 1967). Currently, no rhinos inhabit the Oldupai Gorge. Below the bush layer, medium-height grassland of *Pennisetum stramineum, Cenchrus ciliaris,* and *Dactyloctenium aegyptium* ranging from 0.6 to 1.5 metres is present.

The plains surrounding the gorge comprise open grasslands, not surpassing 0.6 meters in height (Herlocker and Dirschl, 1972). Trees, shrubs, or herbs collectively form less than 2 percent of the total vegetation cover in the area and the dominant species include *Sporobolus marginatus, Digitaria macroblephara*, and the sedge *Kyllinga sp*. (Herlocker and Dirschl, 1972). Sparse patches of herbs, along with local dominants such as *Pluchea monocephala* and *Solanum incanum*, are scattered across the grassland (Herlocker and Dirschl, 1972).

### 1.2.4 Geology

The distribution and characteristics of vegetation types, as well as their utilization by wildlife, are significantly influenced by the underlying soil structure and composition (Anderson and Herlocker, 1973). Within the NCA, a region predominantly characterized by volcanic formations such as alkaline basaltic and trachytic lavas, the landscape includes giant calderas formed from highly explosive rift-related activity (Pickering, 1968; Scoon, 2018). The Serengeti and Ang'ata Salei Plains, covering approximately 3489 km$^2$ within the NCA, are characterized by fine volcanic ash soils (Homewood and Rodgers, 1991). The Ngorongoro Highlands, covering 2690 km$^2$, are associated with an extinct volcanic complex situated within the Eyasi half-graben (Homewood and Rodgers, 1991; Scoon, 2018). Within the Ngorongoro Volcanic complex, which reaches altitudes of 2,500–3,500 meters, there are eight distinct volcanoes, three of which feature large calderas (Scoon, 2018). Additionally, the Eyasi Scarp and Kakesio regions (~1350 km$^2$) comprise of steep scarp slopes descending to the Rift floor, along with rolling plains and low ridges(Homewood and Rodgers, 1991). In contrast, the Gol Mountains (~700 km$^2$) primarily consist of old rifted and eroded hills composed of Precambrian rock formations

(Homewood and Rodgers, 1991). These areas are characterized by crystalline rocks such as quartzites, gneisses, granites, and metamorphosed shales, which predate the volcanic activity (Mills, 2006).

## 1.3 Thesis aims

This thesis aims to advance the methodologies for monitoring and managing rhino populations by developing a robust, Earth-observation-based framework for habitat assessment and conservation. This research is crucial given the NCA’s expanding population of Eastern black rhinos, particularly considering the area's historical complex context, current threats, and ecological dynamics. Although the NCA serves as the focal point for this research, the methodologies and findings are designed to be broadly applicable to rhino conservation efforts in diverse regions. The primary objectives of this research are:

Establish and analyse current land cover in the NCA: This objective aims to establish the current land cover in the NCA using remote sensing methods and ground-truth data. This involves mapping and analysing the existing vegetation cover and land use patterns. The assessment considers historical changes in land cover, driven by land management practices such as the establishment of the NCA as a multiple land-use area, and the subsequent effects of woody encroachment and invasive species (Estes et al., 2006; Mills et al., 2003). By documenting these dynamics, the research provides a comprehensive baseline for understanding habitat changes, their implications for rhino conservation, and offer insights into how land management practices influence habitat quality and availability (Borges et al., 2020; Venter et al., 2018).

Develop an earth-observation-based approach for monitoring land cover changes: The main aim of the objective is to support the sustainable management of the NCA by developing an Earth-observation based approach for monitoring multi-faceted land cover changes occurring over the past 35 years. To achieve this, we employed a Landsat-based monitoring strategy that incorporated regression-based unmixing for the accurate mapping of the fraction of the different land cover types, and combination of linear regression and the BFAST trend break analysis technique. This framework can be applied to various conservation areas to track habitat alterations and guide adaptive management strategies (Swanson, 2007; Tsalyuk et al., 2017; Wulder et al., 2016). This research provides highly accurate information on long-term land cover changes in the NCA that can inform targeted conservation initiatives within the area. Moreover, the identification of specific areas undergoing land changes holds profound significance for black rhino conservation and other wildlife species within the NCA. Recognizing these shifts in habitat composition is essential for implementing effective conservation strategies that address the requirements of critically endangered species and safeguard their habitats.

Evaluate habitat suitability for rhino populations: This objective focuses on using remote sensing and field data to assess habitat suitability for black rhinos within the NCA. The research aims to analyse factors such as vegetation type, seasonal variations, and human impacts to determine habitat quality. By mapping habitat preferences, the study identifies potential areas that may not yet be occupied and assesses how seasonal shifts and anthropogenic factors influence habitat suitability. This approach helps understand the effects of habitat degradation on rhino diets and overall population health, which is crucial for developing adaptable conservation strategies (Estes et al., 2006; Oates and Rees, 2013). Furthermore, integrating ground-truthing with remotely sensed data ensures more precise and reliable results in habitat suitability assessments, highlighting the importance of considering both data sources for effective conservation efforts.

Understand rhino dietary needs and environmental factors: Understanding the dietary habits of black rhinos and the factors influencing their foraging behaviour is crucial for effective conservation. This research aims to investigate how habitat changes affect rhino diets, focusing on key forage species and seasonal variations. Feeding studies are vital for understanding rhinos' ecological roles and habitat needs, as they provide insights into foraging behaviour and dietary preferences (Buk and Knight, 2010; Emslie and Adcock, 1994; Goddard, 1968). By analysing dietary patterns and nutritional challenges, the study will help develop habitat management guidelines that promote the health and sustainability of rhino populations across various landscapes. Additionally, this approach determines the variables affecting rhino presence, identifies preferred forage species, and pinpoint areas capable of sustaining future black rhino populations, contributing to global conservation efforts and the long-term preservation of the species (Kanini, 2009; Muya and Oguge, 2000; Reid et al., 2007).

By addressing these aims, the thesis provides valuable insights to support the development of innovative conservation strategies for the NCA. The research offers a comprehensive, Earth-observation-based assessment that informs approaches to address both historical and current threats, enhance habitat quality, and support the long-term survival of the Eastern black rhino population. These findings will not only improve habitat management practices within the NCA but also provide valuable guidance for enhancing rhino conservation efforts globally.

## 1.4 Thesis layout

This thesis is structured to systematically address the primary research objectives and contribute valuable insights into rhino conservation through an Earth-observation-based framework. Each chapter is designed to build on the previous one, providing a comprehensive analysis of habitat changes, land cover dynamics, and rhino dietary needs. The layout is as follows:

Chapter 2: Sentinel-1 and Sentinel-2 Data for Savannah Land Cover Mapping: Optimising the Combination of Sensors and Seasons

This chapter focuses on optimizing land cover mapping in the NCA using a combination of Sentinel-1 and Sentinel-2 satellite imagery collected across three different seasons. The study tests how different sensor types and seasonal data can be strategically combined to effectively map diverse land cover types within a montane savannah system, which includes mixed savannah and woodland landscapes and a bimodal rainfall pattern.

Given the complexity and heterogeneity of savannah environments, this chapter aims to improve the accuracy of habitat assessments by determining the most effective combinations of sensors and seasonal data. By developing a high-resolution and highly accurate land cover map, this research establishes a baseline for future analyses of land cover changes, contributing to enhanced monitoring capabilities, prevention of biodiversity loss, and more informed conservation strategies in the NCA and similar ecosystems.

Chapter 3: Landsat Time Series Reveal Forest Loss and Woody Encroachment in the Ngorongoro Conservation Area, Tanzania

This chapter focuses on the application of a Landsat-based time series analysis to investigate long-term vegetation dynamics and land cover change processes within the NCA. To achieve this, the chapter employs a combination of advanced remote sensing techniques, including regression-based unmixing to map and quantify the fractional cover of key land cover types such as forest, grassland, shrubland, and bushland. This approach used a combination of linear regression and the BFAST trend break analysis technique for mapping and quantifying the changes. This will help to explain the factors driving changes in the NCA's landscape, whether natural (e.g., herbivory, rainfall variability) or anthropogenic (e.g., land management practices, tourism development). The findings will inform conservation management strategies that are adaptive to both historical influences and current challenges, thereby contributing to more effective conservation efforts for the Eastern black rhino and broader biodiversity in the NCA.

Chapter 4: Identifying Suitable Habitat for Black Rhino in the Ngorongoro Conservation Area, Tanzania

This chapter focuses on evaluating habitat suitability for black rhinos in the NCA by combining both remote sensing and field data. The assessment considers various factors, including vegetation type, seasonal variations, and the impacts of human activities on habitat quality. The research aims to understand how seasonal shifts and anthropogenic factors affect habitat suitability and to identify optimal habitats for black rhinos across different conditions.

By integrating ecological dynamics and feeding preferences, this chapter seeks to pinpoint key areas that could support current and future rhino populations. It highlights the importance of combining ground-truthing with remotely sensed data to improve the accuracy of habitat suitability assessments, recognizing that remote sensing alone may overlook crucial field variables such as shelter locations. This integrated approach is intended to provide a more comprehensive understanding of habitat requirements, which can inform targeted conservation strategies and enhance the sustainable management of black rhino populations in the NCA and other conservation areas.

Chapter 5: Feeding Habits of a Black Rhino Population in the Ngorongoro Conservation Area, Tanzania

This chapter investigates the dietary habits of black rhinos in the NCA, focusing on the impact of habitat changes on their foraging behaviour and nutritional needs. Feeding studies are critical for understanding the foraging behaviour and dietary preferences of rhinos, contributing to the selection of appropriate sites for conservation management and potential reintroductions. The research uses a combination of advanced analytical methods, such as PERMANOVA to evaluate the influence of habitat variables, seasons, and regions on rhino presence, and random forest modelling to identify the key variables that best classify the presence or absence of rhinos.

By examining factors such as seasonal variations, habitat characteristics, and the availability of key forage species, the chapter aims to develop guidelines for habitat management that support the health and sustainability of black rhino populations. The integration of feeding studies with habitat assessments provides a comprehensive understanding of the ecological requirements of black rhinos, offering insights that can inform broader conservation strategies. This chapter contributes to global conservation efforts by identifying key areas for rhino reintroduction and expansion, while also highlighting the importance of combining ground-truthing with remotely sensed data to enhance the accuracy of habitat suitability assessments.

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# Chapter 2 – Sentinel 1 and 2 data for savannah land cover mapping: optimising the combination of sensors and seasons

This chapter has been published (Appendix 2).

Abstract: Savannahs are heterogeneous environments with an important role in supporting biodiversity and providing essential ecosystem services. Due to extensive land use/cover changes and subsequent land degradation, the provision of ecosystems services from savannahs has increasingly declined over recent years. Mapping the extent and the composition of savannah environments is challenging but essential in order to improve monitoring capabilities, prevent biodiversity loss and ensure the provision of ecosystem services. Here, we tested combinations of Sentinel-1 and Sentinel-2 data from three different seasons to optimise land cover mapping, focusing in the Ngorongoro Conservation Area (NCA) in Tanzania. The NCA has a bimodal rainfall pattern and is comprised of a combination savannah and woodland landscapes. The best performing model achieved an overall accuracy of 86.3% ± 1.5% and included a combination of Sentinel-1 and 2 from the dry and short-dry seasons. Our results show that the optical models outperform their radar counterparts, the combination of multi-sensor data improves the overall accuracy in all scenarios and this is particularly advantageous in single-season models. Regarding the effect of season, models that included the short-dry season outperform the dry and wet season models. Additionally, the combination of more than one season is beneficial for the classification, specifically if it includes the dry or the short-dry season. Combining several seasons is, overall, more beneficial for single-sensor data; however, the accuracies varied with land cover. In summary, the combination of several seasons and sensors provides a more accurate classification, but the target vegetation types should be taken into consideration.

## 2.1. Introduction

Savannahs are heterogeneous landscapes combining grassland, open canopy trees and shrubs. These ecosystems occur in tropical and sub-tropical climate zones, mainly in the Americas and Australia, as well as in Africa, where they cover half of the land surface (Solbrig, 1996). Savannah ecosystems are important for biodiversity and the global carbon cycle and provide essential ecosystem services for some of the world's poorest communities (Pfeifer et al., 2013; Poulter et al., 2014; Symeonakis and Higginbottom, 2014; Liu et al., 2015; Schneibel et al., 2017). In recent years, the provision of ecosystems services from savannahs has increasingly declined due to extensive land use/cover changes and subsequent land degradation (Symeonakis and Higginbottom, 2014; Schneibel et al., 2017). Woody vegetation encroachment or densification, attributed to climate change and altered rainfall patterns, can have negative impacts on carbon storage, biodiversity, grazing capacity and tourism (Angassa and Baars, 2000; Eldridge et al., 2011; Berthrong et al., 2012; Gray and Bond, 2013; Stevens et al., 2017; Venter et al., 2018; Zhang et al., 2019). Additionally, management policies (e.g. fire management), herbivore pressure and invasive plant species directly impact savannah dynamics (Niboye, 2010b; Stevens et al., 2017; Venter et al., 2018).

Savannahs in southern and eastern Africa are similar in their ecological structure and function, sharing similar fauna and flora (Fritz and Duncan, 1994; Beale et al., 2013). However, there are key differences in conservation land management. Southern Africa adopted a pro-active approach, using fences, culling, fire, and large-mammal translocation programs (Beale et al., 2013). Conversely, East Africa's protected areas are often unfenced and follow a 'hands-off' approach allowing wildlife to roam freely and intervening as little as possible (Newmark, 2008). In this region, around 20% of the land is officially protected (IUCN & UNEP, 2009); however, due to population growth driving demand for crop and rangeland, pressure on the savannah is increasing. Sustainable ecosystems require an understanding of how savannahs work and how losses of function can be mitigated or prevented through informed management decisions (Beale et al., 2013). Therefore, to improve monitoring capabilities, prevent biodiversity loss and ensure savannah ecosystem services, it is essential to produce high-resolution, up-to-date and highly accurate land cover information (Yang and Prince, 2000; Eisfelder et al., 2012).

Over small areas, traditional methods of land cover mapping, e.g. ground-based surveys and aerial photographs, are able to provide information on the dynamics of savannah vegetation structure and distribution. However, to portray the spatial patterns of vegetation change over larger areas, these techniques are time consuming, limited in extent and expensive, and therefore, inefficient (Yang and Prince, 2000; Eisfelder et al., 2012). In the last five decades, satellite Earth observation (EO) data are increasingly used to map and monitor vegetation cover and its characteristics (Woodcock et al., 2008; Wulder et al., 2012; Adole et al., 2016). The use of EO technologies with open-access data archives provide the opportunity to study inaccessible areas and to assess the vegetative cover and its evolution through time (Eisfelder et al., 2012). Mapping savannah vegetation, however, is challenging due to varying degrees of vegetation cover, high background soil signal and the spectral similarities between land cover types (Müller et al., 2015; Tsalyuk et al., 2017; Zhang et al., 2019). In East Africa, in particular, high cloud coverage represents an additional challenge (Eggen et al., 2016; Morrison et al., 2018).

For almost 50 years, the Landsat archive has been the workhorse for vegetation and land cover mapping and monitoring, mainly due to its unparalleled archive. More recently, Sentinel-2 data with improved spatial and spectral resolution have also been successfully employed to map African savannah vegetation characteristics (Zhang et al., 2019). However, optical data come with their limitations, such as the presence of cloud coverage and the difficulty in discriminating between woody vegetation and grassland (Symeonakis et al., 2018). To address these inherent problems, a number of studies have combined Synthetic Aperture Radar (SAR) data (e.g. from the Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar, ALOS PALSAR); or Sentinel-1, with optical data to improve classifications, as SAR sensors are insensitive to cloud cover, discriminate woody vegetation effectively and are, therefore, particularly helpful for savannah environments (Mathieu et al., 2013; Naidoo et al., 2016; Higginbottom et al., 2018; Symeonakis et al., 2018; Zhang et al., 2019).

Regardless of the sensors used, most studies focussing on African savannah consider either a distinction between woody and non-woody vegetation or represent woody vegetation as a gradient (Naidoo et al., 2016; Higginbottom et al., 2018; Symeonakis et al., 2018; Zhang et al., 2019). However, such information might not always be meaningful as it might obscure important differences between ecologically distinct land cover types. Considering the amount and types of data currently available, there is an opportunity to develop meaningful, detailed classifications of the savannah environment. Within this context, the aim of this study is to create a detailed, high-resolution and highly accurate land cover map of a montane savannah system: the Ngorongoro Conservation Area (NCA) in Tanzania. We used different combinations of optical (Sentinel-2) and radar data (Sentinel-1) from different seasons (wet, dry and the short-dry season) and compared the classification accuracies to address the following research questions:

1. Can Sentinel-1 and Sentinel-2 seasonal imagery be used to accurately map savannah land cover types at the regional scale?
2. Can the combination of optical and radar data improve classification accuracies?

3. How does the combination of data from different seasons influence the accuracy of the classification?

## 2.2. Materials and Methods

### 2.2.1 Study Area

The NCA, located in northern Tanzania, is a protected area and a World Heritage Site that forms part of the Serengeti ecosystem. It covers an area of around 8283 km$^2$ and includes the famous Ngorongoro Crater, the world's largest inactive, intact and unfilled volcanic caldera (Estes et al., 2006; Swanson, 2007). The NCA boarders Loliondo Game Controlled Area to the North, Serengeti National Park to the West, Lake Eyasi to the Southwest, the area between Lake Eyasi, Lake Manyara and Manyara National Park to the South and agricultural communities to the Southeast (Figure 2.1. b & c). Annual rainfall ranges from 450 mm/year in the lowlands to 1200 mm/year in the highlands (Boone et al., 2006) There is a distinctive variation in rainfall patterns, consisting of two wet seasons from March until May and October to December, and two dry seasons from January to February and from June to October ((F. D. L. Hunter et al., 2020), Figure 2.1. a). The temperature ranges between 7°C-15°C in the wet season and 11°C-20°C in the dry season (Amiyo, 2006).

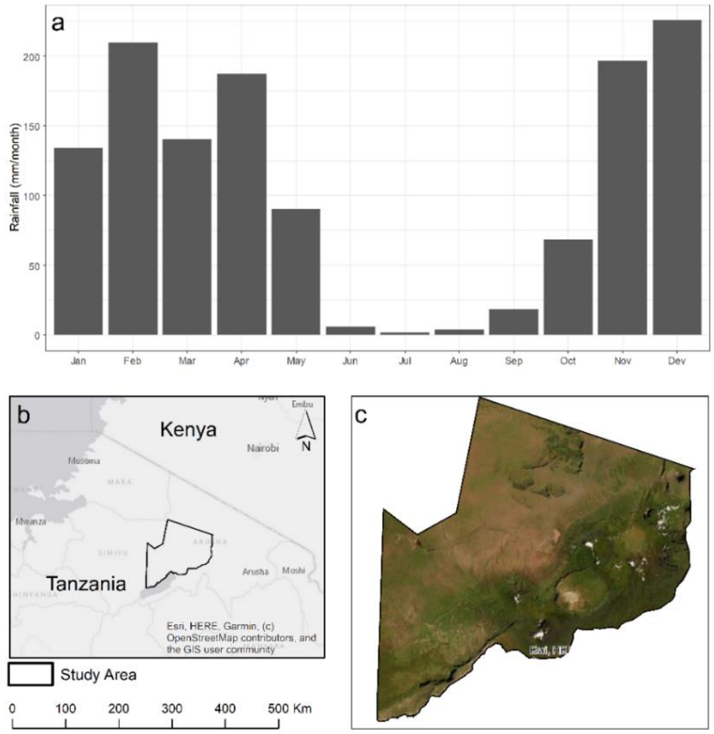

Figure 2.1. (a) ERA rainfall average in the study area for 2018/2019, (b) location of the study area in East Africa, (c) Ngorongoro Conservation Area, Tanzania from Google Earth (Digital Globe).

The NCA is comprised of more than 15000 km$^2$ of savannah habitat (Masao et al., 2015) and is included in the Greater Serengeti Ecosystem (GSE), where the great African wildebeest migration takes place (Swanson, 2007; Masao et al., 2015). The NCA vegetation ranges between highland plains, savannah woodland, forest and savannah grasslands (Herlocker and Dirschl, 1972). The northwest part, bordering with the Serengeti National Park, comprises savannah grassland plains and some woodland areas. Within the Ngorongoro Crater itself, the vegetation comprises mostly of short-to-medium grasses, wetlands, and a soda lake, Lake Magadi. Southwest of the lake is the Lerai Forest, which is degrading and gradually disappearing (Mills et al., 2006). Lerai Forest was dominated by mature *Acacia xanthophloea* trees, which have not been replaced by young *Acacia* trees (Amiyo, 2006). A combination of factors, such as high herbivore pressure, high salinity, water availability and encroachment of invasive species, could explain the forest’s dieback (Herlocker and Dirschl, 1972; Amiyo, 2006; Mills et al., 2006). In the past, Lerai Forest was regularly used by black rhinos for shelter, browsing and breeding (Amiyo, 2006; Mills et al., 2006). Due to vegetation changes or the presence of other herbivores, black rhinos are now rarely seen in this area (Amiyo, 2006; Mills et al., 2006).

The NCA is managed by the NCA Authority (NCAA) as a `multiple land-use area’ to promote biodiversity conservation and the interests of the resident Maasai pastoralists (Homewood and Rodgers, 1991; Niboye, 2010b). In the last 50 years, the NCA followed a ‘hands-off’ management approach. For instance, fire regimes, traditionally implemented by the Maasai and used to improve pasture, control bush encroachment, and reduce tick populations, were banned in 1974 (Amiyo, 2006). This measure is thought to have contributed to woody encroachment, grassland growth and the spread of invasive plant species, which consequently favour species like elephant (*Loxodonta africana*) and buffalo (*Syncerus caffer caffer*) (Amiyo, 2006; Mills et al., 2006; Niboye, 2010b). Fire was used in 2003 to control invasive plant species as it has been identified as an important step towards active management. However, an official fire management programme has not been implemented yet (Amiyo, 2006). Cultivation was also banned in 1974 when the Maasai pastoralists were relocated out of the Ngorongoro Crater (Boone et al., 2006). Nonetheless, in order to support the Masaai communities living within the NCAs boundaries, the cultivation ban was partially lifted in 1992, allowing the cultivation of 1 acre per household (Amiyo, 2006; Boone et al., 2006). Nowadays, the NCAA is looking into more active management approaches to tackle some of the ‘wicked’ problems that the NCA is facing (Harris et al., n.d.), e.g. inbreeding of endangered species such as black rhino (*Diceros bicornis michaeli*), changes in habitat suitability, food security and the spread of invasive species. However, there is a lack of empirical data on these issues that could be used to support and advise decision making.

Herlocker and Dirschl (Herlocker and Dirschl, 1972) carried out the first detailed land cover study in the NCA in 1960s and distinguished eight land cover types: (1) Montane heath; (2) Bamboo forest; (3) Evergreen forest; (4) High woodlands; (5) Low woodlands; (6) Medium grasslands; (7) Short grasslands, and (8) Sand dune grasslands. Here we combined the nomenclature and descriptions of Herlocker and Dirschl (1972; (Herlocker and Dirschl, 1972)) and Pratt and Gwyne (1966) (Pratt et al., 1966), which enabled the identification of nine land cover types:

- Bareland: areas with minimal plant cover that include bare rock, sand, alpine snow and ice, saline or alkaline flats or riverine deposits. These areas often experience extreme environmental conditions, such as low rainfall, high winds, high salinity and toxic or infertile soils that prevent vegetation from developing.
- Bushland: areas of woody plants, bushes or trees, with a closed shrub canopy between 3 to 6 m in height. The closed canopy of bushland thicket has little grazing value and makes it challenging for large animals to navigate through (Pratt et al., 1966).
- Cropland: areas where natural vegetation has been removed or modified and replaced by other types of vegetation that requires human activity to maintain it in the long term. Cropland fields may be fallow at certain times during the year.
- Forest: areas with closed canopy trees of one or more storeys, rising from 7m to ≥40m in height. Bushes and shrubs dominate the ground making it difficult for animals to travel through it.
- Grassland: areas dominated by grasses <25cm to 150cm tall, sometimes with herbs, scarred trees or shrubs, with a high grazing value for both wildlife and livestock. Areas may contain some woody cover and may be almost bare during the dry season and during drought episodes.
- Montane heath: Areas with medium sized woody vegetation (< 1m) that can be shrubs, grasses, ferns and mosses. Montane heath occurs in environments ≥600 m in altitude, usually on mountains, but also on hills with lower and more variable temperatures and rainfall.

- Shrubland: Areas with medium sized woody vegetation (<6m in (Pratt et al., 1966)), generally open canopy, surrounded by grassland or dry land. Some occasional trees and bushes are present depending on location.
- Water: areas that can be lakes, rivers, ponds or reservoirs, which vary with season.
- Woodland: tree-covered area with trees as tall as 20m and an open canopy surrounded by grassland and sometimes shrub but not thicket. These areas are sometimes dominated by only a few species of trees.

### 2.2.1 Data

#### *2.2.1.1. Sentinel-2*

Sentinel-2 is an Earth Observation mission from the European Space Agency's (ESA) Copernicus Programme. It consists of two satellites, Sentinal-2A and Sentinel-2B, launched in 2015 and 2017, respectively (Zhang et al., 2019). Sentinel-2 carries a Multi-Spectral Instrument (MSI) that images 13 spectral bands in the visible, near infrared and shortwave infrared spectral range (SWIR) at 10 to 60 m spatial resolution. The combination of Sentinel 2A and 2B provides a 5-day revisit rate. Sentinel-2 imagery are freely available and accessible through the Copernicus API Hub.

We obtained all Sentinel 2 images that intersected our study area between 01/01/2019 and 30/09/2019, with less than 75% cloud cover, resulting in 521 images (Table 2.1). All image processing was in the Framework for Operational Radiometric Correction for Environmental monitoring (FORCE) software version v.2.0 (Frantz, 2019). Firstly, Level 1C images were downloaded from the Copernicus API hub. Secondly, the raw images were processed to Level 2 using the FORCE L2PS module, applying: atmospheric and topographic correction, cloud and cloud shadow masking, data cubing and downscaling of the 20 m bands using the ImproPhe algorithm (Zhu and Woodcock, 2012; Frantz, Röder, et al., 2016; Frantz, Stellmes, et al., 2016).

**Table 2.1.** Seasonal temporal windows and number of Sentinel images used in each season/

| Season | Start date | Target date | End date | Nº of images |
|---|---|---|---|---|
| Short-dry | 01/01/2019 | 27/01/2019 | 28/02/2019 | 111 |
| Wet | 01/03/2019 | 17/04/2019 | 31/05/2019 | 159 |
| Dry | 01/06/2019 | 17/09/2019 | 30/09/2019 | 251 |

Next, we produced three Best Available Pixel Composites using the L3PS module. The temporal windows were chosen according to the general climatological patterns in the study area but also the specific rainfall dynamics for the year of study (i.e. 2019): March to May for the wet season; June to September for the dry season, and January to February for the short-dry season (Table 2.1). These composites score all available observations within the temporal window selecting the optimal observation based on non-parametric quality scoring. The final products included three composites with 10 bands each to which a Normalised Difference Vegetation Index (NDVI) band was then calculated and added.

##### *2.2.1.2. Sentinel-1*

Sentinel-1 is an Earth Observation mission from ESA's Copernicus Programme consisting of two satellites, Sentinal-1A and Sentinel-1B, launched in 2014 and 2016, respectively (Zhang et al., 2019). Sentinel-1 carries a C-band Synthetic-aperture radar (SAR), which is unaffected by clouds and has been successfully employed in savannah environments for mapping land cover characteristics (Baumann et al., 2018; Zhang et al., 2019). In comparison to the ALOS PALSAR 2 L-band, the C-band is a shorter wavelength with a shallower penetration into open savannah vegetation (Mathieu et al., 2013). The C-band is better at detecting leaves and grasses and therefore more useful for canopy and cropland studies (Mathieu et al., 2013). The L-band is a long wave band more suitable for closed canopy forested environments as it successfully detects woody vegetation (Mathieu et al., 2013).

The Google Earth Engine (GEE) computing platform (Moore and Hansen, 2011; Gorelick et al., 2017) was used to process the Sentinel-1 data and to calculate the metrics from the VV and VH bands (25th, 50th and 90th percentiles and standard deviation). The temporal windows used were the same as for the Sentinel-2 processing. The final products consisted of three composites, one for each season, with eight bands each.

### 2.2.2 Classification strategy

##### *2.2.2.1. Training sample generation*

The training data were collected from high-resolution Google Earth (Digital Globe) imagery acquired between 2013 and 2019. For each land cover type, between 300 and 700 training points were collected, totalling 4430 training points.

### *2.2.2.2. Modelling framework: season and sensor combinations*

In order to determine the best sensor and seasonal combinations to map savannah landscapes, we developed 21 models consisting of combinations of three seasons using Sentinel-1 and 2 imagery (Table 2.2).

**Table 2.2**. The 21 combinations of the models tested.

| Sensor | Data included | Model |
|---|---|---|
| Sentinel-2 (S2) | Dry season s2 | 1 |
| | Short-dry season s2 | 2 |
| | Wet season s2 | 3 |
| | Dry + short-dry seasons s2 | 4 |
| | Dry + wet seasons s2 | 5 |
| | Wet + short-dry seasons s2 | 6 |
| | All seasons s2 | 7 |
| Sentinel-1 (S1) | Dry season s1 | 8 |
| | Short-dry season s1 | 9 |
| | Wet season s1 | 10 |
| | Dry + short-dry seasons s1 | 11 |
| | Dry + wet seasons s1 | 12 |
| | Wet +short-dry seasons s1 | 13 |
| | All seasons s1 | 14 |
| Sentinel-1 and Sentinel-2 combinations (S1&S2) | Dry season S1&S2 | 15 |
| | Short-dry seasons S1&S2 | 16 |
| | Wet season S1&S2 | 17 |
| | Dry + short-dry seasons S1&S2 | 18 |
| | Dry + wet seasons S1&S2 | 19 |
| | Wet + short-dry seasons S1&S2 | 20 |
| | All seasons S1&S2 | 21 |

### *2.2.2.3. Classification validation*

Classifications were carried out in the *R* statistical Software Environment, using the 'RStoolbox' and 'randomforest' packages (Leutner et al., 2018; R Core Team, 2018). The land-cover maps were created using the 'SuperClass' function (Leutner et al., 2018) and random forests (RF) which is a non-parametric machine learning classifier, popular for image classification and land cover mapping (Rodriguez-Galiano et al., 2012; Li et al., 2015; Symeonakis et al., 2018). In African savannahs, random forest classification has successfully been applied in southern Africa (Hüttich et al., 2009; Mishra and Crews, 2014; Symeonakis et al., 2016; Higginbottom et al., 2018) and eastern Africa (Ng et al., 2017; Hamza Khalid Kija et al., 2020).

The final classified maps were validated using a two-stage random sampling procedure as suggested by the best practice guidelines (Olofsson et al., 2014). First, an initial sample of 675 points (75 per class) was collected using a combination of Google Earth pro (version 7.3.3.7786) and ESRI ArcGIS 10.5©. The accuracy was calculated together with the size of the area covered by each land cover class from the classified map with the preliminary higher overall accuracy (Model 4 in Table 2.2). This provided the basis for identifying a suitable validation sample size with a minimum of 100 points per class. The area covered by the 'Water' and 'Cropland' classes was too small and, therefore, they were not considered in the validation process. The validation samples were 2147 in total, covering the remaining seven classes: 82 for 'Bareland'; 218 for 'Bushland'; 103 for 'Forest'; 1262 for 'Grassland'; 56 for 'Montane heath'; 184 for 'Shrubland' and 242 for 'Woodland'.

## 2.3. Results

### 2.3.1. Sentinel-2 and Sentinel-1 seasonal imagery to map savannah land cover types

The multi-sensor and multi-season model, incorporating Sentinel-1 and Sentinel-2 data for both the dry and the short-dry season (Model 18) was the best preforming model, with an overall accuracy of 86.3% ± 1.5% (Figure 2.2 & 3, 2.S1). A land cover map produced from this model is shown in Figure 2.2, with the associated confusion matrix and accuracy statistics in Table 2.3. Adjusting the mapped areas, using stratified area estimation, identified 'Grassland' as the predominant land cover type covering 60% of the study area (5631±106 km$^2$), followed by 'Woodland' (1205 ± 90 km$^2$), 'Shrubland' (922 ±111 km$^2$), and 'Bushland' (842±63 km$^2$). Smaller classes comprised the remaining 8% of the NCA, with 'Forest' accounting for 5% (507 ±44 km$^2$), and 'Bareland' and 'Montane heath' combined covering 3% (276±30 km$^2$).

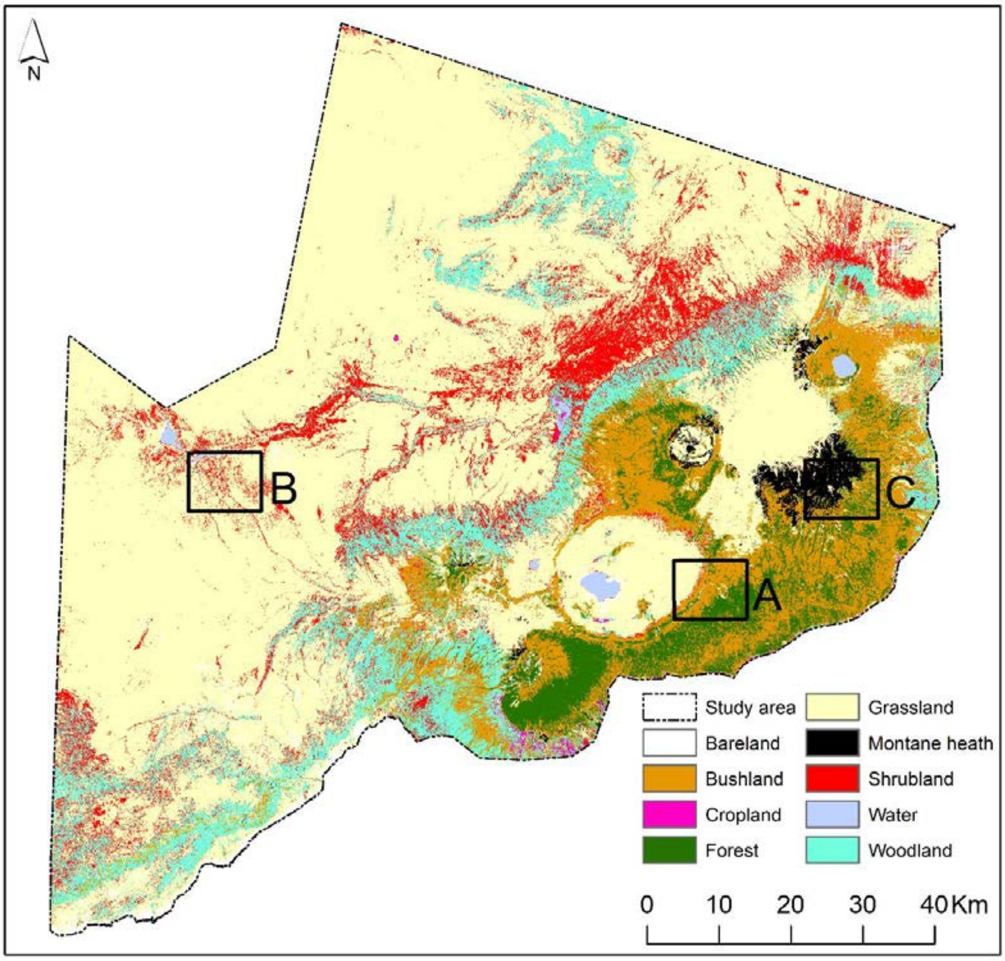

Figure 2.2. Output of the best performing model incorporating Sentinel-1 and Sentinel-2 data for both the dry and the short-dry season (i.e. Model 18). Locations A, B and C are the example subsets that appear in Figure 2.6.

Table 2.3. Confusion matrix for the best performing model incorporating Sentinel-1 and Sentinel-2 data for both the dry and the short-dry season (i.e. Model 18).

| | | Reference | | | | | | | | User’s accuracy |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Ba | Bu | Fo | G | Mh | Sh | Wo | Total | |
| **Mapped** | Bareland (Ba) | 73 | 0 | 0 | 8 | 0 | 1 | 0 | 82 | 0.89 |
| | Bushland (Bu) | 0 | 205 | 22 | 9 | 2 | 17 | 16 | 271 | 0.76 |
| | Forest (Fo) | 0 | 7 | 78 | 0 | 0 | 1 | 0 | 86 | 0.91 |
| | Grassland (G) | 4 | 3 | 0 | 1203 | 2 | 65 | 19 | 1296 | 0.93 |
| | Montane heath (Mh) | 0 | 1 | 0 | 1 | 51 | 1 | 2 | 56 | 0.91 |
| | Shrubland (Sh) | 4 | 1 | 0 | 31 | 1 | 77 | 31 | 145 | 0.53 |
| | Woodland (Wo) | 0 | 1 | 0 | 9 | 0 | 22 | 173 | 205 | 0.84 |
| | Total | 81 | 218 | 100 | 1261 | 56 | 184 | 241 | 2141 | |
| | **Producer’s accuracy** | 0.70 | 0.92 | 0.84 | 0.95 | 0.84 | 0.49 | 0.73 | | |

Models 4, 7, 16, 20 and 21 all achieved accuracies greater than 85%, using different season and sensor combinations (Table 2.2, Figure 2.3). These five models, and the best-performing model, were able to map the majority of the savannah vegetation types, with the exception of 'Shrubland' (Figures 2.4 & 2.5), with comparable accuracies.

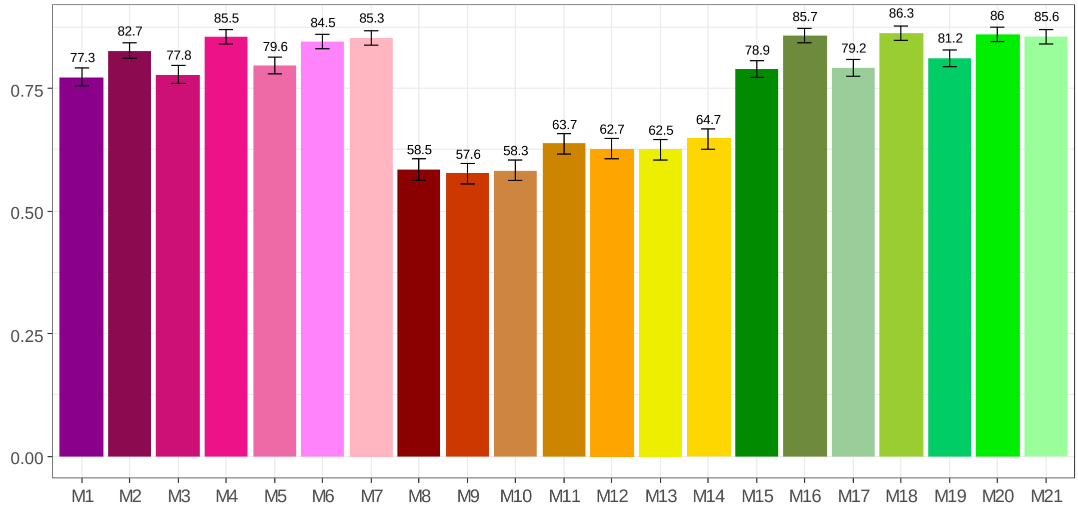

Figure 2.3. The overall accuracies and confidence intervals for the 21 model combinations tested. M1 to M7 includes Sentinel-2 models, M8 to M14 includes Sentinel-1 models and M15 to M21 includes Sentinel-1 and -2 models.

In all models, the most reliably mapped class was 'Grassland', with maximum producer's and users' accuracies of 96% and 92%, respectively achieved by Model 21 (Figures 2.4 & 2.5, 2.S2). The accuracy of the remaining six classes varied considerably in several models. 'Shrubland', for instance, was mapped poorly by all models, with a maximum user's and producer's accuracy of 59% and 54%, respectively, achieved by Model 16. The 'Forest' class was mapped accurately by Sentinel-2 or multi-sensor models (eg. Models 7 and 18). However, Sentinel-1-only models were unable to map it successfully scoring a maximum user's accuracy of 38% and producer's accuracy of 33% achieved by Model 11 (Figures 2.4 & 2.5). The remaining classes, namely 'Bushland', 'Woodland', 'Shrubland' and 'Montane heath' were also mapped more accurately by Sentinel-2 and multi-sensor models than by the Sentinle-1-only models.

Figure 2.4. Producer’s accuracy for different land cover types and models according to Table 2.2.

Figure 2.5. User's accuracy for different land cover types and models according to Table 2.2.

### 2.3.2. The role of C-band SAR

Comparing the two different sensors, Sentinel-2 models outperform the Sentinel-1 ones, in all combinations and land cover types (Figure 2.3). Sentinel-1 models have a much lower overall accuracies and fail to distinguish most land cover types well, especially 'Montane heath', which goes completely undetected in Model 9 (Figures 2.4

& 2.5). In terms of the spatial configuration of the classified land cover maps, those produced by the Sentinel-1 models also show a higher degree of confusion between 'Woodland', 'Bushland' and 'Forest', and tend to overestimate 'Shrubland' (Figure 2.6. A4, B4 & C4). 'Grassland' was the only land cover type that Sentinel-1-only models were able to identify with higher accuracies (>76.8%; Model 10; Figures 2.4 & 2.5). When combining Sentinel-2 and Sentinel-1 data, all models scored higher overall accuracies when compared to their single sensor counterparts (Figure 2.3). For example, the overall accuracy of Model 2 (i.e. Sentinel-2-only, short-dry season) increased from 82.7% (±1.6%) to 85.7% (±1.5%) after the Sentinel-1 data was added (Figure 2.3).

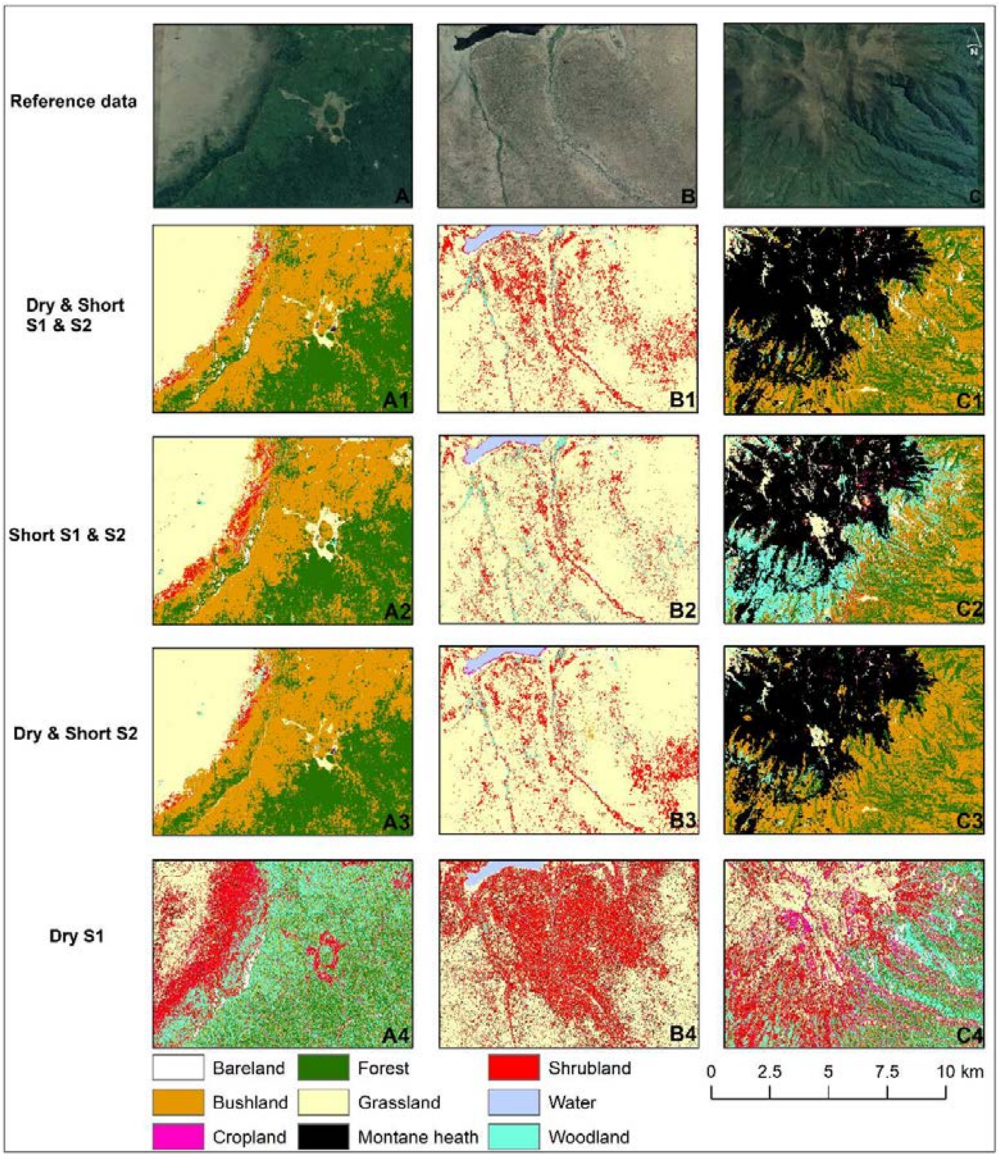

Figure 2.6. Example subsets of the study Area: (A, B & C): the area imagery; (A1, B1, C1): the land cover map for Model 18; (A2, B2, C2): the land cover map for Model 16; (A3, B3, C3): the land cover map for Model 4; (A4, B4, C4): the land cover map for Model 8.

For single season models, adding radar data improved accuracies for nearly all land-cover types, with few exceptions (Figures 2.4 & 2.5). For instance, adding Sentinel-1 data to the short-dry single-season (Model 2), increased the accuracy for most land cover types, except for the user's accuracy of 'Bushland' and producer's accuracy for 'Forest' (Figures 2.4 & 2.5). For multi-season models, adding Sentinel-1 data only improved the overall accuracy slightly (Figure 2.3), and visually the land cover maps are very similar (Figure 2.6. A1, B1, C1 & A3, B3, C3). For instance, the overall accuracy for Model 4 (i.e. Sentinel-2, dry and short-dry seasons) increased slightly from 85.5% (±1.5%) to 86.3% (±1.5%) after the Sentinel-1 data was added; however, this increase is within the respective confidence interval (Figure 2.3). Moreover, adding the SAR data to Model 4 decreased the producer's accuracy for 'Bareland', 'Grassland', 'Forest' and 'Shrubland' and decreased the user's accuracy for 'Shrubland' and 'Montane heath' (Figures 2.4 & 2.5). This decrease in the per-class accuracies for some land cover types occurs in other models, too: when adding Sentinel-1 data to Model 7 (which combines all three seasons; Figures 2.4 & 2.5), a decrease in the producer's accuracy for 'Bareland', 'Bushland', 'Forest' and 'Montane heath' and a decrease in the user's accuracy for 'Forest' and 'Shrubland' is observed.

### 2.3.3. The role of season

Unlike their Sentinel-1 counterparts, Sentinel-2 single season models with data from the short-dry season out-performed dry or wet mono-season ones (Figures 2.3 & 2.7). Additionally, all single season models, using dry or wet season imagery, produced very similar overall accuracies (eg. Model 1 obtained 77.3% and Model 3 obtained 77.8%; Figures 2.3 & 2.7). Both Sentinel-2 and multi-sensor models incorporating the short-dry season, on its own or with other seasons, performed better than other combinations (Figures 2.3 & 2.7). In Sentinel-2-only models, combining the short-dry season with either the wet or dry seasons, improved all land cover classes, except for the producer's accuracy for 'Bareland', in Model 6 and 'Woodland', in Model 4, which performed better with the short-dry season on its own (Figures 2.4 & 2.5). Regarding the SAR-only models, season does not seem to have a clear effect on overall accuracies (Figures 2.3 & 2.7). However, when optical and SAR data were combined, the models that incorporated the short-dry season, obtained overall accuracies >85.6% - this included the best performing model (Model 18; Figures 2.3 & 2.7).

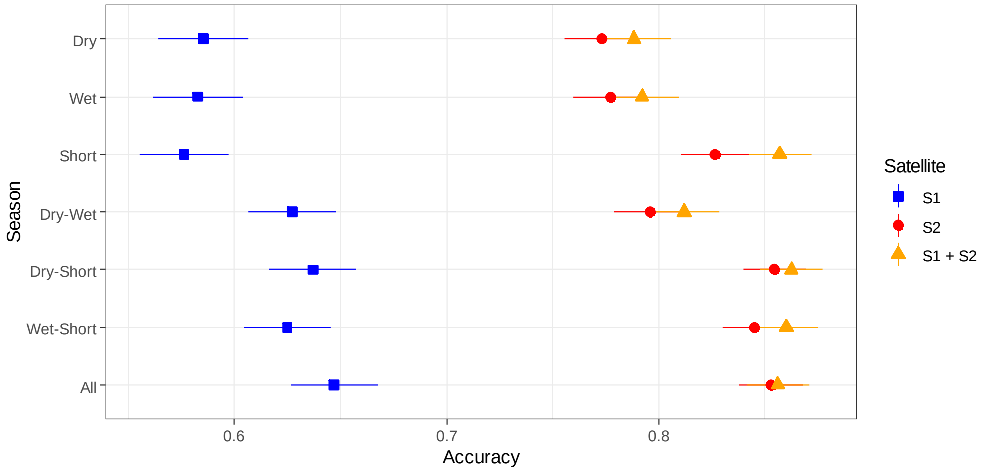

**Figure 2.7.** Overall accuracy results for the 21 models according to season and season combinations.

Combining imagery from more than one season increased model accuracy (Figures 2.3 & 2.7). For Sentinel-2-only models, using only the dry and short-dry seasons produced accuracies of 77.3% ±1.8% and 82.7% ± 1.6%, respectively, while a combination of both, increased the accuracy by 2.8% (to 85.5% ± 1.5%; Figures 2.3 & 2.7). In addition, this combination obtained similar results to the best performing model (Figure 2.6. A1, B1, C1 & A3, B3, C3). For Sentinel-1-only models, the dry and short-dry season models produced accuracies of 58.5% (±2.1%) and 57.6% (±2.1%), respectively; when combined this rises to 63.7% ± 2.1% (Figures 2.3 & 2.7).

The models that combined more than one season scored lower commission and omission errors for most land cover classes (Figures 2.4 & 2.5). For Sentinel-2-only models, the combination of dry and short-dry seasons (i.e. Model 4), increased the accuracy for most land cover types, with the exception of the producer’s accuracy of ‘Woodland’ (Figures 2.4 & 2.5). In addition, the combination of wet and short-dry season (Model 6) increased the accuracy for nearly all land cover types, except for the producer’s accuracy of ‘Bareland’ (Figures 2.4 & 2.5). On the other hand, for multi-sensor models, combining more than one season increased overall accuracies slightly but these varied depending on the land cover type. For instance, the combination of dry and short-dry season data in multi-sensor models (Models 15 and 16) decreased the user’s accuracy for ‘Bareland’ by 8%, of ‘Shrubland’ by 6%, of ‘Woodland’ by 1% and of ‘Bushland’ by 5%. Producer’s accuracy also decreased for ‘Bareland’ (7%), ‘Shrubland’ (6%) and ‘Woodland’ (3%; Figures 2.4 & 2.5). Despite the statistics, there are areas where the opposite holds true, as in the case of the mountains northeast of the Crater

(Figure 2.6.C). In that area the inclusion of the dry season data corrected the wrongly classified 'Woodland' for 'Bushland' (Figure 2.6.C1 & C2).

Interestingly, the combination of all three seasons did not significantly improve the overall accuracy for most of the models. However, this combination performed better than the combination of data from the dry and wet seasons (Figures 2.3 & 2.7). Nonetheless, the three-season models seem to be beneficial for the mapping of specific land cover classes (Figures 2.4 & 2.5). Considering only the Sentinel-2 models, the three-season combination increases the user's accuracy for 'Forest', 'Bareland' and 'Grassland' and increases the producer's accuracy for 'Montane heath', when compared to single- or bi-season combinations (Figures 2.4 & 2.5).

## 2.4. Discussion

### 2.4.1. Can Sentinel-2 and Sentinel-1 seasonal imagery be used to accurately map savannah land cover types at the regional scale?

To improve habitat monitoring, preserve biodiversity and sustain ecosystem services, the provision of moderate-resolution land-cover maps across savannah environments is essential. Mapping savannahs is a challenging task, due to varying vegetation densities, high background soil signal, and the spectral similarities between the dominant land cover types (Müller et al., 2015; Tsalyuk et al., 2017; Zhang et al., 2019). Our results demonstrate that imagery from the Sentinel constellation (optical and C-band SAR) has good utility for mapping complex savannah systems at moderate resolution. Our best performing model -- using a combination of Sentinel-2 and Sentinel-1 data from the dry and short-dry seasons -- achieved an overall accuracy of 86.3 ± 1.5%. This compares favourably with other studies in savannah environments (e.g. (Mishra and Crews, 2014; Higginbottom et al., 2018; Symeonakis et al., 2018; Zhang et al., 2019). To investigate the reliability of mapping savannahs using Sentinel imagery that comes with an undisputed spatial resolution advantage compared to Landsat or MODIS, we examined the role of different sensor and season combinations on mapping accuracies.

### 2.4.2. Can the combination of optical and radar data improve classification accuracies?

Our results show models using solely Sentinel-1 data underperformed their Sentinel-2 counterparts, for all seasons and all land cover types (Figure 2.3). The best Sentinel-2 only model (short-dry season) produced an 85.5% overall accuracy compared to 64.5% for the best Sentinel-1 only model (wet season): a non-trivial difference. This agrees with both Lopes et al. (2019; (Lopes et al., n.d.)) and Higginbottom et al. (2018; (Higginbottom et al., 2018)) who compared optical with radar imagery in West and South Africa, respectively. This could be attributed to SAR-only models incurring errors caused by incidence angle variation, speckle, geolocation accuracy and moisture content (Higginbottom et al., 2018). The results from Naidoo et al. (2016; (Naidoo et al., 2016)) who mapped woody vegetation cover in southern African savannahs show the opposite result, but they employed longer wavelength L-band data (ALOS PALSAR), which are more sensitive to the dense woody vegetation structure (Müller et al., 2015; Higginbottom et al., 2018; Symeonakis et al., 2018).

The SAR-only models were able to successfully identify only the 'Grassland' land cover type (accuracies above 76.8%). 'Montane heath' on the other hand, obtained accuracies as low as 0% in Model 9 and was often confused for 'Grassland', likely due to textural similarities between the two land cover types and their lack of dense or woody plants. Interestingly, the woody classes also scored low accuracies in the SAR-only models, with open 'Woodland' achieving a maximum of 57.5% (Model 10), 'Bushland' 47.2% (Model 8) and closed 'Forest' 37% (Model 10) (Figures 2.4 & 2.5). The relatively large number of woody classes in our study area and the land cover nomenclature we adopted might explain the confusion between them, as previous research shows that combining such classes can improve mapping accuracy from SAR data (Walker and Briggs, 2007; Laurin et al., 2013). In addition, Huttich et al. (2011; (Hüttich et al., 2011)) suggested that using inter-annual metrics of over one or two years could increase accuracies of 'Shrubland' and 'Grassland' classes. Our results also show that SAR only models overestimated 'Shrubland', specifically in low vegetated areas (Figure 2.6. A4, B4 & C4). This can be attributed to the high surface roughness that produces similar signals for trees and shrubs (Zhang et al., 2019; Urban et al., 2020). Zhang et al. (2019; (Zhang et al., 2019)) and Urban et. al (2020; (Urban et al., 2020)) , also showed that radar data overestimate the presence of woody vegetation, for the Sahel and South Africa, respectively.

Previous research recommends combining SAR with optical data for improved land cover mapping (Laurin et al., 2013; Symeonakis et al., 2018; Zhang et al., 2019). Our results show that the combination of Sentinel-2 and Sentinel-1 data achieves higher overall accuracies when compared to single sensor models. Model 2 (Sentinel-2, short-dry season), scored an overall accuracy of 82.7%, increased by 3% when Sentinel-1 data were added (Figure 2.3). The addition of SAR data increased the accuracies for most vegetation types, with the UA for ‘bushland’ and PA of closed ‘forest’ being the only two exceptions. These results are consistent with previous research carried out by Laurin et al. (2013; (Laurin et al., 2013)) and Symeonakis et al. (2018; (Symeonakis et al., 2018)), finding that combining SAR and optical data also decreased the omission and commission errors for all land cover types. Zhang et al. (2019; (Zhang et al., 2019)) suggested adding SAR to optical data as they can correct errors particularly in highly productive areas (e.g. wetlands, irrigated fields and perineal grasses) which can be misclassified as trees.

Our findings agree with the emerging consensus that multi-sensor approaches to land cover mapping perform best. However, we found the benefits of multi-sensor approaches were most evident in mono-temporal models. For instance, adding SAR data to Model 4 (Sentinel-2 data, dry and short-dry seasons), improved its overall accuracy by only 0.8% (Figure 2.3). This slight increase is within the confidence interval of both models (Model 4 and Model 18) and produce a very similar spatial configuration of the mapped land cover classes (Figure 2.6. A1, B1, C1 & A3, B3, C3). Our results, therefore, support those of Higginbottom et al. (2018; (Higginbottom et al., 2018)), who found that the multi-sensor approach was only marginally beneficial (~1%), and at fine scales (30m) the addition of PALSAR data to Landsat may reduce accuracies. Chatziantoniou et al. (2017; (Chatziantoniou et al., 2017)) achieved similar results to ours, suggesting that although SAR data are solely impacted by wind, droughts might also influence the data quality thereby negatively affecting the overall classification accuracy. Therefore, if multi-season data is available, combining more than one sensor might be unnecessary and even counterproductive for specific land cover types (e.g. ‘Shrubland’).

### 2.4.3. How does the combination of data from different seasons influence the accuracy of the classification?

Savannah mapping studies generally use data from the dry season, due to significantly lower cloud contamination and heightened contrasts between woody and grassland components (Haro-Carrion and Southworth, 2018; Higginbottom et al., 2018). We found only small differences in accuracy, less than 1%, between wet and dry season models, for Sentinel-2 and multi-sensor scenarios (Figures 2.3 & 2.7), which agrees with Symeonakis et al. (2018; (Higginbottom et al., 2018)). Interestingly, Sentinel-2 imagery from the short-dry season, which occurs between January and February was highly effective, preforming comparably to the multi-sensor models and outperforming the other single season Sentinel-2 models by 5% (Figure 2.7). The short-dry season, which occurs right after the short rains (from October to December), is characteristic of East Africa and, to our knowledge, this is the first study to examine its utility in mapping savannahs. This season is particularly useful for land cover mapping due to it having cloud free data and being wet enough for herbaceous vegetation to be photosynthetically active, which is not the case during the dry season (Brandt et al., 2016). In the Ngorongoro Conservation Area (NCA), during the short-dry season the grasses in the North-West of the NCA starts to emerge, attracting the great wildebeest migration. Moreover, this season is dry enough to provide noticeable differences in the spectral characteristics of woody and herbaceous vegetation (Naidoo et al., 2016).

We found that models combing dry and wet season imagery outperform their single season counterparts in all scenarios (Figure 2.7). However, compared to other model combinations, Sentinel-2-only and multi-sensor models were improved by including the short-dry season data (Figure 2.7). The dry season (Model 1) and the short-dry season model (Model 2) produced an overall accuracy of 77.3% and 82.7%, respectively. Once combined, the overall accuracy increased to 85.5% (~2.8%), which is very close to the best performing model (Figure 2.3). This agrees with Haro-Carrión and Southworth (2018; (Haro-Carrion and Southworth, 2018)) and Symeonakis et al. (2018; (Symeonakis et al., 2018)), who also reported higher accuracies when combining bi-seasonal data. Adding multi-season data provides additional spectral information and, if available, should be preferred for successfully distinguishing between spectrally similar savannah vegetation classes (Haro-Carrion and Southworth, 2018).

Multi-season models generally scored higher overall accuracies; however, multi-sensor models were less improved. For instance, the increase in the overall accuracy from the combination of Models 15 and 16, which include multi-sensor data for the dry and short-dry seasons, was ~0.6%. This agrees with Symeonakis et al. (2018; (Symeonakis et al., 2018)) who reported the same increase of 0.6% in the overall accuracy for their multi-sensor dry season model by combining sensors and seasons. Regardless of the impact on the overall accuracy, our results show that adding more than one season to multi-sensor models solved misclassification problems in specific areas within the NCA (Figure 2.6). For instance, in the mountains northeast of the Crater (Figure 2.6. C), Model 16 overestimated the open 'Woodland' cover: by adding the dry season data, the classification was improved (Figure 2.6. C1 & C2). These errors in the spatial configuration of the mapped classes can go unnoticed, as the calculation of accuracy statistics is carried out over a limited number of locations compared to the much larger total number of pixels of the study area.

Most multi-season mapping studies consider only the wet and dry seasons or a combination of the two. Our results show that the tri-seasonal models performed better than the wet and dry season models and improved the accuracies for several specific land cover types (e.g. closed 'Forest' and 'Grassland' achieved 92% and 90.6%, respectively in Model 7). However, the overall accuracy did not increase significantly when compared to bi-seasonal models. For example, Model 21, which combines the three seasons and SAR data, obtained an overall accuracy of 85.6%, higher than Model 19 (81.2%), which only included the dry and wet seasons but lower than Model 18 (86.3%), which included the dry and short-dry seasons (Figures 2.3 & 2.7). These results contrast with Hüttich et al. (2011; (Hüttich et al., 2011)) who found that increasing the length of the observation period and inter-seasonal data increases the accuracy of the classification. However, the scholars also mention that highly dynamic classes, such as 'Grassland' and 'Bareland', benefit when longer time series are used which our results support. Whilst there are benefits from using tri-seasonal imagery, it must be noted that the amount of data and time required for pre-processing also increases significantly. Unless tri-seasonal data provide improvements for mapping specific vegetation types of interest, using a combination of the dry and short-dry seasons should suffice.

### 2.4.4. Implications for biodiversity monitoring/ ecosystem monitoring challenges in the area

This study has demonstrated that Sentinel imagery can reliably map land cover in the Ngorongoro Conservation Area (NCA), and the wider Serengeti region. The NCA is globally important for biodiversity conservation due to the presence of iconic megafauna, such as the Eastern black rhino and African elephant. It is among the best locations in the world to see Black Rhino in the wild, attracting thousands of tourists every year. The NCA supports the largest Black rhino population in Tanzania and in recent years this population increased to 56 individuals (Kohi and Lobora, 2019). Currently, there is emerging evidence of a decrease in the quality and quantity of preferable browse and, consequently, a decrease in suitable habitat for black rhino (Makacha et al., 1979; Amiyo, 2006; Niboye, 2010b). Unsuitable habitats and limited browse promote intra- and inter-specific competition for resources and emigration of rhinos out of the Crater and the NCA (Makacha et al., 1979). Our derived land cover map could help monitor Black Rhino habitat quality and identify new locations within the NCA which the population could expand into. In addition, land cover maps can infer rhino home ranges and support anti-poaching efforts in the NCA. Previously, the only detailed land cover survey in the NCA was completed in 1972 (Herlocker and Dirschl, 1972), before several major management policies were introduced that brought about significant environmental changes, e.g. the displacement of pastoralists from the Ngorongoro Crater (Mills et al., 2006; Niboye, 2010b). Therefore, our accurate and up-to-date land cover map could have considerable conservation implications for the NCA, in general, and the black rhino population, in particular, as it provides information essential for the development of sustainable management strategies.

## 2.5. Conclusion

Savannahs are heterogeneous environments providing essential ecosystem services to communities. Currently, they are threatened by extensive land use/cover changes and subsequent land degradation. Mapping these environments is challenging but essential in order to improve monitoring capabilities, prevent biodiversity loss and ensure savannah ecosystem service provision. In this study, we tested how combinations of imagery from different seasons and sensors affects the accuracy of land cover maps for the NCA and provide guidance for future attempts to monitor and understand savannah landscapes. We conclude that the combination of Sentinel-1 and 2 data from the dry and short-dry seasons successfully maps most of the land cover types in the NCA, with ‘Shrubland’ remaining a challenge. Additionally, we found that if SAR data are unavailable, multi-season Sentinel-2 data provide a good alternative, whilst if no multi-seasonal data can be used, a combination of SAR and optical data can be used to accurately map savannah environments with similar results to the best performing model. Finally, we advise that the short-dry season should be preferred over the wet and dry seasons for both multi-sensor combinations and optical data. In conclusion, we provide much needed and highly accurate, medium resolution land cover maps for the NCA, which will support sustainable management and conservation.

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## 2.7 Supplementary material – Chapter 2

Table 2.S1. Overall accuracy of the models tested.

| Sensor | Data included | Model | Accuracy |
|---|---|---|---|
| Sentinel-2 (S2) | Dry season s2 | 1 | 0.77 |
| | Short-dry season s2 | 2 | 0.83 |
| | Wet season s2 | 3 | 0.78 |
| | Dry + short-dry seasons s2 | 4 | 0.85 |
| | Dry + wet seasons s2 | 5 | 0.80 |
| | Wet + short-dry seasons s2 | 6 | 0.85 |
| | All seasons s2 | 7 | 0.85 |
| Sentinel-1 (S1) | Dry season s1 | 8 | 0.59 |
| | Short-dry season s1 | 9 | 0.58 |
| | Wet season s1 | 10 | 0.58 |
| | Dry + short-dry seasons s1 | 11 | 0.64 |
| | Dry + wet seasons s1 | 12 | 0.63 |
| | Wet +short-dry seasons s1 | 13 | 0.62 |
| | All seasons s1 | 14 | 0.65 |
| Sentinel-1 and Sentinel-2 combinations (S1&S2) | Dry season S1&S2 | 15 | 0.79 |
| | Short-dry seasons S1&S2 | 16 | 0.86 |
| | Wet season S1&S2 | 17 | 0.79 |
| | Dry + short-dry seasons S1&S2 | 18 | 0.86 |
| | Dry + wet seasons S1&S2 | 19 | 0.81 |
| | Wet + short-dry seasons S1&S2 | 20 | 0.86 |
| | All seasons S1&S2 | 21 | 0.86 |

Table 2.S2. User’s and Producer’s accuracy of all land cover types and models tested.

| | **Bareland** | | **Bushland** | | **Forest** | | **Grassland** | | **Montane heath** | | **Shrubland** | | **Woodland** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Statistic U: User’s P: Producer’s** | **U** | **P** | **U** | **P** | **U** | **P** | **U** | **P** | **U** | **P** | **U** | **P** | **U** | **P** |
| Model 1 | 0.79 | 0.46 | 0.67 | 0.65 | 0.67 | 0.74 | 0.87 | 0.91 | 0.61 | 0.68 | 0.41 | 0.34 | 0.65 | 0.60 |
| Model 2 | 0.87 | 0.69 | 0.75 | 0.85 | 0.82 | 0.79 | 0.90 | 0.92 | 0.71 | 0.62 | 0.52 | 0.46 | 0.75 | 0.70 |
| Model 3 | 0.86 | 0.54 | 0.69 | 0.72 | 0.65 | 0.66 | 0.87 | 0.90 | 0.61 | 0.57 | 0.45 | 0.35 | 0.63 | 0.66 |
| Model 4 | 0.88 | 0.84 | 0.75 | 0.91 | 0.90 | 0.84 | 0.90 | 0.96 | 0.94 | 0.79 | 0.60 | 0.50 | 0.84 | 0.65 |
| Model 5 | 0.82 | 0.44 | 0.71 | 0.75 | 0.72 | 0.69 | 0.87 | 0.93 | 0.92 | 0.74 | 0.44 | 0.37 | 0.69 | 0.63 |
| Model 6 | 0.89 | 0.61 | 0.75 | 0.88 | 0.86 | 0.80 | 0.90 | 0.94 | 0.88 | 0.73 | 0.59 | 0.49 | 0.80 | 0.73 |
| Model 7 | 0.92 | 0.67 | 0.74 | 0.90 | 0.92 | 0.83 | 0.91 | 0.95 | 0.94 | 0.81 | 0.57 | 0.46 | 0.82 | 0.70 |
| Model 8 | 0.20 | 0.30 | 0.47 | 0.21 | 0.31 | 0.30 | 0.87 | 0.77 | 0.17 | 0.10 | 0.20 | 0.32 | 0.34 | 0.53 |
| Model 9 | 0.34 | 0.35 | 0.35 | 0.22 | 0.28 | 0.19 | 0.82 | 0.78 | 0.00 | 0.00 | 0.12 | 0.16 | 0.32 | 0.51 |
| Model 10 | 0.20 | 0.33 | 0.44 | 0.16 | 0.37 | 0.28 | 0.81 | 0.78 | 0.14 | 0.02 | 0.15 | 0.19 | 0.35 | 0.57 |
| Model 11 | 0.44 | 0.37 | 0.45 | 0.24 | 0.38 | 0.33 | 0.88 | 0.83 | 0.21 | 0.13 | 0.23 | 0.36 | 0.37 | 0.54 |
| Model 12 | 0.40 | 0.27 | 0.46 | 0.25 | 0.31 | 0.28 | 0.86 | 0.82 | 0.22 | 0.13 | 0.21 | 0.34 | 0.41 | 0.58 |
| Model 13 | 0.40 | 0.37 | 0.45 | 0.24 | 0.40 | 0.30 | 0.84 | 0.82 | 0.17 | 0.04 | 0.19 | 0.27 | 0.39 | 0.60 |
| Model 14 | 0.53 | 0.34 | 0.54 | 0.29 | 0.34 | 0.28 | 0.88 | 0.83 | 0.42 | 0.21 | 0.21 | 0.32 | 0.39 | 0.61 |
| Model 15 | 0.83 | 0.40 | 0.71 | 0.67 | 0.69 | 0.78 | 0.90 | 0.91 | 0.67 | 0.78 | 0.42 | 0.43 | 0.63 | 0.62 |
| Model 16 | 0.97 | 0.77 | 0.70 | 0.88 | 0.83 | 0.78 | 0.92 | 0.94 | 0.80 | 0.64 | 0.59 | 0.54 | 0.85 | 0.76 |
| Model 17 | 0.87 | 0.48 | 0.69 | 0.73 | 0.67 | 0.68 | 0.89 | 0.92 | 0.73 | 0.46 | 0.47 | 0.40 | 0.67 | 0.70 |
| Model 18 | 0.89 | 0.70 | 0.76 | 0.92 | 0.91 | 0.84 | 0.93 | 0.95 | 0.91 | 0.84 | 0.53 | 0.49 | 0.84 | 0.73 |
| Model 19 | 0.89 | 0.42 | 0.70 | 0.78 | 0.72 | 0.66 | 0.91 | 0.92 | 0.75 | 0.78 | 0.49 | 0.42 | 0.67 | 0.72 |
| Model 20 | 0.94 | 0.60 | 0.75 | 0.91 | 0.83 | 0.81 | 0.91 | 0.96 | 0.85 | 0.56 | 0.65 | 0.50 | 0.84 | 0.76 |
| Model 21 | 0.97 | 0.56 | 0.76 | 0.89 | 0.84 | 0.81 | 0.92 | 0.96 | 0.96 | 0.75 | 0.56 | 0.48 | 0.82 | 0.71 |

# Chapter 3 – Landsat time series reveal forest loss and woody encroachment in the Ngorongoro Conservation Area, Tanzania

This chapter has been published (Appendix 2).

Abstract: The Ngorongoro Conservation Area (NCA) is of global significance for conservation due to the presence of iconic fauna; understating its vegetation dynamics is increasingly important to improve monitoring, protect biodiversity and ensure sustainable development. Here, we propose a Landsat-based monitoring strategy that incorporates (i) regression-based unmixing for the accurate mapping of the fraction of the different land cover types, and (ii) a combination of linear regression and the BFAST trend break analysis technique for mapping and quantifying land cover changes. Using Google Earth Pro and the EnMap-Box software, the fractional cover of the main land cover types of the NCA were accurately mapped for the first time, namely bareland, bushland, cropland, forest, grassland, montane heath, shrubland, water and woodland. Our results show that the main changes occurring in the NCA consisted of the replacement of forest with bushland: we exemplify this with a case study in the Lerai Forest. We also found declines in grassland and an increase in shrubland in the Serengeti Plains suggesting woody encroachment. These changes threaten the wellbeing of livestock, the livelihoods of pastoralists and of the wildlife dependent on these grazing areas. Some of the land cover changes may be occurring naturally and caused by herbivory, rainfall patterns and vegetation succession, but many are linked to human activity, specifically, management policies, tourism development and the increase in human population and livestock. We recommend that the managers of the NCA conduct trials on fire management to assess their suitability in improving rangeland condition, reducing encroachment, and managing invasive species. Our study provides for the first time much needed and highly accurate information on long-term land cover changes in the NCA that can support the sustainable management and conservation of this UNESCO World Heritage Site.

## 3.1 Introduction

African savannah environments provide essential ecosystem services to communities, sustain endemic biodiversity and play a critical role in regulating carbon cycles (Poulter et al., 2014; Liu et al., 2015; Schneibel et al., 2017; McNicol et al., 2018). In recent years, the provision of ecosystem services from many savannah regions has progressively declined due to agricultural expansion, woodland degradation, invasive species, bush encroachment, climate change, and management policies, putting wildlife and communities at risk (Schneibel et al., 2017; Symeonakis & Higginbottom, 2014; Tsalyuk et al., 2017).

The Ngorongoro Conservation Area (NCA) in Northern Tanzania is a designated United Nations Educational, Scientific and Cultural Organization (UNESCO) World Heritage Site for exceptional natural and cultural values (UNESCO, 2010). It is part of the world's largest intact savannah systems, the Greater Serengeti Ecosystem, which includes the Serengeti National Park and the Maasai Mara, where one of Africa's largest animal migrations takes place (Swanson, 2007; Masao et al., 2015). The NCA also supports the largest population of the critically endangered Eastern Black Rhinoceros (*Diceros bicornis michaeli*) in Tanzania (Amiyo, 2006; Goddard, 1968; Mills et al., 2006). The density and diversity of wildlife in the NCA is of global importance for biodiversity conservation and economically important for Tanzania. For instance, in 2016 over one million tourists visited the NCA, generating revenue of approximately $70 million (Slootweg, 2016, 2017). The NCA is unique as it operates as a multiple land-use model designed to protect not only wildlife but also the lifestyle of the resident Maasai pastoralists (Niboye, 2010b).

The NCA vegetation comprises of a combination of highland forests around the Ngorongoro Crater, savannah woodland and shortgrass plains , Herlocker & Dirschl, 1972). Over the last 50 years, African savannahs have undergone considerable land cover changes, including forest degradation, spread of invasive plant species, and woody encroachment (Amiyo, 2006; Higginbottom et al., 2018; Ludwig et al., 2019; Mills et al., 2006; Symeonakis et al., 2018; Venter et al., 2018). In the NCA highlands, forest degradation is of particular concern, as these forests provide ecosystem services to the Maasai through the provision of fuel wood, traditional medicinal plants, and forage for livestock (Swanson, 2007). Additionally, upland forests provide shelter for wildlife and regulate water resources (Swanson, 2007). In the grassland plains, woody encroachment and invasive species can reduce rangeland carrying capacity, which directly affects wildlife and the Maasai livestock (Venter et al., 2018).

Land cover changes in the NCA are driven by a combination of local and global drivers (Homewood et al., 2001; Masao et al., 2015; Niboye, 2010).Firstly, the Maasai community within the NCA increased from roughly 8,000 in 1959 to almost 100,000 in 2018, with an accompanying livestock population of approximately 800,000 in 2018 (Lyimo et al., 2020; Manzano & Yamat, 2018). Population growth has led to the expansion of settlements, livestock bomas, and demand for water resources (TAWIRI & NCAA, 2020). In addition, tourism, grazing pressure, climate change, and management decisions also seem to be contributors to change (Homewood et al., 2001; Masao et al., 2015; Niboye, 2010). Many of these changes have led to the decline in habitat quality (Amiyo, 2006; Estes et al., 2006; Niboye, 2010b). Less suitable habitats with limited opportunities for browsing and grazing encourage inter- and intraspecific competition for resources, threatening wildlife populations and their distribution, and subsequently raising concerns of biodiversity loss and increasing human-wildlife conflicts (Makacha et al., 1979; Amiyo, 2006; Niboye, 2010b; Hamza Khalid Kija et al., 2020). In addition, for the Maasai pastoralists these changes threaten quantity and quality of pasture resources for livestock and consequently food security. Previous small-scale studies have mentioned ongoing land cover changes within the NCA, but the large-scale dynamics remain poorly understood (Boone et al., 2006; Homewood et al., 2001; Masao et al., 2015). The research available for the NCA is mostly based on surveys and aerial photography, providing highly detailed information at the species level but does not offer a large-scale, holistic coverage (Amiyo, 2006; Herlocker & Dirschl, 1972).

Over the last five decades, Earth-observation (EO) data have increasingly been used to map and monitor land cover (Woodcock et al., 2008; Wulder et al., 2012; Adole et al., 2016). In particular, the Landsat archive provides open-access, long-term data, with 30 meter spatial resolution and six spectral bands that are well suited for vegetation mapping. However, savannah landscapes are challenging to map due to their heterogeneous and complex characteristics, incorporating a mixture of woody vegetation (trees, bushes, and shrubs), different grass species and bare land (Borges et al., 2020; Ludwig et al., 2019; Mathieu et al., 2013; Settle & Drake, 1993; Symeonakis et al., 2018; Venter et al., 2018). Mapping and monitoring change in savannah environments is even more challenging, as most changes occur gradually and incrementally, resulting in subtle spectral changes that are difficult to detect using imagery with a moderate spatial resolution. Recently, the combination of synthetically-generated mixed samples with machine learning regression methods has proved effective for mapping fractional cover in complex environments, (Okujeni et al., 2013; Suess et al., 2018; Senf et al., 2020). A combination of fractional cover or class probability maps with time-series techniques can provide a more ecologically meaningful quantification of change compared to traditional bi-temporal classification comparisons (Schwieder et al., 2016; Schneibel et al., 2017; Souverijns et al., 2020).

There is a pressing need to quantify the extent and magnitude of land cover changes within the NCA, to identify vulnerable areas and prevent potential threats to habitats and livelihoods. The NCA’s multiple-use approach, which attempts to reconcile biodiversity protection and the needs of local people, is a notoriously challenging task (Harris et al., 2020). Moreover, in the context of protected area management, an improved understanding of land cover dynamics is imperative for sustainable development, to support effective land use planning, conserve and manage biodiversity and ensure the long-term survival of wildlife and the prosperity of resident human communities.

The main aim of the paper is to support the sustainable management of the NCA by developing an Earth-observation based approach for monitoring multi-faceted land cover changes occurring over the past 35 years. We build on the approach of Okujeni et al., (2013) to produce near-annual fractional cover maps for nine constituent land cover classes of the NCA. To identify the various change processes we employ two pixel level time-series analyses. Firstly, we employ monotonic linear trend analysis to detect long-term changes in land cover (Herrmann et al., 2005; Higginbottom and Symeonakis, 2014). Secondly, we used the Breaks For Additive Season and Trend (BFAST) piece-wise linear regression method to detect possible breakpoints, specifically for upland forest cover (Grogan et al., 2016; Lewińska et al., 2020; Morrison et al., 2018; Schmidt et al., 2015; Wu et al., 2020). We chose the linear trend analysis to detect long-term, incremental land cover changes, such as shrub encroachment and grassland decline. Meanwhile BFAST is well-suited to identifying abrupt shifts and reversals in trends that may be obscured by monotonic analysis, such as deforestation and regrowth (Verbesselt, Hyndman, Zeileis, et al., 2010).

## 3.2 Study area

The NCA covers an area of around 8,283 km$^2$ (Swanson, 2007, Figure 3.1). It contains the largest, intact volcanic caldera in the Ngorongoro Crater and has highly abundant and diverse wildlife (Estes et al., 2006, Figure 3.1c). Annual rainfall ranges from 450 mm/year in the lowlands to 1,200 mm/year in the highlands (Boone et al., 2007; Figure 3.S1). Rainfall follows a bimodal pattern, characteristic of East Africa, comprising two wet seasons: the main between March and May, and a shorter one between November and December

(Pellikka et al., 2018). During the dry season temperature ranges between 11°C and 20°C, whilst in the wet season it ranges between 7°C – 15°C (Amiyo, 2006).

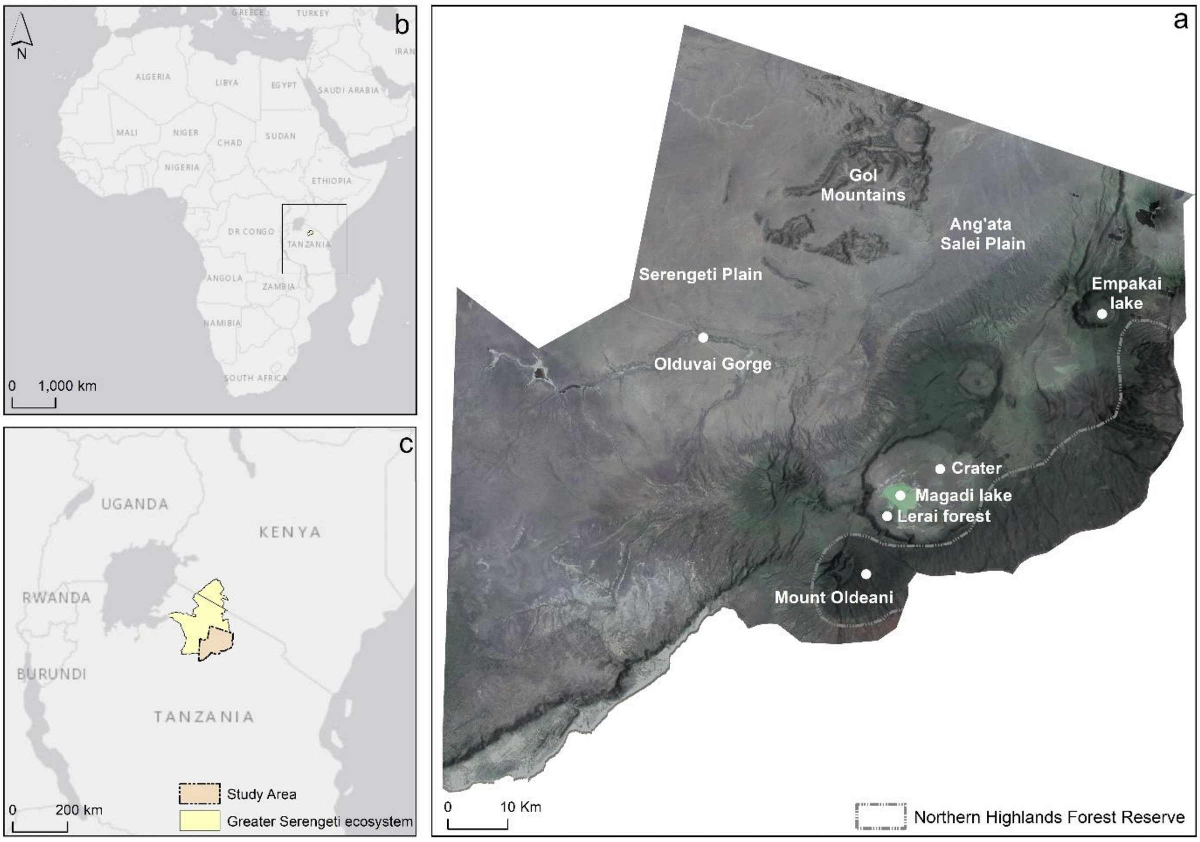

Figure 3.1. The Ngorongoro Conservation Area (a) and its location within Africa (b), Tanzania and the Greater Serengeti ecosystem (c).

## 3.3 Materials and Methods

### 3.3.1 Landsat Image Acquisition and Processing

We acquired and processed Landsat Collections Level 1 Tier 1 imagery from 1985 to 2020. Based on our previous study, we selected images from the short dry season (January – April), which enables the highest separability of the land cover types (Borges et al., 2020). For the 35-year study period, we obtained 26 annual images with cloud cover less than 75%, acquisition dates ranged from 9 January to 28 April (Figure 3.2). No suitable images were available for 1986, 1988, 1991-1994, and 1996-1999. The Landsat collections are pre-processed for atmospheric corrections using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) routine (Masek et al., 2006). Cloud masking was provided by F-mask (Schmidt et al., 2013). The images were topographically corrected using a Sun Canopy Sensor (Gu & Gillespie, 1998) and C-correction approach (Teillet et al., 1982). The Normalised Difference Vegetation Index (NDVI; Tucker, 1979) was calculated using the standard equation and added to the Landsat data. The NDVI is useful in for analysing vegetation in savannahs that do not feature dense forest canopies (Prince and Tucker, 1986). We used the Google Earth Engine cloud-computing environment for all Landsat processing (Gorelick et al., 2017; Moore & Hansen, 2011).

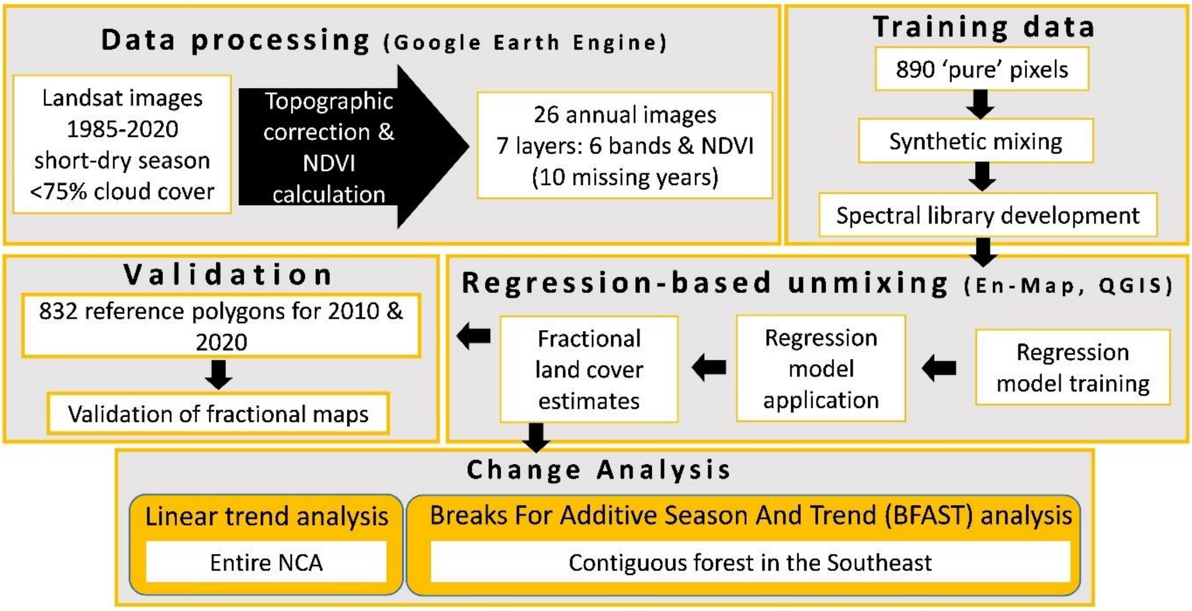

Figure 3.2. Methodological flowchart of our study.

### 3.3.2 Fractional Cover Mapping

#### *3.3.2.1 Training Data Collection*

We employed a land cover classification schema based on the detailed surveys of the NCA undertaken in the 1960s by Herlocker and Dirschl (1972) and Pratt et al., (1966). This aligns with our previous work on land cover classification in the area (Borges et al., 2020), and is ecologically relevant both in terms of habitat usage by species and the management of the park. For instance, the highest densities of black rhino occurs in bushland areas (Emslie, 2020), but in the NCA they can also be found in shrubland, open grasslands and closed canopy forest, as such it becomes increasingly important to distinguish between these classes (Gadiye et al., 2016). In total, we classified nine land cover types, detailed in Table 3.1.

Table 3.1. Description of the nine main land cover types of the NCA, according to Herlocker and Dirschl (1972) and Pratt et al., (1966).

| Land cover types | Description | Examples of land cover |
|---|---|---|
| Bareland | Minimal or no vegetation cover including bare rock, sand, saline or alkaline flats or riverine deposits. |  |
| Bushland | Closed shrub canopy comprising of woody plants, bushes or trees, ranging from 3 to 6 m in height. |  |
| Cropland | Natural vegetation has been removed and replaced by other types of vegetation cover that require human activity to maintain it. |  |
| Forest | Closed canopy trees ranging between to 7-40m or more in height. The ground is mostly covered by bushes and shrubs making it difficult for animals to move through it. |  |
| Grassland | Grasses that vary between short (< 25cm) and tall (150cm). In certain areas, herbs, scarred trees or shrubs can occur. During the dry season and during droughts it can be almost bareland. |  |
| Montane heath | Medium sized vegetation (< 1m) including shrubs, grasses, ferns and mosses, usually at higher altitudes. |  |
| Shrubland | Open canopy with medium sized woody vegetation (< 6 m in Pratt), surrounded by grass or bareland. Some trees and bushes can occur. |  |

| | | |
|---|---|---|
| Water | Ponds, lakes, rivers and swamps (with little or no vegetation cover). |  |
| Woodland | Open or continuous canopy with trees as tall as 20m, often surrounded by shrubs, bushes or grass but not thicket. |  |

For training data, we collected 890 polygon samples from across the NCA, covering the nine land cover classes, based our knowledge of the area, spectral information (Figures S3.2 and S3.3), visualisation of high-resolution imagery within Google Earth Pro and the processed Landsat images (Figure 3.2). The samples were distributed as follows: 20 for Bareland; 94 for Bushland; 11 for Cropland; 50 for Forest; 498 for Grassland; 19 for Montane heath; 82 for Shrubland; 13 for Water, and 103 for Woodland. The samples size was proportional based on our earlier land cover map (Borges et al., 2020), to accommodate the greater species variability within the large classes (e.g grassland) relative to the smaller more classes (e.g. montane heath). We compared multi-temporal Landsat images and aerial photography to select only pixels that remained unchanged throughout the study period (i.e pseudo-invariant features). For each Landsat image, we extracted pixel values to produce an independent annual-level spectral library, creating a total of 26 libraries.

#### *3.3.2.2 Synthetic Mixing*

To create fractional training data from our spectral library we used the EnMAP-box (version 3.6; (EnMAP-Box Developers, 2019)) software to generate synthetic mixture samples (Okujeni et al., 2013; Van der Linden et al., 2015). For each class, we generated 1000 synthetic samples, comprised of different fractional mixtures of all classes. The following processes, described in (Cooper et al., 2020), produced each synthetically mixed sample:

1. We established the likelihood for different multi-class combinations across each pixel, and included endmembers according to this weighting. We set a 20% chance for a two classes mixture, 40% for a three classes mixture and 40% for a four classes mixture.
2. From the target class spectral library, one random endmember was pulled.
3. This selected endmember was randomly allocated a mixing fraction between 0 and 1.

4. Additional endmembers were randomly selected from the additional classes and added.
5. The newly added endmembers were randomly assigned mixing fraction, with the sum of all fractions equalling one.
6. Synthetically mixed spectra were generated based on linear combinations of the assigned mixing fractions.

We repeated this process for every synthetic spectra. Finally, we added the original endmembers to the synthetic samples and assigned mixing fractions of one or zero for spectra belonging to target and non-target classes, respectively.

#### *3.3.2.3 Regression-Based Unmixing*

We used a Random Forest regression to map vegetation class fractions (Breiman, 2001). The Random Forest is a non-parametric machine learning model based on ensembles of regression trees, popular for image classification and land cover mapping (Rodriguez-Galiano et al., 2012; Li et al., 2015; Symeonakis et al., 2018).

The regression-based unmixing was carried out in the EnMAP-Box 3.6 (EnMAP-Box Developers, 2019), an open-source QGIS plugin designed for advanced processing workflows of optical remote sensing data (Van der Linden et al., 2015). The procedure was repeated 10 times and averaged the 10 predictions for each year using the correspondent spectral library. This allowed the inclusion of multiple types of synthetic mixtures into the unmixing process while keeping the training sample size low (Okujeni et al., 2017).

#### *3.3.2.4 Validation of Fraction Maps*

A validation dataset centered on 2010 and 2020 was developed based on visual interpretation of high-resolution imagery in Google Earth Pro (Ludwig et al., 2016). Due to limited Google Earth imagery and uncertain dates for certain images, imagery between 2009 and 2014 was aggregated into 2010 and imagery between 2015 and 2020 was aggregated into 2020. Validation of model predictions prior to 2010 was not possible as earlier images had substantially lower resolution or were unavailable. We validated the model predictions by using a stratified random sampling, based on best practise (Olofsson et al., 2014). We collected 416 reference pixels for each epoch, resulting in 832 reference pixels. For each reference pixel, a 10x10 grid of 3 m squares (Figure 3.S4) was used and the class fractions estimated by a researcher with local knowledge. For statistical validation, we calculated the bias, the coefficient of determination ($R^2$) and the mean absolute error (MAE) between the reference fractions and predicted fractions.

### 3.3.3 Change Mapping

To detect changes in the fractional land cover we employed two complementary time-series analyses. Firstly, to detect the general land cover change we performed a linear regression against time on the annual fractional cover maps of each land cover class (Herrmann et al., 2005). Changes that were statistically ($p > 0.05$) or ecologically (cover in 2020 < 5%) insignificant were masked.

Secondly, to provide more detailed information on changes specifically in the upland forests we applied the Break For Additive Season and Trend (BFAST) method (Verbesselt, Hyndman, Newnham, et al., 2010). BFAST is a piecewise linear regression approach that combines time-series decomposition with structural breakpoint detection. The statistical basis of BFAST is the decomposition of a time-series into trend, seasonal, and residual components; with significant changes in the trend component detected by a moving sum of residuals (MOSUM) test. BFAST was originally developed for NDVI time-series, however it is not specific for any type of data (Verbesselt, Hyndman, Newnham, et al., 2010) and has been applied to other vegetation indexes, rainfall data or Landsat bands. (Horion et al., 2016; Che et al., 2017; Morrison et al., 2018; Platt et al., 2018; Higginbottom and Symeonakis, 2020). We used the 'BFAST0'1 implementation of BFAST, which is tailored for non-seasonal (i.e. annual) data, and allowed for a single breakpoint to occur in the time-series using a $P < 0.05$ significance threshold. The breakpoints identified by BFAST were then classified into six change types, based on De Jong et al., (2013): 1) *monotonic*: increase, 2) *monotonic*: decrease, 3) *reversal*: increase to decrease 4) *reversal*: decrease to increase 5): *interruption:* increase with negative break, and 6) *interruption* decrease with positive break.

Our logic for employing two time-series analyses is as follows: gradual changes (e.g. shrub encroachment, grassland degradation) will be best identified using monotonic trend analysis (Lewińska et al., 2020), whereas BFAST is well suited for identifying sudden changes and reversals that may be obscured within long-term analysis . However, grasslands and non-woody areas will fluctuate more on an annual basis, due to climatic variation, and benefit from a simpler change model. Furthermore, we employ trend analysis over direct comparison of the fractional cover maps to ensure our analysis is robust to variation and noise in the input maps. We expect our annual fractional maps to contain errors and noise which may distort bi-temporal comparisons. This is analogous to post-classification cleaning of hard classification change detections, by removing illogical transitions (e.g.

(Griffiths et al., 2018)) or applying statistical techniques such as Hidden Markov Models (e.g. (Abercrombie and Friedl, 2016).

## 3.4 Results

### 3.4.1 Fraction Maps

The predicted fractional land cover maps (Figure 3.3) successfully distinguished the nine land cover types (Table 3.1), and a discrete land cover map shown in Figure 3.4b was estimated from the fractional map of 2020 (Figure 3.3). We were able to identify transitional areas with highly heterogeneous land cover (Figure 3.3). For instance, most of the NCA is dominated by grassland (Figure 3.3), which transitions into shrubland around the centre. The Highland area (Figure 3.1a) is dominated by woody classes (bushland, woodland, forest). Figure 3.4a shows an red-green-blue composite of the land cover layers aggregated into three main components of savannah landscapes: trees (forest and woodland), shrubs (bushland and shrubland) and grasses (grassland). For bushland and forest, there are areas of clear separation (Figure 3.4a) but there is also some degree of mixture (Figure 3.3). The West side of the NCA mostly comprises of grassland (e.g. the Serengeti Plain) with some patchy shrubland around the Ang’ata Salei plain.

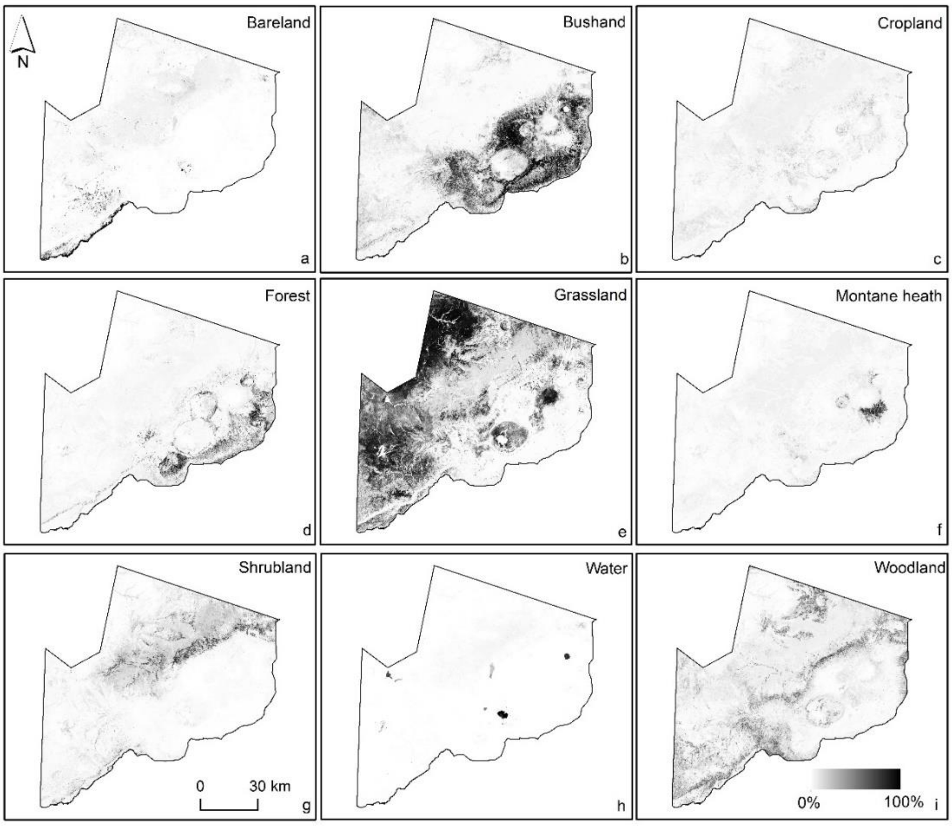

Figure 3.3. Fractional cover maps for the nine main land cover classes of the NCA in the year 2020.

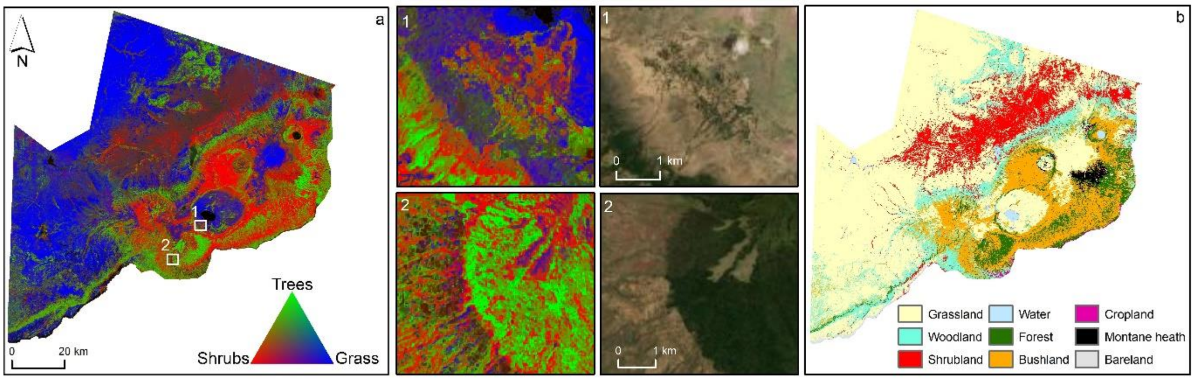

Figure 3.4. (a) RGB composite of the aggregated three main components of savannah landscapes: trees (G, forest and woodland), shrubs (R, bushland and shrubland) and grasses (B) for the year 2020; locations 1 and 2 are example subsets. (b) Land cover ('hard') classification for the year 2020.

Validation statistics for the fractional land cover maps of 2010 and 2020 (MAE and $R^2$) are shown in Table 3.2 (full statistics in Table 3.ST1 and ST2 and scatterplots in Figures S3.5 and S3.6). Most classes performed well, achieving accuracies between $R^2$ 0.61 and 0.95 Figures S3.5 and S3.6). The lowest absolute errors occurred in the bareland class with MAE of 2.8 for 2010 and water with a MAE of 1.63 for 2020. Cropland had highest relative errors with $R^2$ of 0.43 and 0.33 for 2010 and 2020 respectively. Most cross-class confusion occurred in transition eco-zones between grassland-bareland and grassland-shrubland. This was expected due to the highly heterogeneous nature of these regions.

Table 3.2. Accuracy of the fractional land covers for the NCA for the years 2010 and 2020.

| **Land cover** | | **Bare.** | **Bush.** | **Crop.** | **Forest** | **Grass.** | **M. heath** | **Shrub.** | **Water** | **Wood.** |
|---|---|---|---|---|---|---|---|---|---|---|
| 2010 | MAE | 2.80 | 5.08 | 5.34 | 4.69 | 14.18 | 5.64 | 6.00 | 4.47 | 6.70 |
| | $R^2$ | 0.90 | 0.92 | 0.43 | 0.88 | 0.83 | 0.64 | 0.77 | 0.81 | 0.61 |
| | Bias | -3% | -6% | -8% | -6% | -1% | -8% | -3% | -6% | -8% |
| 2020 | MAE | 2.97 | 6.13 | 6.72 | 6.09 | 13.67 | 5.24 | 6.23 | 1.63 | 6.42 |
| | $R^2$ | 0.89 | 0.91 | 0.33 | 0.84 | 0.82 | 0.76 | 0.76 | 0.95 | 0.73 |
| | Bias | -2% | -10% | -9% | -7% | -1% | -8% | -2% | -10% | -8% |

### 3.4.2 Linear Trends

Figure 3.5 shows the statistically significant ($p < 0.05$) linear trends for each individual and cover type. Areas with < 5% cover in the respective class for 2020 were masked. There were notable increases and decreases for all land cover types with most of the change in the ±25% range (Figure 3.6) The most common change in the NCA was decreasing forest by ~25% coverage, which affected roughly 900 km$^2$ (Figures 3.5 and 3.6). The second most common change was grassland coverage declining by 25%, which affected roughly 782 km$^2$ (Figures 3.5 and 3.6). A sizeable amount of grassland also experienced a decline of up to 50% (~493 km$^2$), mostly in the Serengeti plains (Figures 3.5 and 3.6).

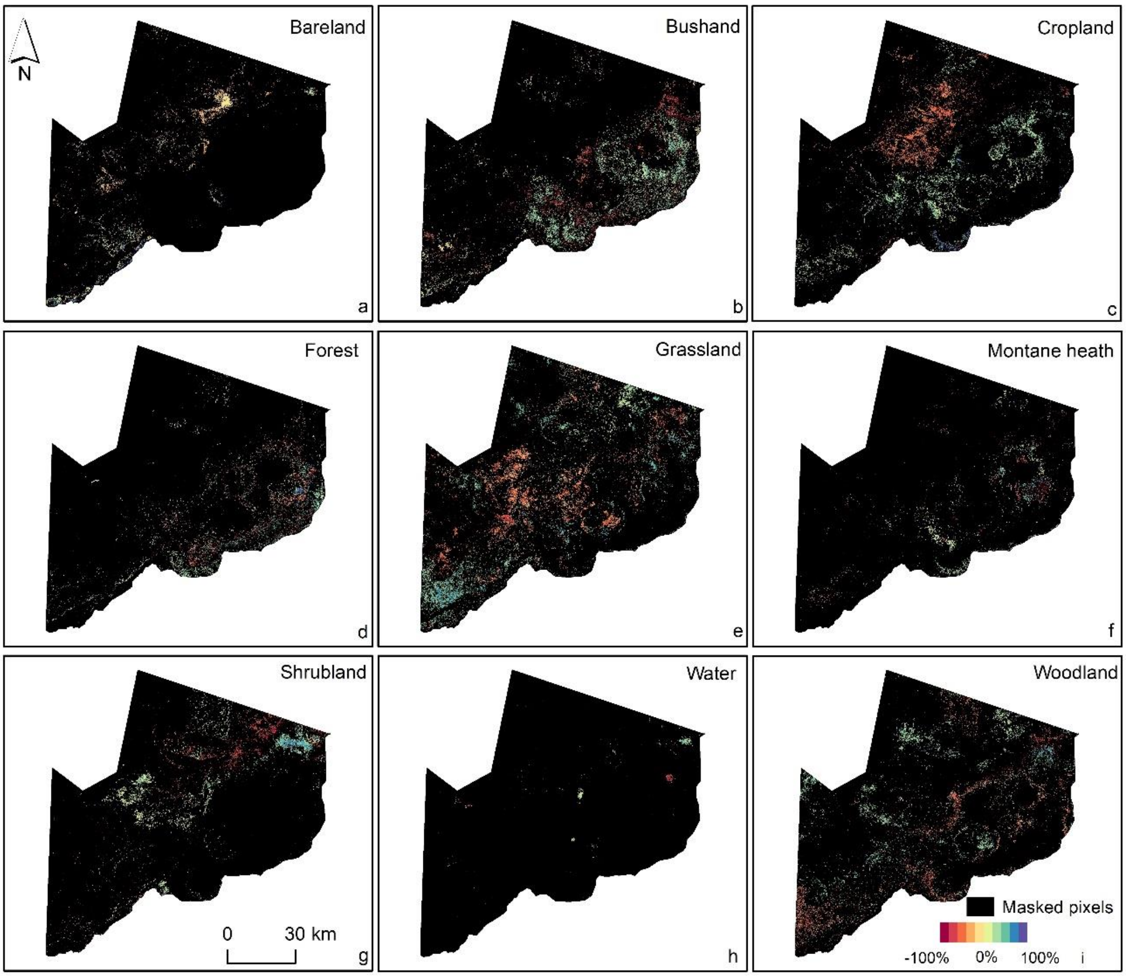

Figure 3.5. Land cover change according to the linear trend analysis in the NCA between 1985 and 2020 for all land cover classes.

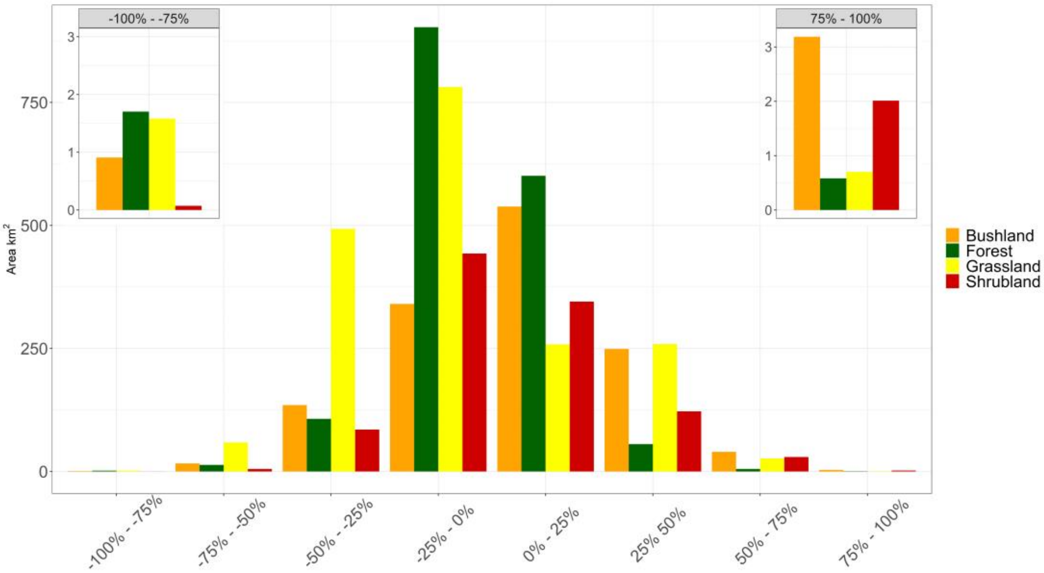

Figure 3.6. Statistically significant ($p < 0.05$) changes in land cover between 1985 and 2020 for forest, bushland, shrubland and grassland.

A majority of forest cover is located in the eastern part of the NCA. Figures 3.7 b and c show a clear reduction in fractional cover, particularly visible around Mount Oldeani, throughout the highlands and in the south-east side of the Crater rim (Figure 3.7d). There is also some patchy increase in forest cover, ranging between 25% and 75% cover in the highlands, outside the NCA border near Mount Oldeani and in the montane areas (Figure 3.7d).

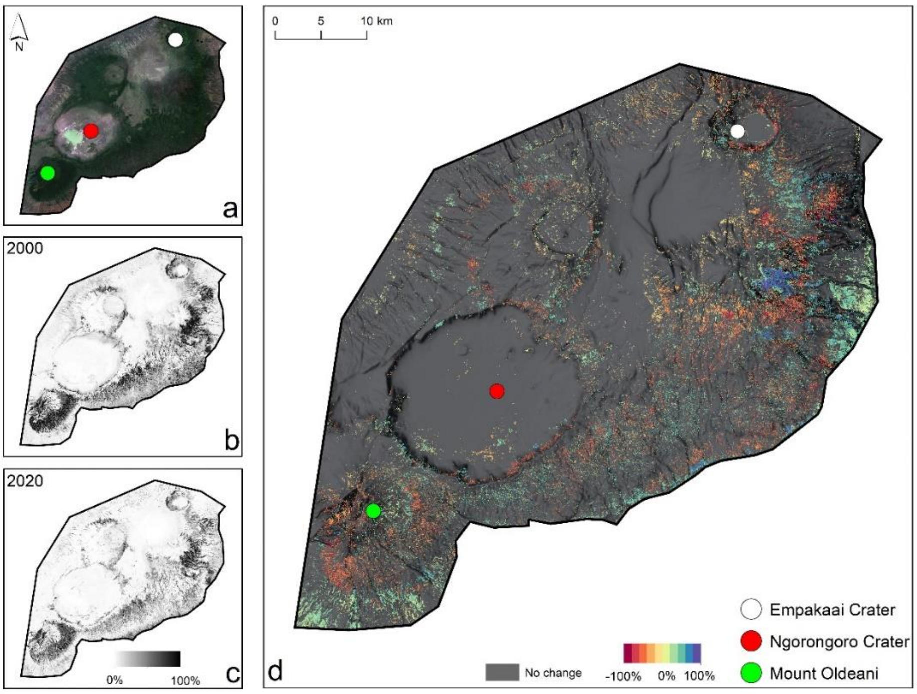

Figure 3.7. True colour composite Landsat image for the year 2000 (a). Fraction of forest cover in the NCA in the year 2000 (b) and 2020 (c). Forest cover change according to the linear trend analysis between 1985 and 2020 in the southeast of the NCA (d).

#### *3.4.2.1 Lerai Forest*

Contrarily to its name, the Lerai Forest mostly comprises of low woodland and bushland with some forest and shrubland. According to our findings, there were both increases and decreases in the fractional cover of forest, bushland and woodland (Figures 3.8 a and c). The most obvious change in the Lerai Forest was the decrease in bushland cover, ranging between -25% and -75% (covering 1.6 km$^2$), and the increase in woodland (+25% covering 1 km$^2$; Figures 3.8 b and c). However, the expansion of woody vegetation, specifically forest and woodland occurred mostly in the southwest side of the Lerai Forest (Figures 3.8 a and c; S7).

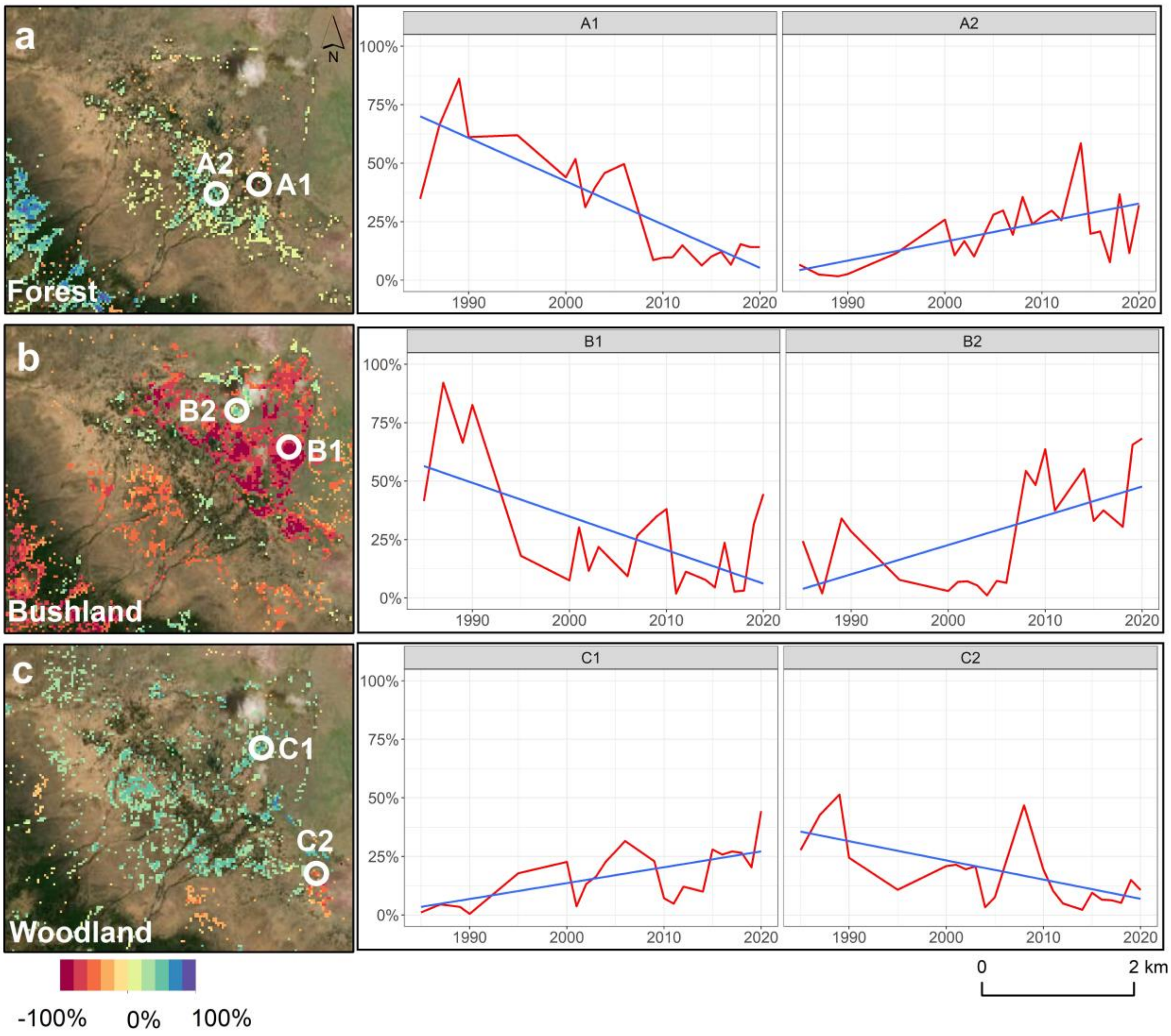

Figure 3.8. a, b, c and respective plots (A1 to C2): linear trend changes in forest, bushland and woodland in the Lerai Forest (this area is the example Location 1 shown in Figure 3.4)

### 3.4.3 BFAST Trends

Most of the forest change detected by BFAST consisted of monotonic increases and decreases (Figure 3.9a). Forest loss was widespread with some focal points in the rim of the Crater, around Mount Oldeani and Empakai Crater. Throughout the Highlands there was also a reversal where forest cover increased but then started to decrease. These shifts in the vegetation occurred mostly between 2004 and 2009 (Figure 3.9b).

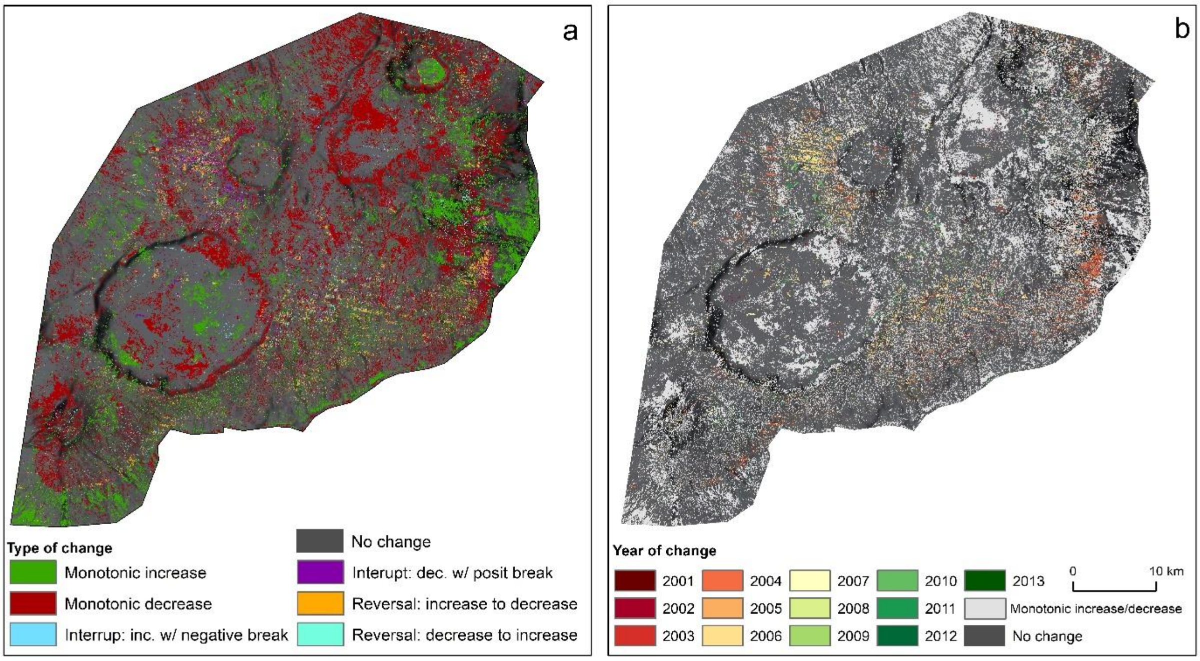

Figure 3.9. (a) BFAST trend analysis results for the southeast side of the NCA showing the type of change in forest cover; (b) the year of change in forest cover.

### *3.4.3.1 Lerai Forest*

The change map produced using BFAST for the Lerai Forest is shown in Figure 3.10. In the northeast side of the Lerai Forest, BFAST detected a consistent monotonic decrease in forest cover (Figure 3.10). Additionally, a large cluster that experienced a monotonic increase occurred in the southwest side of the Forest (Figure 3.10). Although significant, some of those changes were subtle (< 25%; Figure 3.10, location A2) when compared to others (Figure 3.10, location A1). For instance, in location A2 (Figure 3.10) there was a consistent increase in cover which remained low. In A1, forest cover increased until 2008, when it started to decrease but the changes were more pronounced than in A2.

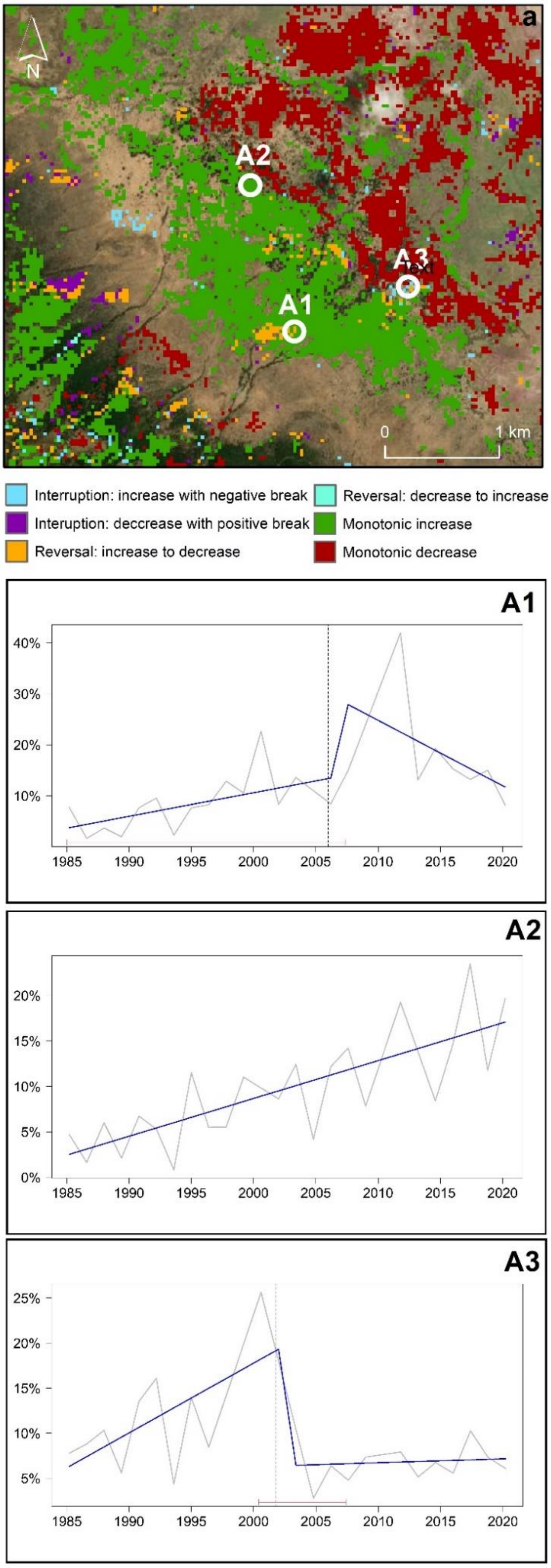

Figure 3.10. Outcome of the trend analysis using BFAST for the Lerai Forest (a). Locations A1-A3 are used as examples of time-series plots at the individual pixel level.

## 3.5 Discussion

Understanding land cover dynamics is increasingly important to improve habitat monitoring, preserve biodiversity and ensure sustainable development (Reed et al., 2009). Over the last 30 years, the NCA has undergone considerable changes but these remain poorly understood due to lack of robust information and detailed maps. Here we demonstrate a Landsat-based monitoring strategy, combining synthetic unmixing, machine learning regression, and time-series analysis, to quantify sub-pixel change in nine land cover classes. Our fractional cover maps for 2010 and 2020 achieved high accuracies for most land cover types (Table 3.2, ST3.1 and ST3.2 and Figures S3.5 and S3.6), distinguishing the nine main land cover classes but also identifying transitional areas with heterogeneous vegetation (Figures 3.3; 4a). Out of our nine land cover types, only cropland scored low accuracies ($R^2$ 0.43 and 0.33 for 2010 and 2020, respectively), whilst the other classes high accuracies ($R^2 > 0.6$, Table 3.2). Souverijns et al., (2020) and (Senf et al., (2020) achieved similar accuracies for comparable land cover types, but Nabil et al., (2020) reported low accuracies for cropland in the Sahel regions. Using fractional cover maps has proven advantageous, as it allows for the detection of more subtle land cover variability and changes that cannot be captured by discrete classifications (Suess et al., 2018; Senf et al., 2020; Souverijns et al., 2020).

Between 1985 and 2020, we identified significant land cover changes; in particular, declines in forest and grassland cover (Figures 3.5-3.7). The most common change using the linear trend analysis was a decrease in forest coverage by ~25%, which affected roughly 900 km$^2$ (Figure 3.6). BFAST also detected a similar trend in the highlands, with a monotonic decrease in forest throughout the period (Figure 3.9a). Contrarily, there was an increase in bushland cover by 25%, which covered 440 km$^2$ (Figure 3.6). These changes are consistent with field studies that have identified forest conversion into bushland due to the removal of larger trees (Amiyo, 2006; Masao et al., 2015; TAWIRI & NCAA, 2020). A report by the Tanzania Wildlife Research Institute (TAWIRI) and the Ngorongoro Conservation Area Authority (NCAA) in 2020 also found a decrease in forest cover between 1978 and 2018. These changes were linked to human disturbances namely clearing for settlement or cultivation and searching for thatching materials and fuel wood (Kija et al., 2020; Masao et al., 2015; TAWIRI & NCAA, 2020). In addition, (Mills, 2006), studied the dieback of *Acacia xanthophloea* (commonly known as fever tree and can reach 25 meters) in Ngorongoro

Crater identified natural disturbances, specifically herbivory, (mainly by elephants, *Loxodonta africana*), disease, and salinity as contributors for the demise of large trees.

Forest decline has previously been reported across Africa and is a common indicator of land degradation (Higginbottom & Symeonakis, 2020; McNicol et al., 2018). Souverijns et al., (2020) mapped thirty years of land cover changes over the Sudano-Sahel and detected forest degradation based on fractional cover maps. McNicol et al., (2018), who used radar data to study losses in carbon due to deforestation and forest degradation in savannahs, reported similar trends. Our results support those findings and show that Landsat data and fractional cover maps can be used to detect and monitor forest degradation. Forests have an important role providing critical ecosystem services and supporting biodiversity. As such, forest degradation threatens human populations, as they provide wood, natural remedies, and forage for livestock and wildlife, which also depends heavily on the resources that the forest supplies (Swanson, 2007). In addition, forests promote carbon sequestration and therefore, directly affect global carbon budgets and climate change ( McNicol et al., 2018; Venter et al., 2018). In the NCA, degradation of forests threatens the pastoralist livestock economy plus availability of good habitat for wildlife species adapted to such particular forest type.

**Serengeti Plains**

The loss of palatable grasses has been identified as a threat to wildlife, the Maasai pastoralists and the NCA ecosystem as a whole (Amiyo, 2006; Mills et al., 2006). We found that grassland cover decreased in the NCA during the study period (Figure 3.5 and 6). Figure 3.6 shows between 25% and 50% decrease in grassland cover (493 km$^2$ to 782 km$^2$), mostly located in the Serengeti plains (Figures 3.5 and 3.6). In the same area, the increase in shrubland (~345 km$^2$) and woodland cover (~497 km$^2$) is also visible (Figures 3.5 and 3.6). Previous research reported a decline in grassland and woody encroachment in the NCA which supports our findings (Amiyo, 2006; Niboye, 2010b; Masao et al., 2015). The no-burning policy imposed in the 1980s, was identified as a main driver for land cover changes, specifically woody encroachment in the NCA (Amiyo, 2006; Homewood et al., 2001). In addition, grazing pressure, by wildlife and livestock, also facilitates development of woody plant communities by removing fine fuels and reducing fire frequency and intensity (Archer et al., 2017).

Shrub encroachment, often linked to grassland decline and land degradation, is a serious threat to ecosystem services and biodiversity (Higginbottom & Symeonakis, 2020; Symeonakis et al., 2018). Previous research found an increasing trend of woody cover throughout Africa (Higginbottom et al., 2018; Ludwig et al., 2019; Symeonakis et al., 2018 ). Venter et al., (2018), reported that encroachment is accelerating over time and that African savannahs are at high risk of widespread vegetation change. Stevens et al., (2016), measured woody cover change between 1940 and 2010 and found similar results in areas with low rainfall (< 650mm). Contrarily to forest degradation, shrub encroachment can have a positive impact in carbon storage (McNicol et al., 2018). However, the loss of grassland areas raises issues for wildlife, the Maasai pastoralists, and their livestock (Niboye, 2010b). In the Serengeti plains, densification and encroachment of woody cover can have a negative effect on ground water recharge, grazing potential (Angassa & Baars, 2000; Stevens et al., 2017), tourism, (Gray & Bond, 2013) and is related with increased costs for woody vegetation clearing (Grossman & Gandar, 1989). Woody encroachment into grasslands can potentially be reversed by a combination of management (frequent fires) and climatic events (drought; Roques et al., 2001). In these areas, using fire as a management strategy, can decrease shrub and invasive species, and has been successfully employed throughout the continent (Sankaran et al., 2005; Venter et al., 2018). Additionally, reducing grazing pressure by decreasing livestock numbers can positively affect grassland areas (Archer et al., 2017). As such, given the infeasibility of reducing livestock numbers, trailing fire management to assess the potential for limiting encroachment and improving rangeland condition may be beneficial.

**Lerai Forest**

The earliest records of change in the NCA dates back to the 1960s, when the dieback of the Lerai forest was first suggested (Amiyo, 2006; Mills, 2006). Our results show contrasting trends: a significant decline in woody cover within the original range of Lerai Forest (Figure 3.S7) and an overall increase in forest cover in the periphery (Figures 3.8a, 3.10). These results suggest that Lerai Forest is re-establishing outside its original range (Amiyo, 2006). Mature fever trees, which can reach heights up to 25 meters and require high water tables (Homewood et al., 2001), dominated the Forest, however since their decline they have not been replaced by young *Acacia* trees (Amiyo, 2006). The decrease in ground water availability, due to higher influx of tourism and diversion of streams, as well as floods of the salt lake, Lake Magadi, contributed to an increase in soil salinity, which negatively affects vegetation (Amiyo, 2006; Boone et al., 2007; Mills, 2006). Mills (2006) suggested that sodicity (e.g. the accumulation of sodium salt in the soil) can exacerbate salinity-induced drought stress in vegetation, by limiting entry of rainwater into the soil, which was already low due to a reduced rainfall (Figure 3.S1). Furthermore, sodicity can promote sodium concentrations in trees, which has an additional detrimental effect by attracting elephants and other herbivores (Homewood et al., 2001; Mills, 2006). Management strategies were implemented and in 2006, the stream was diverted back to supplying the Forest (Mills, 2006, Figure 3.10, location A1). This increased the freshwater supply to the area and promoted the flushing of salts from the soil (Mills, 2006). The southwest side, closer to the Crater rim, is more fertile and has a lower soil salinity due to its proximity to the stream, which explains the increase in forest and woodland cover (Figures 3.8 a and c; 3.10 location A1; Elisante et al., 2013, Mills, 2006). Exclusion of elephants from Lerai was considered in 2006 but was never implemented (Mills, 2006). The dieback in Lerai may be jeopardizing the long-term conservation of the black rhinoceros (*Diceros bicornis michaeli*) population in the caldera (Mills, 2006). Historically, the Lerai Forest was used for shelter and browse by the rhinos and it has been suggested it was also critical for hiding new-born rhinos from predators (Goddard, 1967, 1968). Consequently, the recovery of the Lerai Forest is an essential priority for the success of black rhino population in the NCA (Mills et al., 2006).

## 3.6 Conclusion

Mapping and quantifying land cover changes is increasingly important to improve habitat monitoring, preserve biodiversity and ensure sustainable development (Reed et al., 2009). Savannah landscapes, such as the NCA, however, are heterogeneous and complex combinations of vegetation. Our results demonstrate that the regressing-based unmixing approach is effective in mapping several spectrally similar vegetation types. In addition, the combination of linear trend analysis and BFAST analysis provided highly detailed insights into land cover change throughout the 35-year study period. We identified two dominant land change dynamics: the replacement of uplands forest with bushland, and a transition from grassland to shrubland in the Serengeti Plains. These changes threaten the wellbeing of livestock, and consequently the livelihoods of pastoralists but also the wildlife dependent on grazing areas. Changes are likely due to a combination of climate change and natural occurring changes, such as rainfall patters, vegetation succession, herbivory; and human activities, namely, management policies, tourism and increase in human populations and livestock. In conclusion, we provide much needed and highly accurate information on long-term land cover changes in the NCA, which can support sustainable management and conservation. In addition, our methodological approach can be applied elsewhere to understand savannah changes.

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## 3.8 Supplementary material - Chapter 3

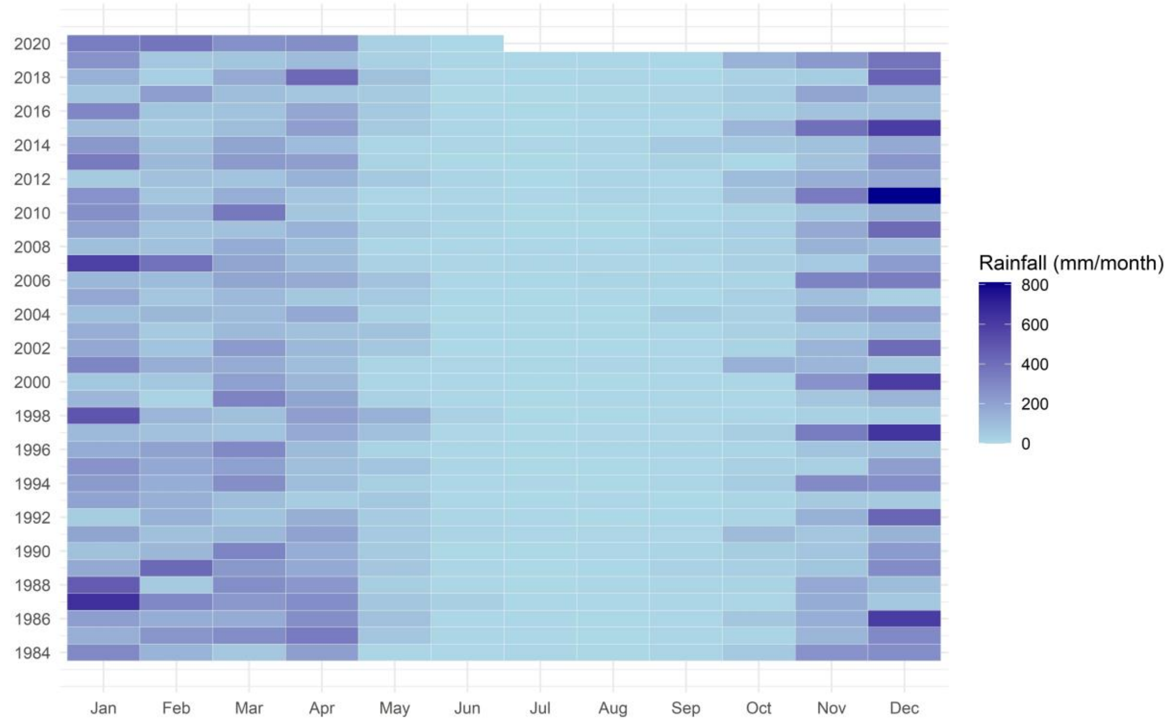

Figure 3.S1. Rainfall in The Ngorongoro between January 1985 and June 2020.

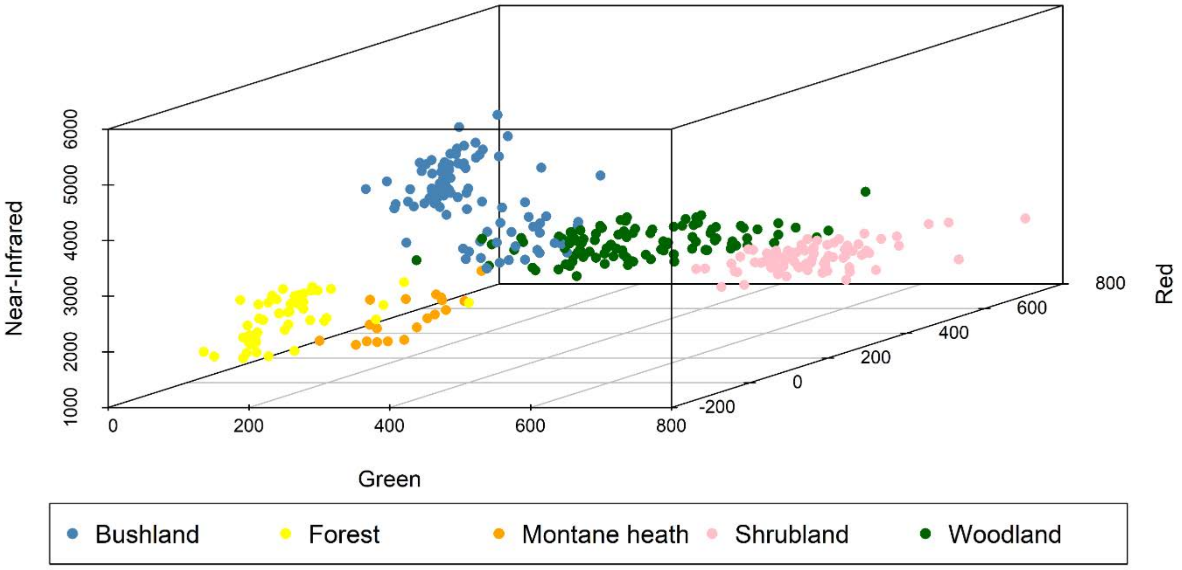

Figure 3.S2. Example of spectral data using near-infrared, green and red bands for bushland, forest, montane heath, shrubland and woodland for the year 2020.

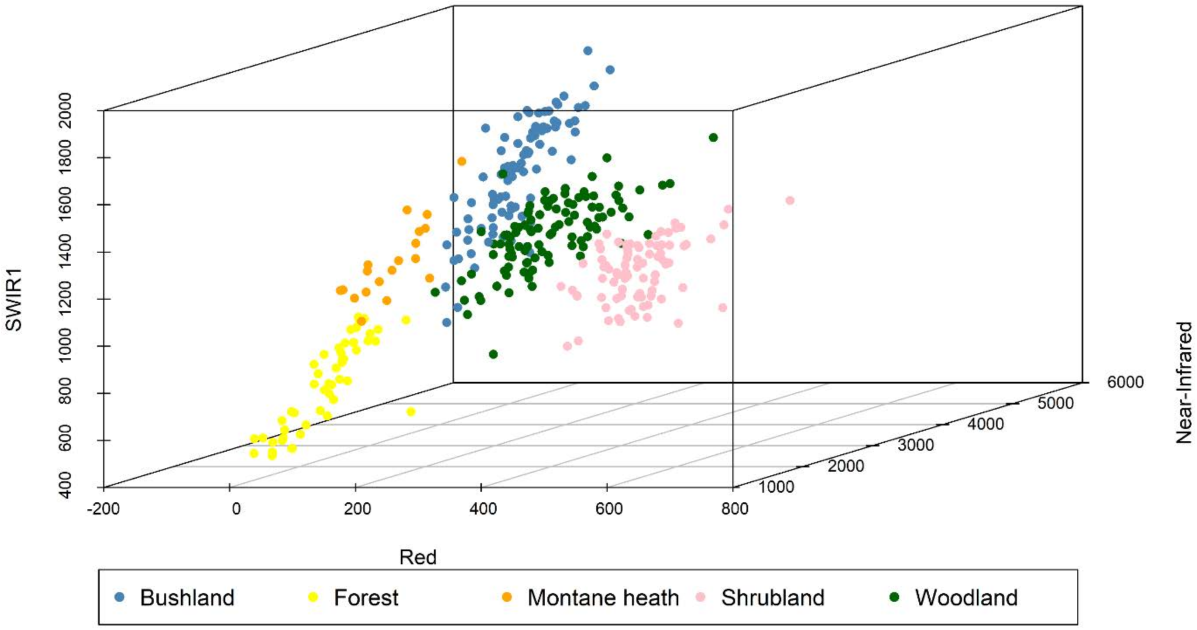

Figure 3.S3. Example of spectral data using SWIR, red and green bands for bushland, forest, montane heath, shrubland and woodland for the year 2020.

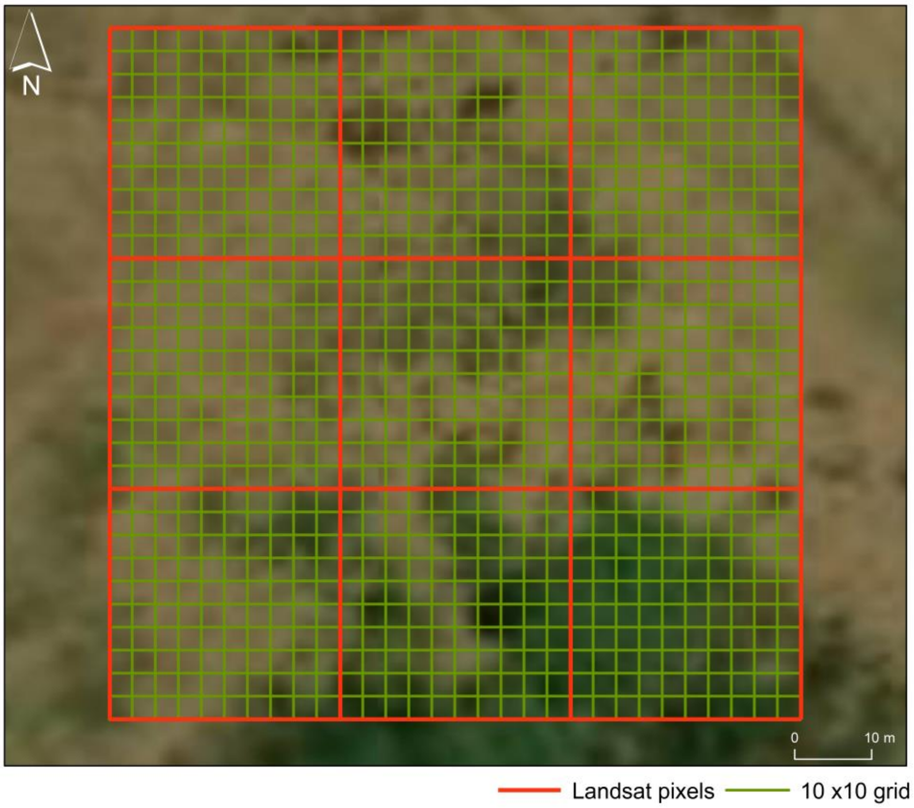

Figure 3.S4. Grid used for validation.

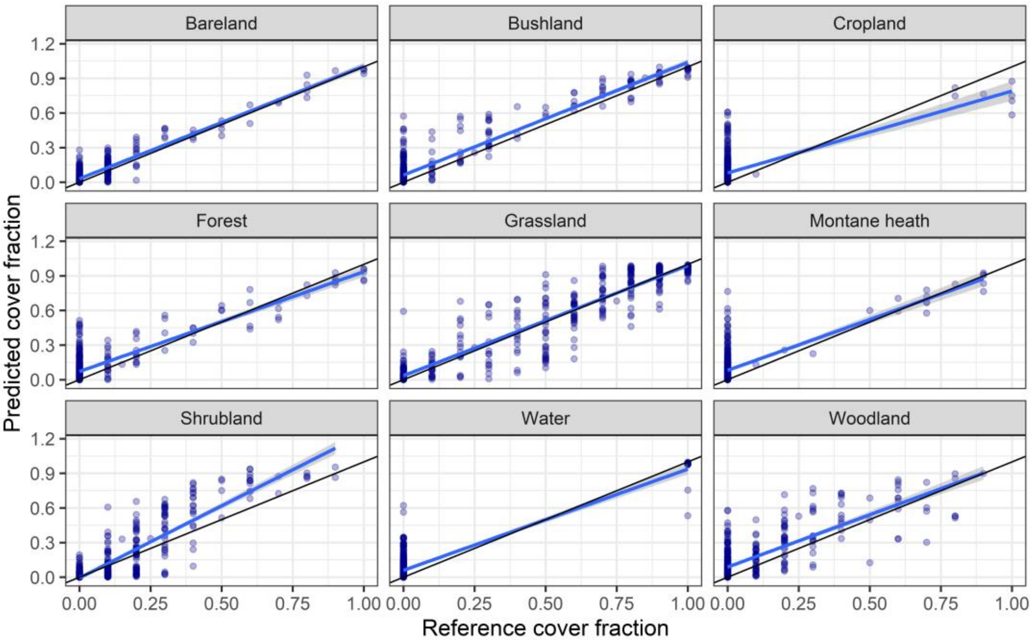

Figure 3.S5. Validation 2010

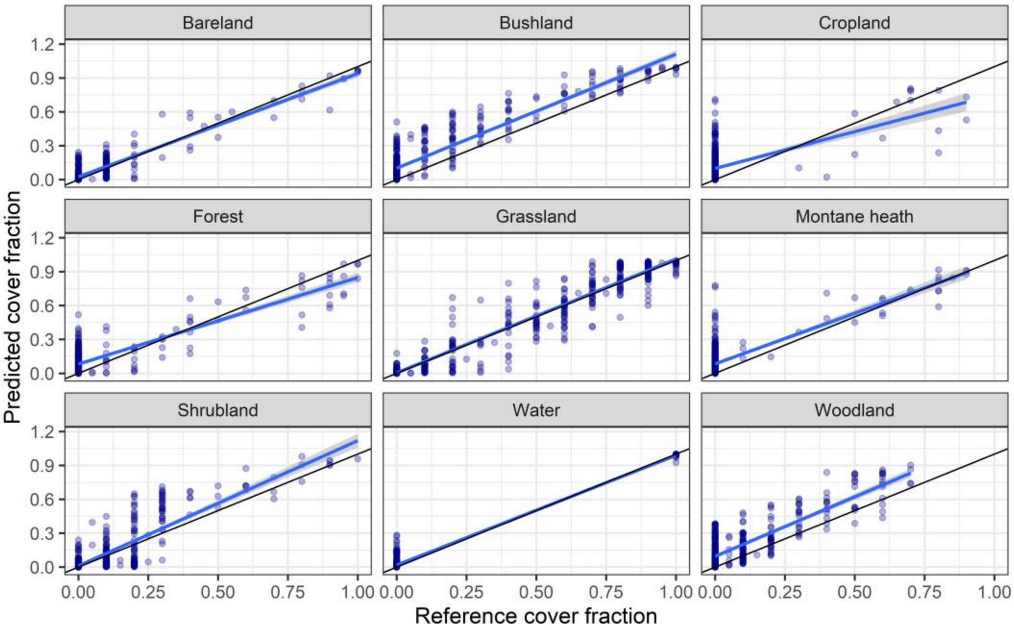

Figure 3.S6. Validation 2020

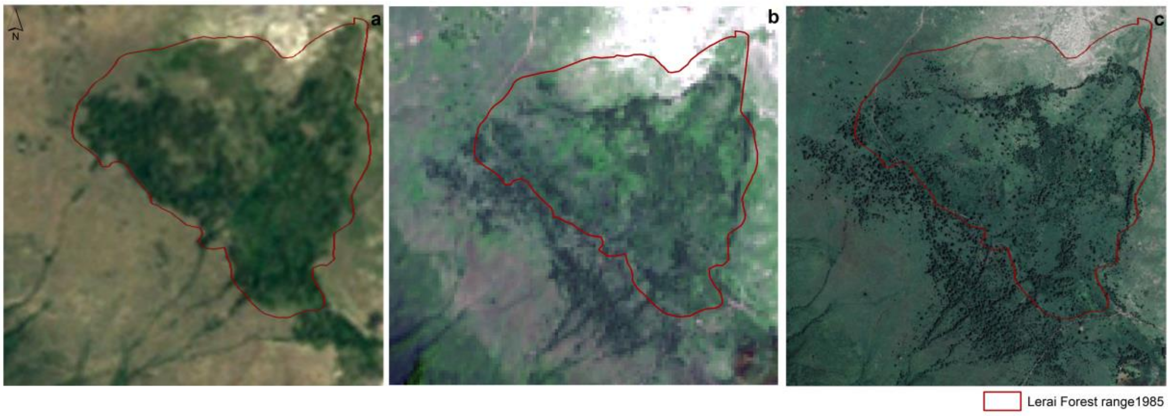

Figure 3.S7. Lerai Forest range: (a) Landsat imagery in December 1985; (b) Landsat imagery in February 2020; (c) CNES/Airbus in January 2020.

Table 3.ST1. Full validation statistics 2010

| Landcover | Bareland | Bushland | Cropland | Forest | Grassland | Montane heath | Shrubland | Water | Woodland |
|---|---|---|---|---|---|---|---|---|---|
| ME | 0.15 | 1.34 | 3.59 | 2.38 | -11.76 | 3.38 | -3.26 | 2.55 | 1.14 |
| ME.se | 0.25 | 0.41 | 0.45 | 0.34 | 0.78 | 0.42 | 0.41 | 0.40 | 0.53 |
| MAE | 2.80 | 5.08 | 5.34 | 4.69 | 14.18 | 5.64 | 6.00 | 4.47 | 6.70 |
| MAE.se | 0.21 | 0.33 | 0.40 | 0.28 | 0.68 | 0.36 | 0.32 | 0.36 | 0.43 |
| RMSE | 5.17 | 8.43 | 9.76 | 7.38 | 19.79 | 9.20 | 8.93 | 8.61 | 10.95 |
| RMSE.se | 4.27 | 9.30 | 20.06 | 7.10 | 27.86 | 12.61 | 7.76 | 14.04 | 18.46 |
| $R^2$ | 0.90 | 0.92 | 0.43 | 0.88 | 0.83 | 0.64 | 0.77 | 0.81 | 0.61 |
| cor | 0.95 | 0.96 | 0.66 | 0.94 | 0.91 | 0.80 | 0.88 | 0.90 | 0.78 |

Table 3.ST2. Full validation statistics 2020

| Landcover | Bareland | Bushland | Cropland | Forest | Grassland | Montane heath | Shrubland | Water | Woodland |
|---|---|---|---|---|---|---|---|---|---|
| ME | -0.64 | 3.66 | 3.83 | 2.19 | -11.97 | 3.16 | -3.74 | 0.10 | 2.28 |
| ME.se | 0.29 | 0.39 | 0.51 | 0.46 | 0.75 | 0.38 | 0.40 | 0.26 | 0.43 |
| MAE | 2.97 | 6.13 | 6.72 | 6.09 | 13.67 | 5.24 | 6.23 | 1.63 | 6.42 |
| MAE.se | 0.25 | 0.30 | 0.43 | 0.36 | 0.68 | 0.32 | 0.31 | 0.25 | 0.31 |
| RMSE | 5.86 | 8.66 | 11.07 | 9.56 | 19.49 | 8.45 | 8.93 | 5.38 | 9.02 |
| RMSE.se | 6.40 | 6.86 | 19.40 | 13.35 | 27.74 | 10.39 | 7.73 | 11.02 | 7.78 |
| $R^2$ | 0.89 | 0.91 | 0.33 | 0.84 | 0.82 | 0.76 | 0.76 | 0.95 | 0.73 |
| cor | 0.94 | 0.95 | 0.58 | 0.91 | 0.90 | 0.87 | 0.87 | 0.97 | 0.86 |

# Chapter 4 – Assessing habitat suitability for black rhino in the Ngorongoro Conservation Area

Abstract: Efforts to identify optimal habitat for wildlife conservation are crucial for preserving biodiversity and promote sustainable coexistence between wildlife and communities. Our study focuses on identifying potential black rhino habitat within the Ngorongoro Conservation Area (NCA) during both wet and dry seasons, while also assessing the impact of human activities on habitat quality. Approximately 36% of the NCA is suitable for black rhino throughout the year, however, seasonal shifts influence habitat suitability. Anthropological factors impact habitat suitability, but this depends on the season. During the wet season, when human factors are reduced, habitat suitability increases to 53.6%. On the other hand, in the dry season, browse availability decreases and rhinos become less selective of areas where they move to fulfil their nutritional requirements, with anthropological pressures becoming less important. Our study also identified areas that are consistently suitable throughout seasons and not severely impacted by human factors, such as between the Olmoti and Ngorongoro Craters. The Oldupai Gorge only highlights small suitable patches, however, it used to sustain a large population of rhinos in the 1960s. Land cover changes seems to have decreased the suitability of the Gorge, but the area should be studied further before being deemed unsuitable. Lastly, our study also found that is imperative to combine ground truthing with remotely sensed data. Remote sensing heavily relies on theoretical data and often overlooks crucial field variables such as shelter locations. Therefore, integrating these approaches ensures more precise and reliable results in habitat suitability assessments. Overall, the findings provide valuable insights into identifying suitable habitat for black rhinos and highlight the need for enhanced conservation efforts to safeguard populations amidst changing environmental and anthropogenic pressures.

## 4.1 Introduction

Conservation and management of critically endangered species is an urgent priority due to escalating threats to biodiversity worldwide. To ensure species long-term survival, it is essential to understand habitat requirements and the factors influencing animal distribution (Boyce et al., 2016; Emslie, 2020). These requirements comprise a range of ecological factors, including browse availability, water sources, breeding areas, and shelter

(Tatman et al., 2000; Freeman et al., 2014). Additionally, understanding these parameters provides valuable insights for land-use planning, protected area establishment, and the creation of wildlife corridors (Emslie, 2020). Such measures promote gene flow, reduce habitat fragmentation, and facilitate movement between suitable habitats, all of which are vital for genetic diversity and viability of wildlife populations (Kohi and Lobora, 2019; Emslie, 2020). By identifying and preserving areas that fulfil population requirements, conservation efforts can focus on targeting strategies that maintain or restore critical habitats necessary to ensure species recovery.

The black rhino (*Diceros bicornis*) is a critically endangered species with a global population of circa 5,630 individuals, approximately 1,000 of which are Eastern black rhino (*D. b. michaeli*), mostly located in Kenya and Tanzania (Knight, 2019; Emslie, 2020). They are generally solitary, or form small family groups, reaching sexual maturity at around 5-7 years with a lifespan of approximately 35-40 years (Goddard, 1967; Emslie and Adcock, 1994). Black rhinos are selective browsers, generally preferring the woody species found in savannah and bushveld areas (Emslie, 2020). Although the primary threat to black rhino is poaching - driven by high demand for rhino horn - habitat loss from deforestation, livestock grazing, human settlement development and agricultural expansion poses an increasing threat to rhino populations (Leader-Williams, 2002; Chanyandura et al., 2021). Habitat loss also increases intra-species competition for limited resources, further exacerbating the population’s vulnerability to external pressures (Landman et al., 2013).

The Ngorongoro Conservation Area (NCA) in Tanzania serves as a crucial stronghold for the Eastern black rhino, hosting approximately 30% of the country's total population (Kohi and Lobora, 2019). In recent years, increased anti-poaching patrols and monitoring in the NCA have allowed the black rhino population to reach 55 individuals (Kohi and Lobora, 2019). Given this recent population growth, it is essential to identify habitat areas capable of supporting a growing, and eventually larger, rhino population (Emslie and Brooks, 1999; Kohi and Lobora, 2019). By pinpointing these areas, conservation efforts can prioritize their protection and that of their preferred habitat, thus promoting a favourable environment for black rhino conservation (Buk and Knight, 2012; Lush et al., 2015).

Seasonal variations significantly impact plant growth and availability, influencing the nutritional content and abundance of preferred browse for black rhinos (Baltensperger and

Joly, 2019; Van Moorter et al., 2020). During the dry season, the reduction in green browse prompts rhinos to seek areas with higher browse density or to adapt their movement patterns to find alternative food sources, and therefore investigating seasonal patterns becomes crucial in evaluating habitat suitability (Baltensperger and Joly, 2019; Van Moorter et al., 2020).

Black rhinos tend to avoid areas of human activity, such as settlements and roads (Muntifering et al., 2021). In 2013, the NCA received over 647,000 visitors, with more recent numbers approaching one million (Melita, 2015; Slootweg, 2016). This growth has generated substantial economic revenue and facilitated extensive infrastructure growth, but also led to higher rates of disturbance in and around the Crater (Harris et al., 2020). The Maasai community residing in the NCA also increased from approximately 8,000 people in 1959 to nearly 100,000 by 2018 (Manzano and Yamat, 2018; Lyimo et al., 2020). Alongside this demographic expansion, the estimated livestock population associated with the community surpassed 800,000 in 2018 (Manzano and Yamat, 2018; Lyimo et al., 2020). The combination of these factors provides a unique opportunity to study how human disturbances impact black rhino habitat suitability.

Species distribution models (SDMs) combine species occurrences with spatial data based on environmental and ecological variables of a given geographic area to predict species distributions (Elith et al., 2006). SDMs are widely used in invasive species management, climate change impact assessment, habitat restoration, ecological research, land use planning and wildlife management (Guisan and Zimmermann, 2000; Guisan and Thuiller, 2005; Araújo and New, 2007; Peterson et al., 2008; Guisan et al., 2013; Kramer-Schadt et al., 2013). SDMs can provide information that facilitates efficient conservation management by pinpointing key habitats, potential migration corridors, and areas that require increased protection (Guisan and Thuiller, 2005; Elith and Leathwick, 2009). For instance, Pratzer et al., (2023) showed how combining SDMs with dispersal scenarios could provide valuable information regarding potential habitat expansion of large carnivores. Hybrid models combining SDMs with population dynamics have also been used in Canada to identify essential habitat areas for the Ord's kangaroo rat (*Dipodomys ordii*; (Heinrichs et al., 2010).

Previous conservation efforts for black rhinos have focused on establishing protected areas and increasing security using anti-poaching patrols and fencing (Brett, 1993). However, habitat quality and food availability are equally important factors that need to be considered to sustain and promote population growth (Muya and Oguge, 2000; Mills et al., 2003; Buk and Knight, 2010). Within this framework, the overarching aim of this research is, therefore, to provide the NCA management with accurate data to support black rhino population expansion and conservation.  We do this by providing answers to the following research questions: (i) how does seasonal variability impact habitat suitability for black rhino; (ii) how do human disturbances impact habitat suitability; and (iii) in the absence of field data, can theoretical models be used to predict habitat suitability.

## 4.2. Study area

The NCA is a protected area located in northern Tanzania. During the wet season, temperatures fluctuate between 7.5° and 14.5 °C, while in the dry season, they range from 10.6° to 19.6 °C (Amiyo, 2006). Rainfall demonstrates distinct patterns featuring two wet seasons from March to May and October to December, as well as two dry seasons from January to February and June to October (Frederick D. L. Hunter et al., 2020). Annual rainfall varies from 450mm/year in lowlands to 1200 mm/year in highlands (Boone et al., 2006).

The NCA includes diverse vegetation types, including highland grassland plains, open canopy woodland, closed canopy forests, and savannah grasslands (Borges et al., 2020; Herlocker and Dirschl, 1972, Figure 4.1). The vegetation suitable for grazing is essential for wildlife but also Maasai livestock that either reside within, or are passing through, the NCA (Swanson, 2007). The NCA has an open border policy that allows grazing livestock for resident and non-resident Maasai; however, the Northern Highland Forest Reserve and the Crater floor are restricted areas (Swanson, 2007.

Changes in management policy over the years have been a source of conflict between communities and the Ngorongoro Conservation Area Authority (NCAA; Amiyo, 2006; Boone et al., 2006). For instance, a lifting of the cultivation ban led to an increase in cultivated areas (Boone et al., 2006; Niboye, 2010; Masao et al., 2015). The conversion of land to cultivation fields creates environment pressures through vegetation changes and habitat patchiness (Scogings et al., 2012; Wigley et al., 2014). Additionally, a fire ban implemented 32 years ago contributed to grass growth and spread of invasive plant species as there was no vegetation control other than herbivory (Niboye, 2010). The spread of invasive unpalatable grass species decreases the pasture suitable for cattle so the pastoralists resort to cultivation to sustain their households (Swanson, 2007). A shift from traditional pastoral systems to cultivation, combined with an increase in human population, poses a serious threat to the ecosystem and is likely to be detrimental in the long-term (Mills et al., 2003; Niboye, 2010).

The NCA has undergone significant habitat changes, particularly experiencing forest loss and woody encroachment (Borges et al., 2022). While some of these changes may be natural, driven by herbivory, rainfall, and vegetation succession, many are attributed to human activities, including management policies, tourism development, and the expanding human population and livestock (Mills et al., 2003).

With regards to rhino populations, in 1966, the Crater and Oldupai Gorge areas within the NCA (Figure 4.1) supported 108 and 69 rhinos, respectively (Goddard, 1967). By 1993, poaching had reduced rhino population to just 13 individuals (Kohi and Lobora, 2019). More recently, a relatively high rate of growth has been reported, leading to the current total of 55 animals as of 2018 (Kohi and Lobora, 2019).

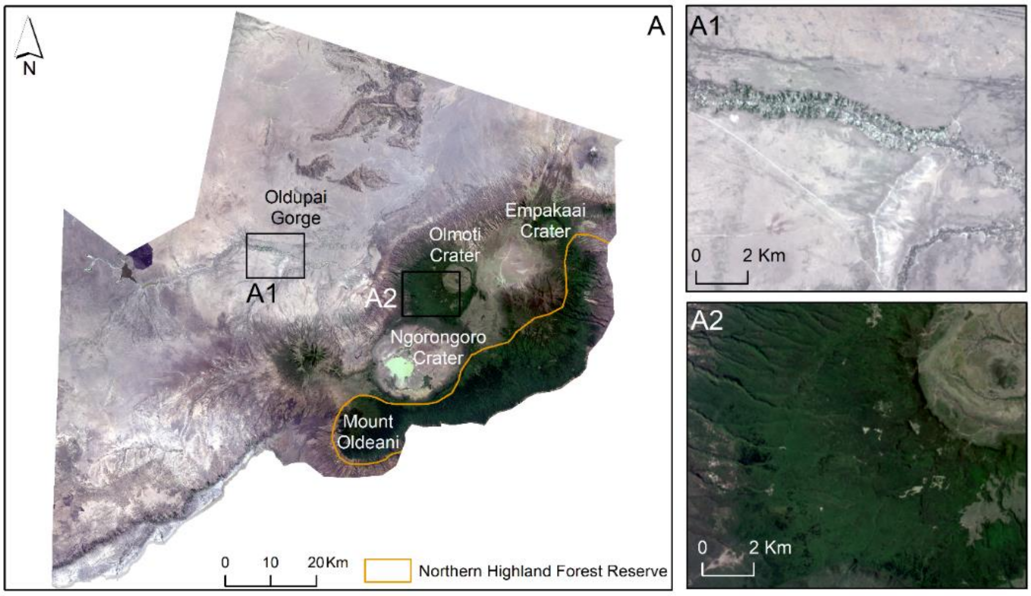

Figure 4.1. The Ngorongoro Conservation Area. Locations A1 and A2 are example subsets.

## 4.3. Datasets and methods

Field data on the presence/absence of animal species are invaluable for habitat suitability modelling. However, it is often the case that conducting fieldwork is not feasible, e.g., due to armed conflict in the area of interest. We mapped rhino habitat suitability in the NCA with and without field data on rhino presence and compared the outcomes to assess whether, in the absence of field data, a theoretical habitat suitability model can be used instead. The Ngorongoro Crater was included in the analysis but has been filtered out from the maps at the request of the NCAA to ensure the safety of the resident rhinos

To model habitat suitability with field data, we first assumed that areas currently used by rhinos are suitable and used satellite imagery to identify other suitable areas beyond their current range. We employed a comprehensive approach integrating Sentinel-2 and PlanetScope images, vegetation indices and human distribution data. We employed the Recursive Feature Elimination (RFE) technique and random forest (RF) algorithm to identify the most relevant features that contribute to habitat suitability prediction (Breiman, 2001; Guyon et al., 2002; Demarchi et al., 2020). RFE systematically evaluates different combinations of features and eliminates the least significant ones reducing model complexity (Guyon et al., 2002). The model was trained with presence and pseudo-absence data collected in the field. To assess the effect of seasonal variability on habitat suitability, we used satellite data from both the dry and the wet seasons and assessed them separately. To investigate how habitat suitability is impacted by the presence of humans and livestock, we ran the RFE and RF with two versions of the human activity data: one with the current situation and a simplified one with all settlements and livestock removed, together with some of the roads. The output was four suitability maps: one for each season, with the current human activity data and with the simplified less intense version.

To map habitat suitability without field data: we employed fuzzy logic using land cover data (scored according to their ability to fulfil rhino diet requirements) and human disturbances (using both the current situation as well as the simplified, less intense version, Borges et al., 2020; Goddard, 1968; Muntifering et al., 2021). Fuzzy logic analysis is widely used in predictive modelling to map habitat suitability (Adriaenssens et al., 2004; Zabihi et al., 2017; Gwynn and Symeonakis, 2022; Pestka et al., 2023). The fuzzy approach assigns a probability score to classes identifying the ranges between boundaries of each class and can be employed in the absence of field data (Woodcock and Gopal, 2000; Qiu et al., 2014). The output was two suitability maps: one with the current human activity data and one with the simplified one.

### 4.3.1 Datasets

#### *4.3.1.1 Sentinel-2*

We used all Sentinel 2 images acquired over the study area between 1 March 2022 and 30 September 2022 with less than 75% cloud cover. Level 2 images were processed into analysis ready data products using the Framework for Operational Radiometric Correction for Environmental monitoring (FORCE) software version v.3.7 (Frantz, 2019), following the approach and parameters detailed in Borges et al. 2020. Finally, we calculated 14 vegetation indices (Table 4.1) that have been employed in vegetation studies to detect habitat types. These were then added to the Sentinel-2 spectral bands.

Table 4.1. Vegetation indices added to the Sentinel-2 stack.

| **Name** | **Equation and derivation** | **Reference** |
|---|---|---|
| Normalized Difference Vegetation Index (NDVI) | (NIR – R)/(NIR + R) | Tucker, 1979 |
| Green Normalized Difference Vegetation Index (GNDVI) | (NIR – G)/(NIR + G) | Gitelson et al. 1996 |
| Normalized Difference Red Edge (NDRE) | (NIR-RE1)/(NIR+RE1) | Barnes, 2000 |
| Modified Normalized Difference Water Index (MNDWI) | (G-SWIR1)/G+SWIR1) | Xu, 2006 |
| Normalized Difference Water Index (NDWI) | (NIR – SWIR1)/(NIR +SWIR1) | Gao, 1996 |
| Inverted Red Chlorophyll Index (IreCI) | (NIR – R)/(RE1/RE2) | Frampton, 2013 |
| Pigment Specific Simple Ratio (PSSRa) | NIR/R | Blackburn, 1998 |
| Normalized Difference Index 4 and 5 (NDI45) | (RE1 – R)/(RE1 + R) | Delgido, 2011 |
| Chlorophyll Index Red-Edge (CIRE) | ((NIR/RE1) – 1.0) | Gitelson et al., 2006 |
| Sentinel-2 Red-Edge Position (S2REP) | 705 + 35 * ((((NIR +R)/2) – RE1)/(RE2 -RE1)) | Frampton, 2013 |
| MERIS Terrestrial Chlorophyll Index (MTCI) | (NIRred – Red_edge) / (Red_edge – Red) | Dash and Curran, 2004 |
| Modified Soil-Adjusted Vegetation Index 2 (MSAVI2) | [(RE1 – R) – 0.2 * (RE1 -G)] * (RE1 / R) | Richardson, 1977 |
| Modified Chlorophyll Absorption in Reflectance Index (MCARI) | 2.5 * ((NIR – R)/((NIR + 6* R – 7.5 * B) + 1)) | Daughtry, 2000 |
| Enhanced Vegetation Index (EVI) | (2.5*((NIR – R)/ ((NIR + (2.4 * R) + 1)) | Liu, 1995 |

#### *4.3.1.2 PlanetScope*

Planet data were extracted from the Planet Labs Public Benefit Corporation (PBC) database for the dry (October 2022) and the wet season (March 2022) at a spatial resolution of 4.7 meters (Planet Team, 2022). Adding the Planet data to the analysis enhances the spatial resolution, facilitating the distinction of spectrally similar habitats (Symeonakis et al., 2019).

#### *4.3.1.3 Human activity*

Settlement data were incorporated in the habitat suitability analysis, including the location of villages, towns, tourism infrastructure and any other building identifiable in the high-resolution Google imagery (CNES/Airbus). The initial settlement data, obtained from the 2012 Population and Housing Census, were extracted from the Tanzania National Bureau of Statistics database (nbs.go.tz) and updated using Google Earth Pro (v. 7.3.6.9326, Ludwig et al., 2016) to account for changes since the initial census.

Black rhinos are known to avoid areas that humans frequent, namely surrounding lodges, camping sites, roads or settlements (Muntifering et al., 2021). In the NCA specifically, this behaviour has been suggested as a possible driver of rhino distribution (Mills et al., 2003; Gadiye et al., 2016). To establish how settlements impact habitat suitability, a new simplified settlement layer was created which only included the lodges and ranger stations and excluded villages. We created the road network data via Manual digitisation over Airbus imagery acquired between 2016 and 2022 using Google Earth Pro (v. 7.3.6.9326, Ludwig et al., 2016). We identified all existing main roads used for tourism as well as smaller roads used by the local population to reach villages and towns. To assess the effect of roads on habitat suitability, we also developed a simplified road dataset, which included only tourism-related roads, as these roads are expected to continue being used in the foreseeable future.

Finally, the livestock presence/absence data were created based on current NCA policies. Currently, livestock is permitted anywhere except in the Ngorongoro Crater and the Northern Highland Forest Reserve. For the reduced activity version, livestock was removed from all the NCA.

#### *4.3.1.4 Land cover layer*

The land cover layer we used in our modelling came from our previous work in the area Borges et al., (2020): this dataset was based on Sentinel 1 and Sentinel 2 data from the dry and short-dry season and comprises of nine land cover classes at a 10m resolution (overall accuracy of 86.3 ± 1.5%).

#### *4.3.1.5 Rhino presence data*

The training samples were collected between March and September 2023 to cover both the wet and dry seasons. A total of 272 samples were collected: 109 presence and 163 pseudo-absences. Each data point comprised of 30-m diameter circular plots. Presence data were established through the identification of direct signs, such as rhino sightings, or indirect signs, like tracks, bites on vegetation or dung. Pseudo-absence data refers to an area where there were no recorded sightings of black rhinos by the monitoring team over the years. Pseudo-absence data were randomly collected in areas that exhibited comparable conditions in terms of vegetation composition, geography, water presence, etc., known to be suitable for black rhinos (Phillips et al., 2006, 2009).

### 4.3.2 Methods

#### *4.3.2.1 Recursive Feature Elimination*

We used Recursive Feature Elimination (Guyon et al., 2002) in RStudio environment to identify the optimal band combination, for highest accuracy, out of the 31 available bands (10 Sentinel-2, 14 VIs, 4 PlanetScope, 3 human disturbance) for the two distinct seasons. The random forest algorithm, embedded in RFE, is an efficient non-parametric machine learning model based on ensembles of regression trees, commonly used for image classification and land cover mapping (Rodriguez-Galiano et al., 2012; Li et al., 2015; Symeonakis et al., 2018).

Each season had its own training data and 80% was allocated to train the model with the remaining 20% left aside for validation. RFE systematically evaluates different combinations of bands by eliminating the least significant bands and assessing their impact on model performance (Guyon et al., 2002). This approach helps identify the most informative bands for accurate classification of habitat (Higginbottom et al., 2018). The RFE process was conducted separately for the dry and wet seasons to determine the best band combination for each season. Validation was then performed, and the prediction maps produced for each season using the best band combinations identified through the RFE and the *raster* package in *R*.

### *4.3.2.2 Fuzzy analysis*

To assess rhino habitat suitability, each land cover type was assigned a score based on available information on habitat utilisation for the NCA (Table 4.2, Goddard, 1968). The scoring system ranged from 0.0 to 1.0 (Table 4.2), with 0.0 representing unsuitable habitat and 1.0 representing highly suitable habitat, as suggested by Gwynn (2022) for the allocation of fuzzy membership scores.

Table 4.2. Suitability score for each land cover type.

| **Land cover type** | **Score** | **Justification** |
|---|---|---|
| Bareland | 0.0 | No browse available |
| Bushland | 1.0 | High browse available, shelter, water sources |
| Cropland | 0.0 | No browse available, human-wildlife conflicts |
| Forest | 0.4 | Moderate browse available, shelter, water sources |
| Grassland | 0.0 | Little browse and no shelter |
| Montane heath | 0.0 | Little browse available |
| Shrubland | 1.0 | High browse available, shelter, water sources |
| Water | 0.0 | Usually salt water, no browse available |
| Woodland | 0.6 | Browse available, shelter, water sources |

We applied fuzzy logic to develop scored maps based on land cover types expected to fulfil rhino food requirements, and human disturbances, identifying areas that were expected to be suitable (Goddard, 1968; Borges et al., 2020; Muntifering et al., 2021). Fuzzy membership (linear) was applied separately to the current and simplified versions of the roads and settlements datasets, generating suitability maps for each variable. Distances from the roads or settlements between 0km and 2.5km were scored as unsuitable (=0), while distances over or equal to 2.5km were assigned a value of 1.0 (i.e., suitable). These values were based on expert knowledge and corroborated by the presence data during the field work. The categorical land cover data was reclassified according to Table 4.2, followed by the fuzzy membership steps described above. Finally, fuzzy overlaying was employed, and the three outputs were added together to create the habitat suitability map without field data.

## 4.4. Results

### 4.4.1 Habitat suitability using field data

The best combination of layers for the wet season (Table 4.3) included 11 bands and achieved an accuracy of approximately 76.2%. For the dry season, the best data combination comprised of 13 layers and achieved an accuracy of 88.2%.

Table 4.3. Best combination of layers from RFE for both seasons.

| **Wet season** | **Dry season** |
|---|---|
| Roads | Sentinel-2 REDEDGE3 |
| MSAVI2 | Sentinel-2 REDEDGE1 |
| Settlements | Sentinel-2 BROADNIR |
| NDVI | Sentinel-2 Red |
| NDWI | Sentinel-2 Green |
| Planet Scope NIR | Planet Scope NIR |
| NDRE | Settlements |
| Livestock | Sentinel-2 SWIR1 |
| Planet Scope Blue | Sentinel-2 Blue |
| Planet Scope Red | Planet Scope Blue |
| Sentinel-2 REDEDGE1 | CRE |
|  | PSSRa |
|  | GNDVI |

The NCA comprises of approximately 3377 km$^2$ (36.9%) of potentially suitable habitat for black rhino during the wet season alone (Figure 4.2A). Similarly, during only the dry season, the suitable habitat covers approximately 3263 km$^2$ (35.6%) of the NCA. The area that remains suitable through both seasons covers 1912 km$^2$. This includes the Ngorongoro Crater (NC), which has been filtered out at the request of the Ngorongoro Conservation Area Authority (NCAA) to ensure animal safety. The Oldupai Gorge is mostly unsuitable except for a few patches during the dry season and around the Gorge during the wet season (Figure 4.2 A1-B1). The area between Olmoti Crater and the NC (Figure 4.2 A2-B2) remains suitable for black rhino throughout both seasons.

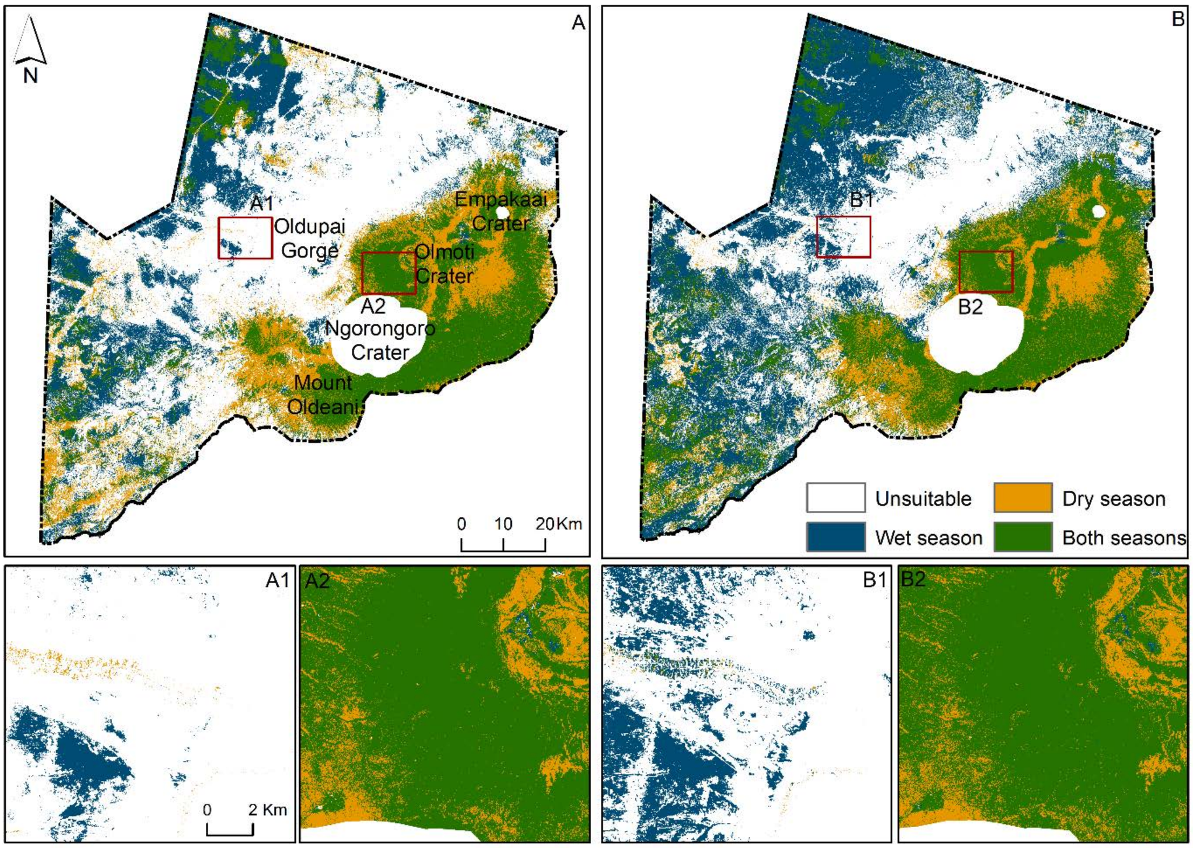

Figure 4.2. Suitable habitat with current human disturbances (A); and with simplified human disturbances (B). A1 -B2 are example subsets. The Ngorongoro Crater has been removed for safety reasons.

Under simplified human disturbances, the suitable area during solely the wet season area increases by 1526.5 km$^2$ (16.7%) covering 4903 km$^2$ (53.6%) of the entire area (Figure 4.2B). During the dry season the NCA remains almost unchanged covering approximately 3344 km$^2$ (35.5%) once the human disturbances are simplified (Figure 4.2B). The area that remains suitable through both seasons improved by 312 km$^2$ covering 2224 km$^2$. The Oldupai Gorge and surrounding area becomes more suitable once human disturbances are simplified during the wet season (Figure 4.2 B1). The area between Olmoti Crater and the NC suitable for black rhino under both seasons (Figure 4.2 B2).

### 4.4.2 Habitat suitability without field data

The suitability maps of the fuzzy membership analysis show woody vegetation areas as dark green (>90% suitability, Figure 4.3 A). Most of the NCA, including the Serengeti plains and the NC, is comprised of open grasslands with little or no vegetation and is classified as unsuitable (<27% suitability, Figure 4.3 A). When human disturbances are reduced the suitable area increases throughout (Figure 4.3 B). The Oldupai Gorge and highlands between the NC and Olmoti Crater also become more suitable (Figure 4.3 A1-A2, B1-B2).

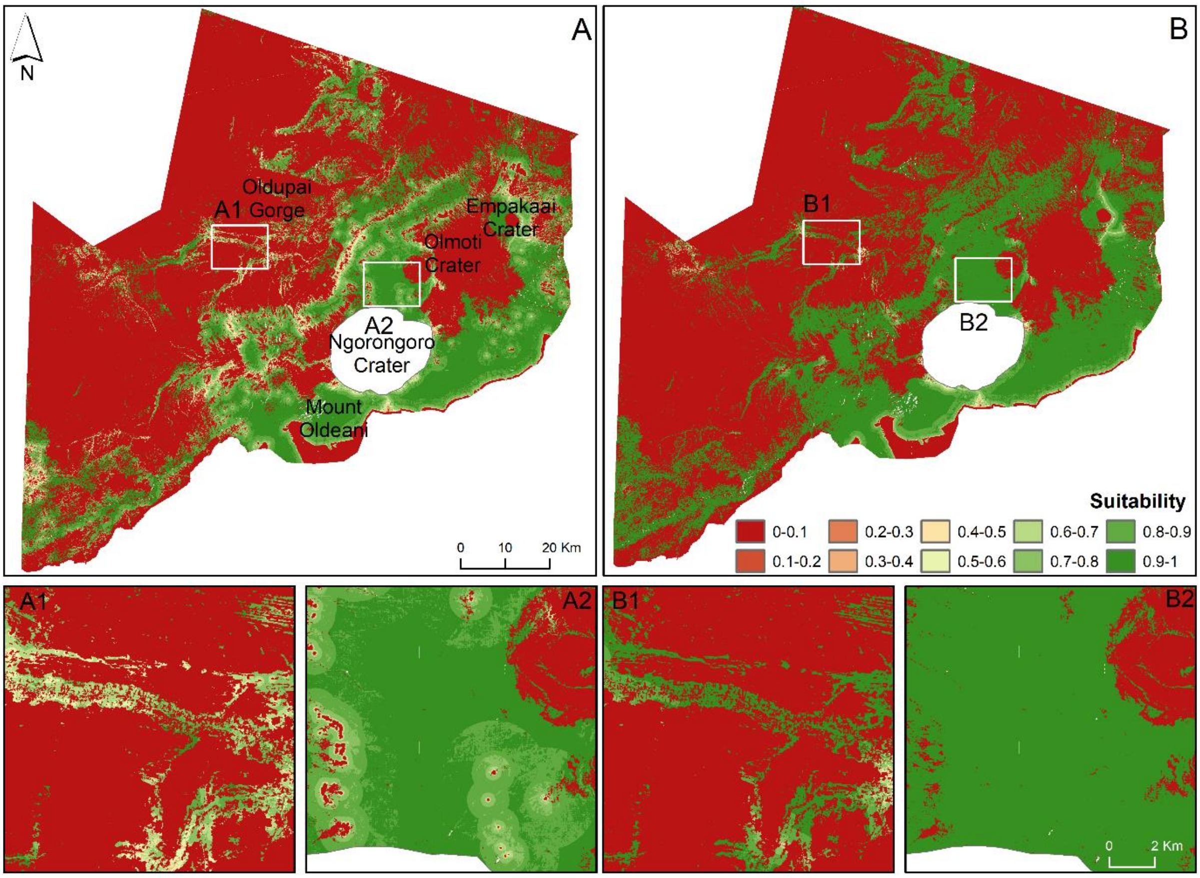

Figure 4.3. Fuzzy membership output maps with current human disturbances (A); and with simplified human disturbances (B). A1 – B2 are example subsets. The Ngorongoro Crater has been removed for safety reasons.

## 4.5. Discussion

Identifying optimal habitat suitability is paramount for targeted conservation efforts, to safeguard biodiversity and promote sustainable coexistence between wildlife and communities (Emslie, 2020). In the context of critically endangered species, such as the black rhino, it becomes increasingly important to detect key habitat that can support growing populations (Kohi and Lobora, 2019; Emslie, 2020). Here, we identified potential black rhino habitat, for the wet and dry seasons and assessed how human activities impact habitat quality within the NCA.

Our results show that when mapping habitat, using dry season data (88.2%) produces higher accuracy results then during the wet season (76.2%). Dry season data is often preferred due to lower cloud cover and higher contrasts between grass and woody plants (Haro-Carrion and Southworth, 2018; Higginbottom et al., 2018) . There are also differences between the best combination of data for each season (Table 4.3). For instance, during the dry season the spectral bands are more relevant than anthropogenic factors when mapping suitability (Table 4.3). The natural seasonal shifts can explain this, as the decrease in browse availability forces the animals to frequent areas with different vegetation (Baltensperger and Joly, 2019; Van Moorter et al., 2020). Contrarily, during the wet season, when there is plenty of browse available, the anthropogenic factors (roads, settlements, and livestock presence) become more important to identify suitable habitat as the availability of more food often means that the rhinos can be more selective (Table 4.3).

### Seasonal differences

During the dry season potentially suitable habitat for black rhino covers 35.6% (3263 $km^2$) of the NCA (Figure 4.2A). However, in context of conservation, it is essential to account for seasonal changes as often wildlife is confined to protected areas and unable to migrate long distances (Baltensperger and Joly, 2019; Van Moorter et al., 2020). Surprisingly, the suitable area was only 1.4% higher (114 $km^2$) during the wet season than the dry season (Figure 4.2B). In the NCA, bushland cover often includes palatable browse, water resources and shelter, and therefore suitable for rhino (Goddard, 1968; Herlocker and Dirschl, 1972; Borges et al., 2022). Most of the bushland cover in the rim of the Crater is comprised of evergreen species and we would expect fewer seasonal changes (Figure2, Borges et al., 2020; Herlocker and Dirschl, 1972).

The Serengeti plains, west of the NCA, are suitable mostly during the wet season but become unsuitable as the season changes (Figure 4.2A). This shift in suitability is expected as the vegetation comprises of seasonal species that lose their leaves or die during the dry season (Herlocker and Dirschl, 1972). The area surrounding Oldupai Gorge remains mostly unsuitable throughout both seasons except for a few patches (Figure 4.2 A1). In the 1960s, the Gorge supported a population of 69 black rhinos (Goddard, 1967). In comparison to the Crater population, these individuals probably occupied larger home ranges to fulfil the nutritional requirements which suggests that the vegetation was already less desirable than in the Crater (Goddard, 1967). In addition, over the last decades the Oldupai Gorge experienced changes in the vegetation, specifically the loss of woody cover (Borges et al., 2022). Land cover changes impact vegetation composition and likely contributed to the disappearance of the black rhino population from the Oldupai area.

**Anthropogenic factors**

Anthropogenic activities have a profound influence on wildlife habitats, often posing significant challenges to the conservation of endangered species such as rhinos (Emslie, 2020; Muntifering et al., 2021). One of the main drivers for rhino distribution is browse availability, however, areas with adequate browse would be deemed unsuitable due to anthropogenic factors (Odendaal-Holmes et al., 2014). In Namibia for instance, human presence has been linked to an increase in calf-mortality (Hearn et al., 2000; Odendaal-Holmes et al., 2014). As such, human disturbances should be considered when identifying areas that could support a black rhino population. Our findings support previous studies suggesting that human activities are major drivers in rhino location and habitat stability but there are seasonal variations (Goddard, 1967; Mukinya, 1977; Buk and Knight, 2012; Muntifering et al., 2021).

During the wet season, our analysis pinpointed roads as the predominant predictor of rhino habitat suitability with location of settlements and livestock presence also playing a role (Table 4.3). Once human activities are removed from the model there is a clear increase (16.7%) in suitable habitat and 53.6% of the NCA becomes suitable (Figure 4.2B). Conversely, the dry season presents a contrasting scenario, where limited browse resources, due to seasonal shifts, reduce the importance of human disturbances (Table 4.3, Figure 4.2B). Settlements, however, continue to play a role but to a lesser extent than observed during the wet season (Table 4.3).

Rainfall variability between the wet and dry season is highly linked to vegetation growth and rainfall, thereby impacting browse availability for large herbivores in arid and semi-arid environments (Beytell, 2010). During the wet season, due to higher rainfall, there is a higher availability of browse so rhinos can afford to seek alternative areas with reduced human disturbance (Goddard, 1967; Beytell, 2010; Odendaal-Holmes et al., 2014). When the dry season arrives, and browse is limited, rhinos become less selective and frequent different areas (e.g. nearer the roads) in order to fulfil their nutrient requirements (Goddard, 1967; Beytell, 2010; Odendaal-Holmes et al., 2014).

### Habitat suitability with and without field data

In small protected areas, field-based mapping offers crucial insights into the fluctuating patterns of savannah vegetation structure and distribution. However, in larger areas, field techniques are time consuming and expensive, rendering them less practical (Yang and Prince, 2000; Eisfelder et al., 2012). As a result, there is a growing reliance on Earth Observation data to identify and monitor habitat cover and its characteristics, as it provides valuable insights even when field data is unavailable (Woodcock et al., 2008; Wulder et al., 2012; Adole et al., 2016). Black rhinos can survive in wide range of habitats, including marsh areas, forests and even deserts and browse availability is a driver of their distribution and habitat preference (Klingel and Klingel, 1966; Goddard, 1968; Leader-Williams, 1989; Kotze and Zacharias, 1993; Lush et al., 2015). However, the highest densities of black rhinos occur in savannah areas and bushvelds, mainly due to the higher availability of woody species (Emslie, 2020). Our results show that areas with higher bushland cover, namely the Highland Forest reserve, NC rim, and between Olmoti Crater and the NC, are the most suitable areas to sustain a black rhino population (Figure 4.3, A2-B2) which also agrees with Figure 4.2 A2-B2. These areas have an abundance of browse and are located away from human activities and as in Figure 4.2A and 2B, the removal of these from the model have a positive impact in habitat suitability (Figure 4.3A and 3B).

When compared to Figure 4.2A, areas like the Oldupai Gorge area and the Serengeti plains produce contrary results (Figure 4.3A). The Oldupai Gorge is classified as suitable habitat as it comprises of woodland and shrubland cover, classes with a higher score regarding browse availability (Figure 4.3 A1, Table 4.2). Additionally, areas such as the Serengeti plains, primarily grasslands, appear as unsuitable (red, Figure 4.3A) due to lower woody cover which has little to no feeding value for rhino (Emslie and Adcock, 1994). Grassland was given a score of zero because of black rhino diets comprise of woody plant species (Table 4.2, Buk and Knight, 2010; Emslie and Adcock, 1994; Ganqa et al., 2005). However, the NCA black rhino population is unique in a way that they spend a lot of time on the Crater floor, which is mostly grassland, to feed on herbs or sleep (Goddard, 1967, 1968). Without field data, the Gorge and the Serengeti plains would have been misidentified, potentially posing significant threats to the NCA's long-term rhino population growth. To enhance the accuracy of our findings, it is imperative to combine ground truthing with remotely sensed data. Remote sensing heavily relies on theoretical data and often overlooks crucial field variables such as shelter locations. Therefore, integrating these approaches ensures more precise and reliable results in habitat suitability assessments.

## 4.6 Conclusion

Emerging research shows a decline in both the quality and quantity of browse in NCA, and consequently a decrease in suitable habitat for black rhinos (Amiyo, 2006; Kohi and Lobora, 2019; Borges et al., 2022). An increase in competition for resources drives rhinos out of the Crater to potentially dangerous areas, therefore, there is an urgent need to identify suitable areas that can support an increasing black rhino population (Kohi and Lobora, 2019). Approximately 36% of the NCA is suitable for black rhino throughout the year (Figure 4.2A) and under the current conditions the impact of season is minimal (improvement of 1.4%from the dry to the wet season). Additionally, anthropological factors impact habitat suitability, but this depends on the season (Figure 4.2A-B). During the wet season, when human factors are reduced, habitat suitability increases to 53.6% which agrees with previous research (Figure 4.2, Baltensperger and Joly, 2019; Van Moorter et al., 2020). On the other hand, in the dry season, browse availability decreases and rhinos become less selective of areas where they move to fulfil their nutritional requirements, with anthropological pressures becoming less important (Figure 4.2, Baltensperger and Joly, 2019; Van Moorter et al., 2020).

Our study identified areas that are consistently suitable throughout seasons and not severely impacted by human factors, such as between the Olmoti and Ngorongoro Craters, (Figure 4.2 A2-B2). Over the last decades, the area experienced a decrease in forest cover, and increase in bushland and the vegetation has not been surveyed since the 1960s (Goddard, 1968; Herlocker and Dirschl, 1972; Borges et al., 2022). Since bushland is associated with browse availability, areas such between the Olmoti and Ngorongoro Craters are likely to contain suitable browse. Contrastingly, the Oldupai Gorge currently only highlights small suitable patches (Figure 4.2 A1) and used to sustain a large population of rhinos in the 1960s (Goddard, 1967). Land cover changes seem to have decreased the suitability of the Gorge, but the area should be studied further before being deemed unsuitable. Ultimately, areas that are deemed suitable for rhino require increased security and detailed vegetation surveys to detect the presence or absence of rhino preferred browse. Areas that are deemed unsuitable should be surveyed more thoroughly, particularly if in the past they used to be occupied by black rhino.

Finally, the use of theoretical models in the absence of field data has proven effective but has limitations. The discrepancies observed in areas like the Oldupai Gorge and Serengeti plains underline the need for ground truthing to ensure accurate habitat assessments. Therefore, combining remote sensing with field-based methods is crucial for making informed conservation decisions that will support the growth and stability of the black rhino population in the NCA. These insights are vital for directing future conservation efforts and ensuring the long-term survival of black rhinos.

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# Chapter 5 - Feeding ecology of black rhino in the Ngorongoro Conservation Area, Tanzania

Abstract: Feeding studies provide critical insights into foraging behaviour and dietary preferences and contribute to conservation efforts by helping to select appropriate sites for conservation management and reintroductions. We examined the factors influencing distribution and dietary habits of black rhinos in the Ngorongoro Conservation Area (NCA) across different seasons. A PERMANOVA was employed to assess the influence of habitat variables, seasons, and regions on black rhino presence. Additionally, random forest modelling was also used to identify the key variables that best classified the presence or absence of rhinos. Seasonal variations significantly impacted rhino diets, leading to visible changes in feeding patterns observed between wet and dry seasons. The Crater grasslands emerged as important feeding areas, particularly in the wet season. Additionally, there was a strong preference for plants present in the swamps and an avoidance of invasive species that cover the Crater floor. When the vegetation in the Crater dries, the Lerai forest, the Crater rim and Lemala become increasingly important. These areas are likely to be suitable because of a combination of preferred browse, water, areas for shelter and potential breeding. We also found that rhino prefer sites with browse that is available <1m of height rather than high density bushland. Despite experiencing significant dryness during the dry season, the Oldupai area retained the browse species crucial for black rhino and was identified as an ecologically suitable site even though it currently does not support rhino. Overall, our study contributes valuable insights into the ecological dynamics and feeding preferences of black rhinos in the NCA. The information can be used to identify sites into which the NCA’s rhino population could expand.

## 5.1 Introduction

Conservation strategies often rely on the reintroduction or introduction of species into areas where they were previously absent due to various threats (Armstrong and Seddon, 2008; Angeli and Fitzgerald, 2021). Moreover, environmental changes may render former habitats unsuitable for reintroduction (IUCN, 2013; Peers et al., 2016). To ensure the success of re/introductions, detailed studies on feeding ecology are necessary, as they provide crucial insights into the species' dietary needs and habitat preferences (IUCN, 2013). These studies are essential to improve habitat quality of currently occupied areas, estimate carrying capacities, and identify potential expansion areas for populations, whether through natural dispersal or reintroductions (Goddard, 1968; Reid et al., 2007; Ngoti, 2017) .

The black rhino (*Diceros bicornis*) is a critically endangered species, with a global population of 5,630 individuals; around 1,000 Eastern black rhinos (*D. b. michaeli*) are resident in Kenya and Tanzania (Knight, 2019; Emslie, 2020). The main threat to black rhinos is poaching for their horns (Leader-Williams, 2002; Chanyandura et al., 2021). However, land cover changes, which often reduce food availability and increase inter- and intra-specific competition for resources, pose an increased risk to rhino populations (Leader-Williams, 2002; Amin et al., 2006; Emslie, 2020; Chanyandura et al., 2021). Black rhinos are selective browsers, able to browse up to 220 plant species, but tend to rely heavily on a limited number of plant species that are high in protein and water content and low in phenols and aromatics (Emslie and Adcock, 1994; Ganqa et al., 2005; Buk and Knight, 2010). Browse availability affects the distribution and habitat preference of black rhinos, with higher densities observed in savannah areas and bushvelds, where woody species are more abundant (Emslie, 1999). Thick bush, often with unpalatable woody species, is used more for protection and shelter than for feeding (Kotze and Zacharias, 1993).

Currently, the primary model for rhino conservation is the use of fenced sanctuaries which have ‘known’ Ecological Carrying Capacities (ECCs, Amin et al., 2017). With populations rising, particularly in Kenya, there is an emerging shift from fenced sanctuaries to intensive protection zones (IPZs) which are unfenced areas within larger protected areas (Okita-Ouma et al., 2007; Landman et al., 2013). Within any sanctuary or protected area, it is crucial to carefully manage the population size to ensure it remains slightly below the Ecological Carrying Capacity (ECC), a measure essential for the growth of the global black rhino population (Omari, 2009). This approach often involves the selection of individuals from populations with positive growth rates, which are then translocated to alternative areas with the potential to sustain new populations (Linklater et al., 2012).

The Ngorongoro Conservation Area (NCA) in Tanzania is an unfenced protected area that serves as a crucial stronghold for the black rhino population, hosting approximately 30% of the country's total population (Kohi and Lobora, 2019). In the 1960s, the black rhino population was comprised of 108 individuals in the Ngorongoro Crater (NC) and 69 in Oldupai Gorge (Goddard, 1968). Heavy poaching reduced that population to 13 individuals in 1996 (Goddard, 1967, 1968; Kiwia, 1989; Moehlman et al., 1996). By 2018 the population had increased to 55 individuals (11 probable) in the Crater, but there were none in the Oldupai area (Kohi and Lobora, 2019). Despite this increase, and absence of poaching, the NCA population has not reached previous numbers and feeding behaviour and preferences have not been surveyed since the 1960s (Goddard, 1968; Kohi and Lobora, 2019). Additionally, habitats frequented by rhinos have likely changed through human activities, increased numbers of other herbivores, spread of invasive plants and changes in management policy (Niboye, 2010; Borges et al., 2022). Examining rhino diet in the NCA serves as a vital tool for assessing whether specific areas still provide adequate food resources and for identifying areas for potential translocations.

The NCA has been operating as a multiple land-use model, aiming to protect not only wildlife but also the traditional lifestyle of the resident Maasai pastoralists (Amiyo, 2006; Niboye, 2010). Expanding human settlements, agricultural activities, and infrastructure development have resulted in habitat fragmentation and escalated human-wildlife conflicts within the area (Kideghesho et al., 2021; Linuma et al., 2022). Simultaneously, undesirable invasive plant species have proliferated extensively within the NCA and now cover most of the Crater floor, leading to a decline in habitat quality for wildlife (Foxcroft et al., 2006; Ngondya et al., 2016, 2019). However, the NCA stands out as a particularly unique ecosystem where rhinos coexist within human-modified landscapes, a phenomenon rarely studied as most research focuses on protected areas devoid of human presence. These distinct characteristics may provide valuable insights into the dynamics of wildlife conservation in landscapes where human and natural elements intersect, offering important lessons for conservation efforts in similar contexts worldwide.

Feeding studies on black rhino provide essential insights into foraging behaviour and dietary preferences, facilitating a better understanding of their ecological role of rhinos and their habitat requirements (Goddard, 1968; Emslie and Adcock, 1994; Buk and Knight, 2010). Furthermore, such studies contribute to global conservation efforts by identifying key areas that can sustain a populations of black rhino (Muya and Oguge, 2000; Reid et al., 2007; Omari, 2009). Our ultimate goal is to contribute to the long-term conservation of black rhinos in the NCA and to achieve this, we (1) determined the variables that affect rhino presence and feeding; (2) identified species preferred by rhino (3) identified areas that can sustain a future black rhino.

## 5.2 Study Area

The NCA (Figure 5.1), located in northern Tanzania, is a World Heritage Site that is part of the Serengeti ecosystem and includes the world's largest intact volcanic caldera, the Ngorongoro Crater (Estes et al., 2006). The temperature ranges between 7° and 15°C in the rain season and 11° and 20°C in the dry season and altitude between 1000m and 3800m y (Herlocker and Dirschl, 1972; Amiyo, 2006). Annual rainfall ranges from 450mm/year in the lowlands to 1200 mm/year in the highlands (Boone et al., 2006). The rainfall follows a bimodal pattern, consisting of two wet seasons (March to May and October to December), and two dry seasons (January to February and June to October, Mwabumba et al., 2022). The vegetation in the NCA is highly diverse and comprises highland grassland plains, open canopy savannah woodland, closed canopy forests, and savannah grasslands (Herlocker and Dirschl, 1972; Borges et al., 2020). However, in recent decades, the area has experienced woody encroachment and a loss in forest and grassland cover (Borges et al., 2022).

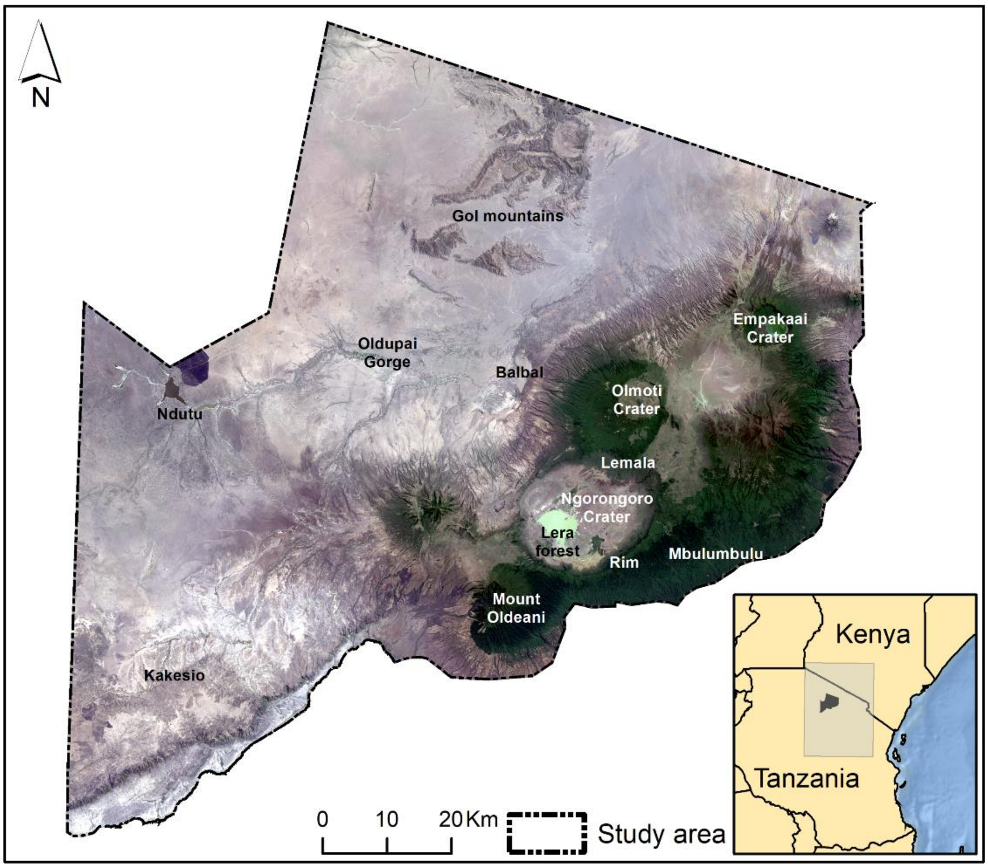

Figure 5.1. Ngorongoro Conservation Area with key regions highlighted.

## 5.3 Methods

### 5.3.1 Data collection

Vegetation surveys were conducted in the NCA for a period of 6 months during the wet season (March - June 2023) and dry season (June-September 2023). The locations comprised of areas known to be frequented by rhinos (following the rhino monitoring teams' advice), areas where direct observations occurred or rhino signs were found (e.g. bites in plants, dung piles, tracks) and in 'control' locations where there was no prior evidence of rhino occupation, and which covered the range of different vegetation types of the NCA. The GPS coordinates for the random locations were extracted from 1x1km grid over an NCA map. In total we sampled in 13 different regions as shown in Figure 5.1. The Crater floor is mostly grasslands (from here onwards Crater grasslands) and the Lerai forest comprises of woodland and bushland, and as in Goddard's (1968), the two were sampled separately (Figure 5. S1.; Herlocker and Dirschl, 1972).

At sampling locations (136 in the dry season and 136 in the wet season) the vegetation was sampled in 30m diameter circular plots. The centre of the plot was marked, XY coordinates recorded and two 30m tape measures were laid out in a cross shape aligned with the cardinal compass points (Appendix 1 Figure 5.S1.)

To calculate an index of browse availability, herbs, shrubs, and trees whose canopies overlapped at least one of the measuring tapes were recorded and an estimate of their volume calculated (Appendix 1 Figures 5.S1 and S2). Only vegetation <2m was included, since rhinos are unable to reach heights above 2m (Muya and Oguge, 2000). To calculate the volume of each individual plant, a shape was chosen (sphere, cylinder, cube/cuboid, or cone) and the measurements for each collected (Appendix 1 Figure 5.S2). For shrubs and trees which crossed over the 2m limit, only the portion below the limit was included. When more than one species was present within a clump, the proportion that each species contributed to the clump was estimated and then attributed a shape.

Each plant was inspected for black rhino bite marks which have a distant sharp-cut edge at 45° angle (Gadiye, 2016). When a bite was encountered, the species and a rough estimate of time (over 1 week or under 1 week) of bite were recorded following the ranger's advice. A description of the area and the main grass species within the plot were noted and all trees (DBH>6cm), were identified, and their diameter measured (at 1.5m from the ground) and damage to the plants caused by elephants was recorded as zero (no damage), low (some twigs, small branches damaged) and extensive (major branches, broken trees). Any other evidence of elephant or rhino such as within the plot was also recorded.

The presence of invasive species was also recorded. Invasive plants are native or non-native species that aggressively spread in new environments, outcompeting native vegetation and disrupting natural ecosystems (Ngondya et al., 2016). In the NCA the most common invasives are *Gutenbergia cordifolia* (native)*, Bidens schimperi* (native)*, Datura stramonium* (non-native)*, Tagetes minuta* (non-native)*, Argemone mexicana* (non-native), *Lippia javanica* (native) and *Eleusine jaegeri* (native, Ngondya et al., 2016, 2017).

Canopy cover was measured every 5m along each tape, including one at the plot centre (13 total). For each reading, a sighting was taken ‘the wrong way’ through one side of 8x binoculars. A score from 0 to 5 was recorded based on what percentage of the view was covered by canopy. 0=no cover, 1=20%, 2=40%, 3=60%, 4=80%, 5=100%. A complete canopy cover would have a score of 65 (5 x13). Density (mid-level density) was measured using a 2m pole. One recorder stood at the centre of the plot and another at the end of each tape (N, E, S and W) holding the pole horizontally 1m above the ground. The central recorder uses 8x binoculars to count the number of bands that can be seen (not obstructed by vegetation). Readings should vary between 0 in very dense plots to 160 in very open ones. Lastly, ground cover was also measured. The 2m pole was placed every 1m along each arm of the tape measure and the height of grass (if present) recorded. The type of substrate which the end of the pole touched and any substrate/low level vegetation within 10cm (hand width) of the base of the pole, was also recorded. Ground cover categories were – live grass, dead grass, rock, bare soil, herb or tree.

### 5.3.2 Statistical analysis

*Habitat Variables*

The mean and standard deviation of several habitat variables (canopy cover, vegetation density, grass height (cm), ground cover (dead grass, live grass, soil, herbs, shrubs, tree and rock), browse available, elephant presence (1) or absence (0)) was calculated for plots with evidence of rhino presence rhino and plots without evidence. The analysis was conducted using R version 4.3.1. A Permutational multivariate analysis of variance (PERMANOVA) was employed to determine if these variables, seasons and regions influence black rhino presence (Anderson, 2001; Oksanen et al., 2022). PERMANOVAs are commonly used in community ecology to compare the multivariate structure of ecological communities. It is particularly valuable because it allows for the comparison of different communities even when the data are not normally distributed (Anderson, 2001). This is achieved by using permutation tests, which are robust to violations of normality assumptions. This method assesses whether there are significant differences among groups of samples (e.g., communities) based on dissimilarity or distance matrices derived from ecological data.

The adonis2 function was used within the vegan package with 999 permutations, and the data were tested to ensure the assumptions for the PERMANOVA were met using the betadisper function (VEGAN package, Appendix 1 Figure 5.S3, Oksanen et al., 2022). Although homogeneity of variances (or group dispersions) is not a strict prerequisite for PERMANOVA, it significantly impacts the outcomes, in conjunction with data independence (Anderson et al., 2008). Therefore, testing dispersion alongside PERMANOVA is particularly beneficial with smaller datasets, as a significant result could indicate that disparities in variances contribute to observed discrepancies in PERMANOVA result (Anderson et al., 2008).

### *Random forest modelling*

We employed random forest (RF) to determine which variables were the best performers in terms of classifying the presence and absence plots. RF is a nonparametric machine learning classifier that combines decision trees with bootstrapping and aggregation (Breiman, 2001; Rodriguez-Galiano et al., 2012). Twenty-one variables were tested against rhino bites. The data was randomly split and 70% was used to train the random forest model and 30% to perform the validation (Breiman, 2001).

The analysis yields a 'variable importance' graph, which shows the ‘mean decrease in accuracy’ measure for each of the variables. These measures indicate each variable’s impact on the model in predicting outcomes and distinguishing between absence and presence sites (Garzón et al., 2006). A decrease in prediction accuracy when a particular variable is randomly permuted, indicates the variable's importance in maintaining the model's accuracy (Han et al., 2016).

*Browse Preferences*

The volume of the individual plants of each species with bites was calculated and compared to the total volume available of that species. Browse preference was assessed using Ivlev's (1961) electivity index as follows:

$$Ei = \frac{(ri - pi)}{(ri + pi)}$$

Where $E_i$ is the measure of electivity, $r_i$ is the volume of eaten species *i*, and $p_i$ is the total volume of species *i*. The index ranges between 1 and -1, where -1 indicates total avoidance, 0 indicates no selection or avoidance, and 1 indicates total selection.

## 5.4 Results

### 5.4.1 Drivers of rhino presence

*Season and region*

The results from the perMANOVA test found that rhino presence is impacted by Region (F =10.71, p-value = 0.001) and relatively less by Season (F =3.24, p value = 0.052). During the wet season most rhino presence occurred in the Crater grasslands (69.8%). During the dry season rhino presence occurred mostly in the rim (32.6%), followed by Lerai forest (28.3%), Lemala (21.7%) and the Crater grasslands (17.4%, Figure 5.2).

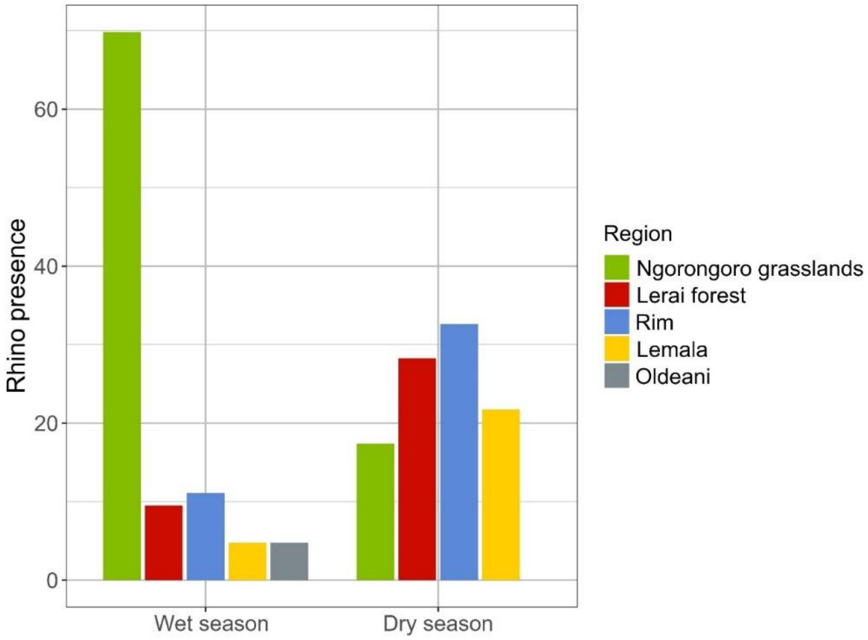

Figure 5.2. Proportion of black rhino presence per season.

*Habitat variables*

Rhino presence was associated with areas with higher canopy and shrub cover and lower soil and rock cover. There is also a preference for sites with lower vegetation density and lower browse availability. Rhino and elephant frequented the same regions (Table 5.1).

Table 5.1 Comparison of mean values and standard deviation of the statistically significant variables between black rhino presence and absence.

| Rhino | Presence<br>Mean (sd) | Absence<br>Mean (sd) | F | *p-value* |
|---|---|---|---|---|
| Canopy cover | 16.4 (15.9) | 14.3 (15.5) | 2.71 | 0.02 |
| Density | 43.8 (56.9) | 55.1 (62.6) | 4.39 | 0.001 |
| Browse available (per plot) | 80.6 (130.6) | 94.2 (107.6) | 6.51 | 0.001 |
| Soil coverage | 11.6 (11.9) | 19.1 (20.2) | 2.09 | 0.019 |
| Shrub coverage | 21.3 (12.6) | 19.4 (15.0) | 2.16 | 0.02 |
| Rock | 1.04 (5.46) | 3.92 (10.1) | 1.91 | 0.028 |
| Elephant presence | 0.70 (0.46) | 0.39 (0.49) | 1.91 | 0.032 |

### 5.4.2 Random Forest modelling

Our model shows that rhino choice depends on plant species and browse availability (Figure 5.3). Grass cover, region and season are other drivers of rhino choice (Figure 5.3). Browse availability, elephant presence, shrubs, soil and herb coverage influence both rhino presence (Table 5.1) and rhino food choice (Figure 5.3). The out-of-bag (OOB) prediction accuracy of the model was 11.18%. When the model was validated against the test data, the overall accuracy 89.3% (p <0.001, McNemar’s test p=0.04, Table 5.2). The model also identified sites in the Rim and Oldupai currently unoccupied by black rhino that have similar characteristics and species composition to areas where rhino is currently present (Table 5.2, Appendix 1 Tables 5.S1 and S2).

Table 5.2 Confusion matrix for the random forest model.

| | Actual | | Class |
|---|---|---|---|
| Predicted | Absence | Presence | error |
| Absence | 152 | 11 | 0.07 |
| Presence | 16 | 93 | 0.15 |

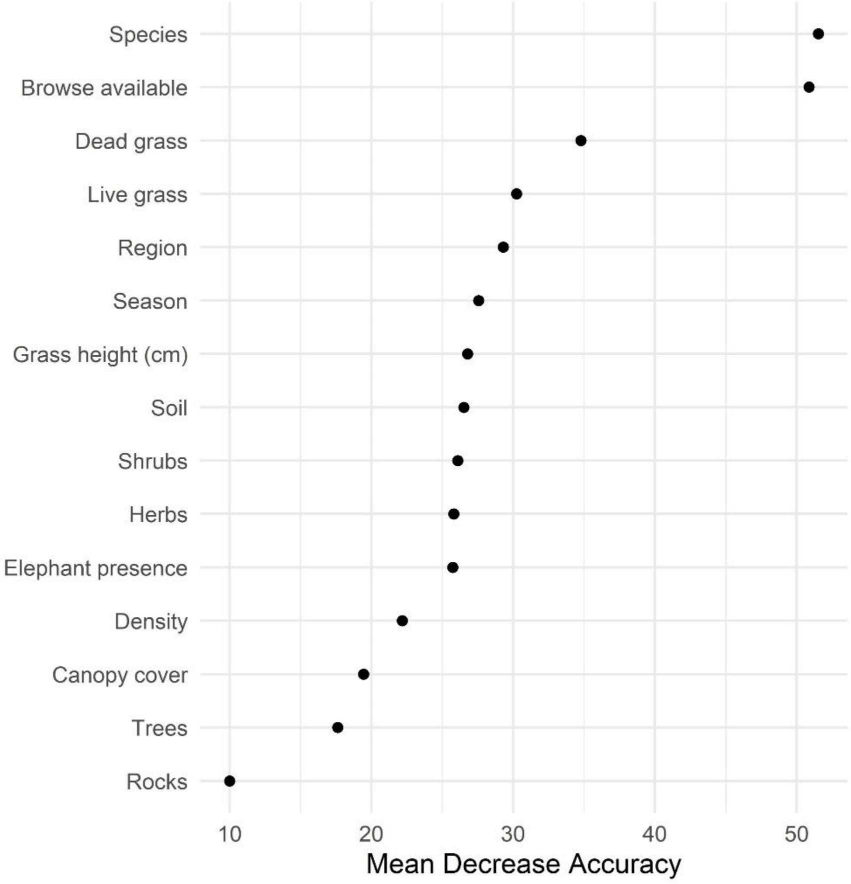

Figure 5.3 Variable importance generated from the randomforest model.

### 5.4.3 Species preferred by rhino

Of all the species browsed by rhino (Appendix 1 Table 5.S4), the Ivlev's (1961) electivity index revealed a strong preferences for *Cyperus imensus* (E = 85.1%) and *Schoenoplectiella confusa* (E = 84,9%) which are both present in the swamps in the Ngorongoro Crater. There was also 'rejection' of *Gutenbergia cordifolia* (E = - 14.9%) an invasive species now widespread throughout the NCA, *and Lippia javanica* (E = - 29.4%) a shrub that is encroaching the Crater grasslands. Only species that were bitten more than 6 times are present in Table 5.3 but the full data is available in Appendix 1 Table 5.S4.

Table 5.3 List of species preference by rhino based on bites and availability. (i) stands for invasive species.

| *Species* | *Bites* | *Times present* | *Preference (E)* |
|---|---|---|---|
| *Cyperus imensus* | 12 | 12 | 0.851 |
| *Schoenoplectiella confusa* | 39 | 47 | 0.848 |
| *Amaranthus hybridus* | 15 | 93 | 0.608 |
| *Ludwigia stolonifera* | 12 | 18 | 0.607 |
| *Aeschynomene schimperi* | 19 | 28 | 0.571 |
| *Nicoteba betonica* | 12 | 39 | 0.528 |
| *Abutilon mauritianum* | 38 | 119 | 0.521 |
| *Lantana trifolia* | 90 | 127 | 0.475 |
| *Pavonia urens irakuensis* | 13 | 60 | 0.472 |
| *Bidens pilosa* | 18 | 104 | 0.431 |
| *Achyranthes aspera* | 149 | 398 | 0.376 |
| *Baccharoides lasiopus* | 11 | 37 | 0.344 |
| *Clausena anisata* | 8 | 30 | 0.276 |
| *Pavonia urens* | 54 | 152 | 0.097 |
| *Abutilon longicuspe* | 57 | 166 | 0.041 |
| *Meiosperma bracteatum* | 14 | 164 | 0.008 |
| *Gymnosporia senegalensis* | 9 | 145 | -0.147 |
| *Gutenbergia cordifolia* (i) | 12 | 272 | -0.149 |
| *Lantana ukambensis* | 20 | 128 | -0.210 |
| *Solanum incanum* | 17 | 367 | -0.216 |
| *Lippia javanica* (i) | 36 | 228 | -0.294 |
| *Hibiscus aponeurus* | 13 | 140 | -0.376 |
| *Crotalaria vallicola* | 7 | 27 | -0.379 |
| *Tagetes minuta* (i) | 26 | 308 | -0.411 |
| *Cyathula polycephala* | 7 | 90 | -0.491 |
| *Hibiscus fuscus* | 27 | 111 | -0.530 |

| | | | |
|---|---|---|---|
| *Sida cuneifolia* | 24 | 46 | -0.614 |
| *Indigofera arrecta* | 12 | 41 | -0.748 |
| *Ocimum gratissimum* | 17 | 189 | -0.787 |

## 5.5 Discussion

### 5.5.1 Crater grasslands and Lerai forest

Understanding the dietary preferences and habitat use of black rhinos is crucial for their effective management (Goddard, 1968; Emslie and Adcock, 1994; Buk and Knight, 2010). The Ngorongoro Crater is often regarded as the most suitable habitat for black rhino within the NCA boundaries (Gadiye, 2016) but it is clear that the rhinos move between different regions depending on season, to fulfil their nutritional needs (Figure 5.2, Table 5.1, Goddard, 1968; Gadiye, 2016). During the wet season, rhino presence was most obvious in the Crater grasslands (69.8%, Figure 5.2). Rhinos can survive in a wide range of habitat but previous research carried out in the Masai Mara, found that most rhinos occurred in open grasslands and shrubland with a few scattered trees, particularly during feeding (Mukinya, 1977).

During the dry season rhino presence occurred in the rim (32.6%), Lerai forest (28.3%) and Lemala (21.7%). The Crater grasslands accounted for only 17.4% of the rhino presence plots (Figure 5.2). Rhino diet in the Ngorongoro Crater during the wet season comprises mostly of herbs, forbs and legumes (Goddard, 1968; Gadiye, 2016). These tend to disappear or dry up during the dry season and shrubs such as, *L.javanica* become more important (Goddard, 1968; Gadiye, 2016). We found that, although *L.javanica* is part of their diet, it is often under-used and it only makes up for a small part of their overall diet (Table 5.2, Goddard, 1968). As black rhinos are water-dependent browsers. It is not surprising that they use the Lerai forest more in the dry season – it has a supply of water throughout the year and many of the plants remain in leaf even during the dry season (Herlocker and Dirschl, 1972; Mills et al., 2003).

The three most preferred species, *Cyperus imensus* (E = 85.1%) and *Schoenoplectiella confusa* (E = 84,9%) and *Aeschynomene schimperi* (E = 57.1%) are abundant in the swamps in the Crater floor (Table 5.2, Goddard, 1968). These species are heavily browsed by rhino during the dry season and since the swamps have water available throughout the year, they become increasingly important as the dry season approaches (Goddard, 1968; Gadiye, 2016). In the 1960s, swamps were regularly used by black rhinos for shelter and browsing, but more recent research suggested that rhinos no longer visited these areas because of elephant presence (Klingel and Klingel, 1966; Goddard, 1968; Amiyo, 2006; Landman et al., 2013). We found that rhinos are using the swamps throughout the year, irrespective of the elephants – there was a positive relationship between the presence of rhino and elephant (Table 5.1).

One of the biggest threats the NC is currently facing is the spread of invasive plant species (Mills et al., 2003; Kohi and Lobora, 2019). We found evidence of bites in most of the invasive species in the NC, including dried plant parts during the dry season but all were under-used (e.g. *G. cordifolia, T. minuta, B. schimperi*, Table 5.2, Appendix 1 Table 5.S4). These findings contrast with previous research that found a strong preference for *G. cordifolia* during the wet season and avoidance of dried specimens (Goddard, 1968; Gadiye, 2016). Ultimately, all the preferred species (Table 5.2) were part of rhino diets in the NC in the 1960s, which shows that the Crater is still a suitable site for black rhino in terms of browse availability as well as security (Goddard, 1968).

### 5.5.2 Rim and Lemala

The rim surrounds all of the Crater and is an isolated area that is often described as ideal black rhino habitat, comprising montane forest and bushland communities (e.g. *Vachellia lahai, Nuxia congesta, Bersama abyssinica, Cassipourea molassana,* Herlocker and Dirschl, 1972). Although Lemala is geographically close to the rim, the vegetation composition includes mostly shrubland and patches of grassland (Herlocker and Dirschl, 1972; Borges et al., 2020, 2022). The combination of the rim (32.6%) and Lemala (21.7%) accounted for 54.3% of rhino presence during the dry season (Figure 5.2). During the wet season black rhino fed in proximity to wallow sites, seasonal streams, and waterholes but when these dry up, they move to areas with permanent water supplies (e.g. riverine habitats, manmade reservoirs) and evergreen palatable herbs and shrubs (Oloo et al., 1994). Although black rhino diet in Lemala and the rim has not been studied before, Gadiye, (2016) also noted the movement of rhinos from the Crater floor to the Rim during the dry season. This shift in feeding areas will influence diet composition (Goddard, 1968; Gadiye, 2016).

The rim vegetation is dominated by a mosaic of *Gymnanthemum auriculiferum* and *Crotalaria agatiflora* (Herlocker and Dirschl, 1972). *Pavonia urens irakuensis*, *Clutia* *abyssinica, Lantana trifolia* and *Lippia javanica* are also abundant (Table, 5.S3, Herlocker and Dirschl, 1972). These species are all browsed by rhino (Appendix 1 Table 5.S4), however there is as strong preference for *L. trifolia* (47.5%) and *P. urens irakuensis* (47.2%, Table 5.2). *Eleusine jaegeri* commonly known as 'highland tussock grass' (locally called 'buffalo grass') is also present in the rim, and it has expanded its range since the 1960s (Table 5. S3 and S4, Herlocker and Dirschl, 1972; Amiyo, 2006). It is highly unpalatable for livestock and other herbivores, raising concerns of the loss of palatable plant species, however we did find evidence of rhino bites in some specimens (Appendix 1 Table 5.S4). This is not completely surprising since black rhinos are known to consume toxic species, and previous research also shows evidence of rhinos consuming *E. jaegeri* in the NCA (Goddard, 1968).

The model predicted that the rim includes several sites deemed suitable for black rhino that are currently unoccupied by rhino (Appendix 1 Table 5.S1). Land cover changes in these areas have contributed to an increase in bushland and shrubland, thereby enhancing the availability of browse—a critical factor for rhino shelter and breeding (Figure 5.3, Table 5.1, Roques et al., 2001; Smit et al., 2010; Borges et al., 2022). Moreover, the rim contains an abundance of preferred browse for feeding and a constant water supply throughout the year (Table 5.3 and 5.S3, Herlocker and Dirschl, 1972). The northern part of the Crater, between the NC and Olmoti, which is included within the rim, combines the ideal vegetation composition, and remains relatively isolated from human disturbances, both tourists and settlements (Muntifering et al., 2021). This unique combination of characteristics renders the area ideal habitat for a potential expansion of the black rhino population in the NCA. It can be accessed through Lemala which was also deemed suitable for black rhino, thus further expanding the potential range and connectivity of habitats available for rhinos within the broader Rim region.

### 5.5.3 Oldupai Gorge Area

Historically, the Gorge was part of a corridor between the Ngorongoro and the Serengeti National Park (D. Maige, NCAA, 2023, *pers. comm.*). Rhinos used to migrate from the Crater to the Rim, towards Balbal and through Oldupai Gorge, to Ndutu and to the Serengeti (D. Maige, NCAA, 2023, *pers. comm.*). In the 1960s, there was a population of 69 rhinos in the Oldupai area but after heavy poaching, during the 1970s and 80s, it disappeared (Kiwia, 1989; Moehlman et al., 1996; Oates and Rees, 2013). Our results show that the area is still suitable for black rhino (Appendix 1 Table 5.S1). Oldupai is characterized as typical thornbush habitat, covered in *Acacia-Commiphora* scrub, mixed with extensive growths of wild sisal *Sanseveria ehrenbergii, Euphorbia tirucalli, Salvadora persica*, and *Barleria eranthemoides* (Goddard, 1967; Herlocker and Dirschl, 1972). This habitat combines lower vegetation density and browse availability but higher shrub cover which are all positively associated with rhino presence (Table 5.1). The shrubs that cover the area are shorter than in other places in the NCA, which is why the density and browse available are also lower in these areas (Table 5.1, Herlocker and Dirschl, 1972). This suggests that rhinos prefer sites with browse that is available <1m of height, so although the volume is lower, it is physically easier for them to reach than between 1 to 2m.

Currently, all the species that were part of rhino diet in the 1960s still occur in Oldupai and surrounding areas (Table, 5.S2, Goddard, 1968). This was somewhat unexpected due to land cover changes, namely the shrub encroachment the area experienced in the last few decades, however, this increase could also mean an associated increase in preferred browse (Borges et al., 2022). During the dry season, Oldupai becomes much drier than the Crater and most water sources dry up (Goddard, 1968). Since season plays an important role in rhino presence, regions like Oldupai will experience a greater impact than places like Oldeani and the rim, that mostly support evergreen species (Figure 5.2, Oloo et al., 1994). In the 1960s, rhinos that resided in the Gorge were consuming *Euphorbia tirucalli*, *Sansevieria ehrenbergii* and *Cissus quadrangularis* during the dry season for their water content (Goddard, 1968). Interestingly, we also found evidence of bites in *Euphorbia tirucalli,* however, this occurred in a different region of the NCA (Appendix 1 Table 5.S4).

The Oldupai area has high numbers of livestock and settlements, and the road that links the NCA to the Serengeti (Herlocker and Dirschl, 1972). During the dry season the grasslands appear to be over-grazed but during the wet season, herbs such as *Solanum incanum, Indigofera basiliora,* and *Indigofera bogdanii* rapidly emerge which seems to benefit black rhino (Goddard, 1968). The *Indigofera* species are known to be very palatable to rhinos and *Indigofera basiliora,* is particularly important during the dry season where it is still available (Appendix 1 Table 5.S2; Goddard, 1968). As such, regions classified as suboptimal grazing pastures for other herbivores*,* could provide suitable habitat for rhinos (Goddard, 1967, 1968). Therefore, heavily overgrazed areas should not be viewed as inherently detrimental; rather, they may be regarded as an integral component of an ecosystem that sustains a diverse array of herbivores (Goddard, 1967, 1968).

The Oldupai region was identified as potentially suitable for rhino habitat based on its ecological characteristics; however, it's crucial to consider the presence of humans, which was not explicitly measured in our assessment. Rhinos tend to avoid areas with human activity, highlighting the need to assess and mitigate human presence in potential reintroduction areas (IUCN, 2013; Muntifering et al., 2021, Chapter 4). Additionally, security concerns related to poaching must be addressed and intense monitoring must be achievable before recommending an area for rhino reintroduction (IUCN, 2013). These factors underscore the importance of comprehensive assessments that account for both ecological suitability and human-related factors when evaluating potential reintroduction sites for critically endangered species like the black rhino.

## 5.6 Conclusion

We examined the dietary habits of black rhinos in the Ngorongoro Conservation Area across wet and dry seasons, relying on observable signs as indicators of rhino presence, namely bites in plants, dung piles and direct observations (Gadiye, 2016). The NCA includes a diverse range of habitats, each playing a crucial role in supporting rhino populations through different seasons (Figure 5.2). The ideal habitat for rhino comprises of areas with higher canopy cover and rich in shrubs <1m that are easy to reach, instead of heavily dense areas. Seasonal variations significantly impacted rhino diets, leading to noticeable changes in feeding patterns. The Ngorongoro Crater emerges as a critical habitat for rhinos, particularly during the wet season when palatable herbs dominate the floor (Figure 5.2).

During the dry season, when the Crater vegetation dries, rhinos shift in their distribution patterns, favouring areas such as the rim, Lemala and the Lerai forest where water sources and preferred browse remain available throughout the year. The rim, characterized by montane forest and bushland communities, provides promising habitat for rhinos, offering both shelter and a variety of browse options (Herlocker and Dirschl, 1972). The presence of rhinos in these areas underscores their adaptability to different habitats and the significance of these regions in sustaining populations year-round.

The Oldupai Gorge area was flagged as suitable rhino habitat, despite historical declines in rhino populations due to poaching (Goddard, 1968). The habitat characteristics of Oldupai, namely the thornbush habitat and vegetation composition, show its potential suitability for future rhino populations. However, human presence and security concerns related to poaching pose significant challenges that need to be addressed before considering this area for rhino reintroduction efforts. By addressing both ecological suitability and human-related factors, we can ensure the success of conservation initiatives aimed at safeguarding critically endangered species like black rhinos. Comprehensive assessments that combine habitat suitability, human activity, and security concerns are crucial in identifying suitable reintroduction and translocation sites and ensuring the long-term survival of rhino populations (IUCN, 2013).

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## 5.8 Appendix 1

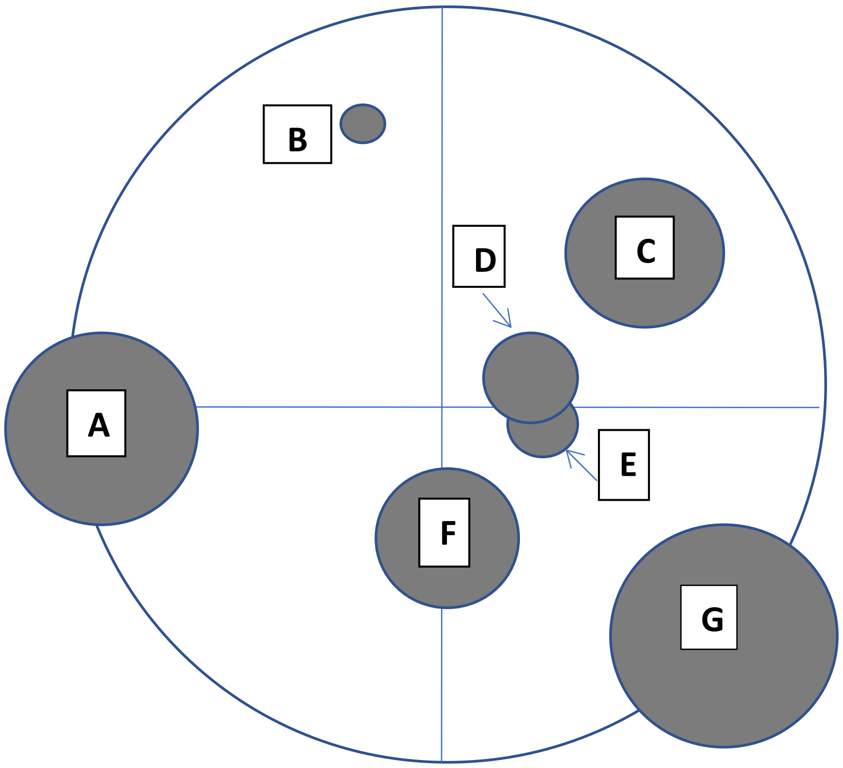

Figure 5.S1. Estimate browse availability (BA) – trees/bushes A, D, E and F would be in the sample, B, C and G would not.

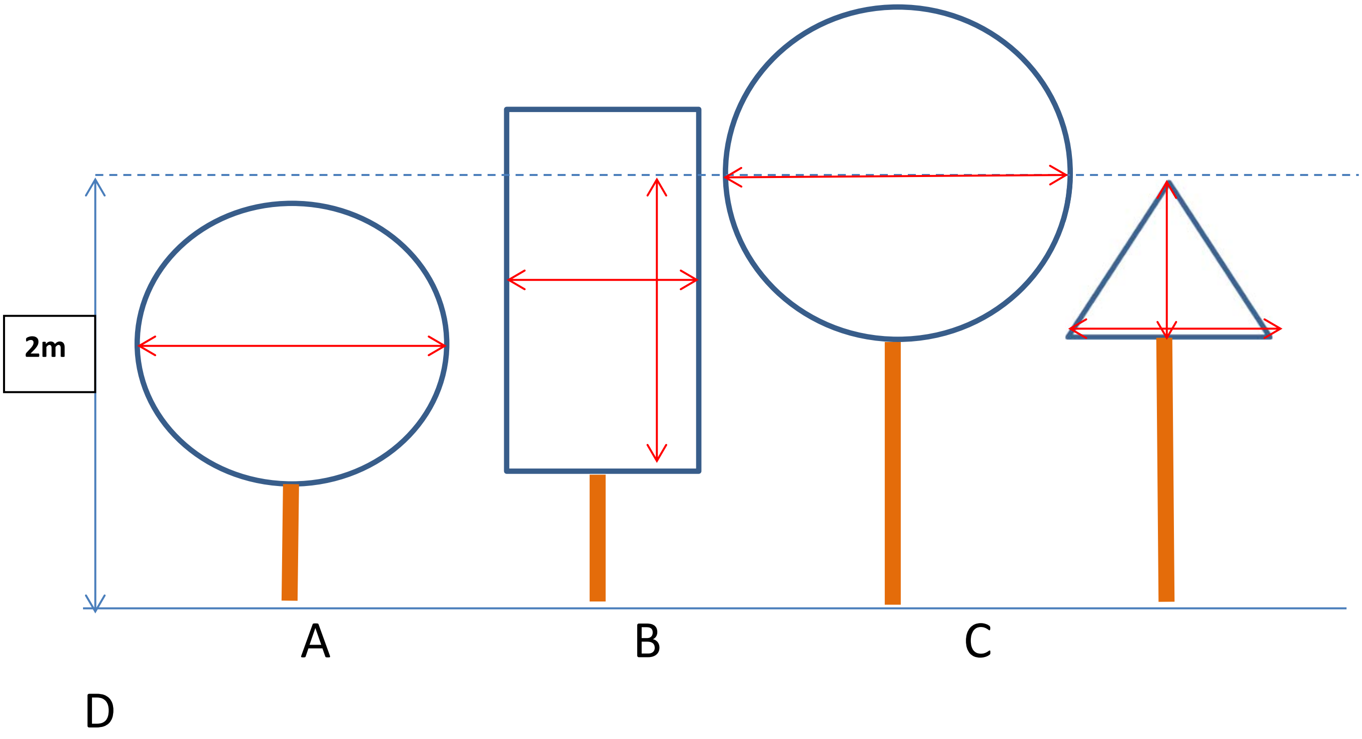

Figure 5.S2. Calculate the volume of browse <2m. D may be the other way up! For C, calculate the volume of a hemisphere.

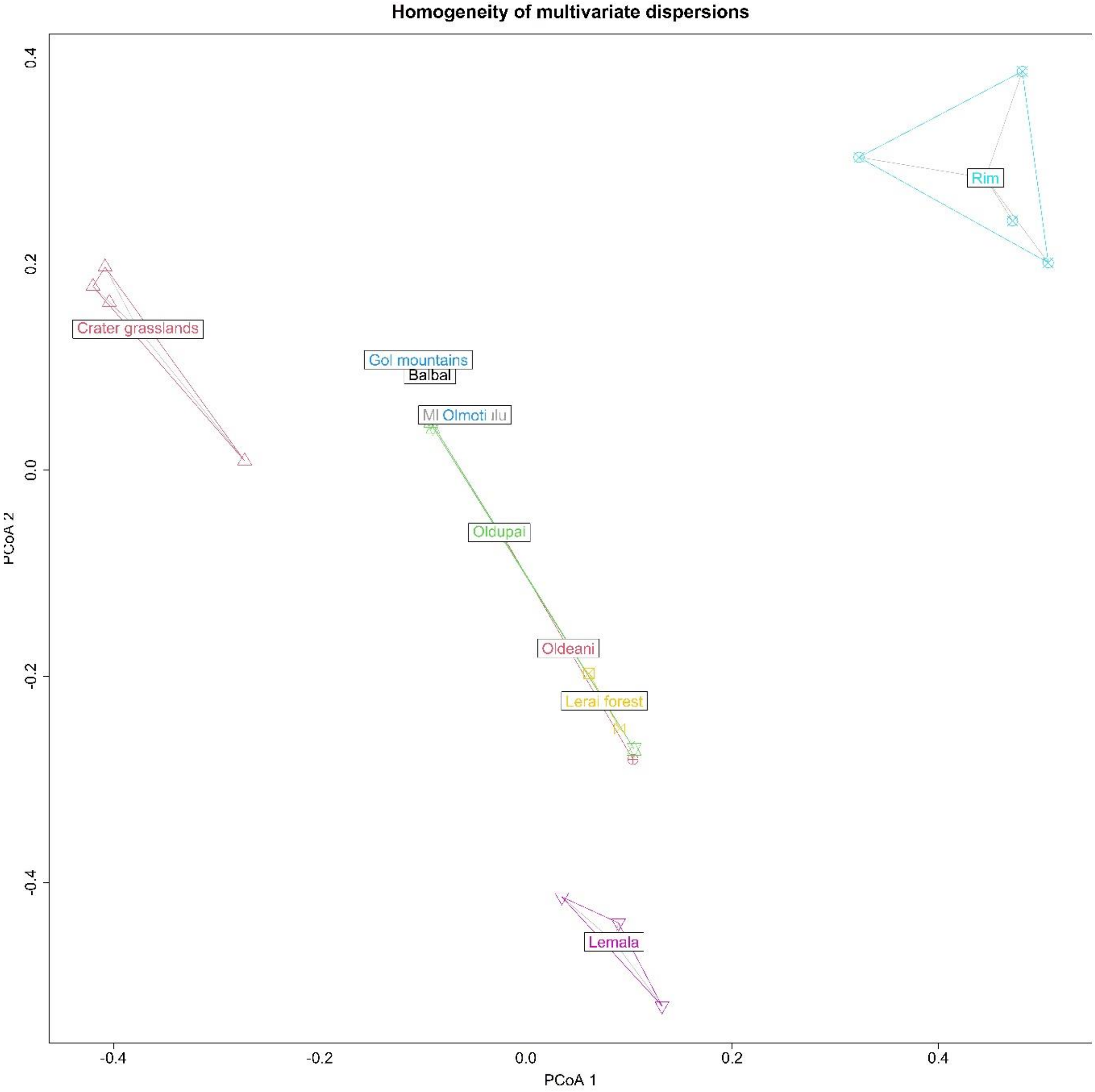

Figure 5.S3. Homogeneity of multivariate dispersions results showing the differences between sites. Empakaai, Olmoti, Kakesio, Ndutu, and Mbulumbulu overlap completely because the average distance to centroid is 0.

Table 5.S1. Location of plots currently unoccupied by black rhino

| | Predicted plots |
|---|---|
| Oldupai Gorge | 7 |
| Rim | 5 |
| Ngorongoro Crater | 3 |
| Balbal | 1 |

Table 5. S2 Plant species present in Oldupai

| Oldupai | | |
|---|---|---|
| *Abutilon mauritianum* | *Commiphora madagascariensis* | *Kalanchoe lanceolata* |
| *Abutilon rehmannii* | *Commiphora merkeri* | *Kleinia longiflora* |
| *Acacia drepanolobium* | *Cordia monoica* | *Lantana viburnoides* |
| *Acacia mellifera* | *Crotalaria laburnifolia* | *Leonotis spp.* |
| *Acacia nilotica* | *Cyathula orthacantha* | *Leucas deflexa* |
| *Acacia senegal* | *Cynodon dactylon* | *Lycium shawii* |
| *Acacia seyal* | *Cyphostemma lentianum* | *Maerua triphylla* |
| *Achyranthes aspera* | *Datura stramonium* | *Melhania parviflora* |
| *Aerva javanica* | *Dichrostachys cinerea* | *Nicoteba betonica* |
| *Aloe volkensii* | *Dracaena hanningtonii* | *Pupalia lappacea* |
| *Argemone mexicana* | *Eragrostis spp.* | *Ricinus communis* |
| *Asparagus flagellaris* | *Euphorbia tirucalli* | *Ruellia bignoniiflora* |
| *Aspilia pluriseta* | *Glinus lotoides* | *Salvadora persica* |
| *Atriplex brenanii* | *Grewia bicolor* | *Sansevieria ehrenbergiana* |
| *Balanites aegyptiaca* | *Grewia lilacina* | *Sarcostemma viminale* |
| *Barleria eranthemoides* | *Gutenbergia cordifolia* | *Senegalia mellifera* |
| *Blepharis hildebrandtii* | *Helichrysum glumaceum* | *Sida chrysantha* |
| *Boerhavia diffusa* | *Heliotropium curassavicum* | *Sida cordifolia* |
| *Boscia integrifolia* | *Hibiscus cannabinus* | *Solanum incanum* |
| *Capparis tomentosa* | *Hibiscus spp.* | *Solanum setaceum* |
| *Chenopodium opulifolium* | *Hypoestes forskaolii* | *Sphaeranthus bullatus* |
| *Cissus cactiformis* | *Hypoestes triflora* | *Tagetes minuta* |
| *Cissus quadrangularis* | *Indigofera arrecta* | *Talinum portulacifolium* |
| *Coleus igniarius* | *Indigofera basiflora* | *Tribulus terrestris* |
| *Coleus spp.* | *Ipomoea jaegeri* | *Vachellia abyssinica* |
| *Combretum apiculatum* | *Ipomoea longituba* | *Vachellia tortilis* |
| *Commiphora africana* | *Justicia betonica* | *Ximenia caffra* |
| *Commiphora kua* | *Justicia cordata* | |

Table 5. S3 Plant species present in the Rim

| Rim | | |
|---|---|---|
| *Abutilon longicuspe* | *Discopodium spp.* | *Ocimum gratissimum* |
| *Acacia seyal* | *Dolichos oliveri* | *Ocimum lamiifolium* |
| *Acalypha ornata* | *Dovyalis abyssinica* | *Olea africana* |
| *Achyranthes aspera* | *Ekebergia capensis* | *Osyris lanceolata* |
| *Amaranthus hybridus* | *Eleusine jaegeri* | *Ouret lanata* |
| *Asparagus africanus* | *Erythroxylum spp.* | *Pavonia burchellii* |
| *Asparagus asparagoides* | *Euclea divinorum* | *Pavonia urens* |
| *Aspilia mossambicensis* | *Euclea spp.* | *Pavonia urens irakuensis* |
| *Auclea simpliformis* | *Euphorbia candelabrum* | *Periploca linearifolia* |
| *Baccharoides lasiopus* | *Euphorbia murielii* | *Phyllanthus fischeri* |
| *Basella alba* | *Euphorbia spp.* | *Phytolacca dodecandra* |
| *Bersama abyssinica* | *Euphorbia terracina* | *Piper capense* |
| *Bidens pilosa* | *Euphorbia tirucalli* | *Psiadia punctulata* |
| *Bidens schimperi* | *Flacourtia indica* | *Rhamnus prinoides* |
| *Boscia angustifolia* | *Grewia similis* | *Rhamnus staddo* |
| *Boscia integrifolia* | *Gutenbergia cordifolia* | *Rhynchosia minima* |
| *Buddleja polystachya* | *Gymnanthemum auriculiferum* | *Rotheca myricoides* |
| *Cadaba farinosa* | *Gymnosporia senegalensis* | *Rubia cordifolia* |
| *Carissa spinarum* | *Helichrysum schimperi* | *Rubia spp.* |
| *Carthamus caeruleus* | *Helichrysum spp.* | *Salvia spp.* |
| *Cassipourea malosana* | *Heteromorpha arborescens* | *Salvia splendens* |
| *Catha edulis* | *Hibiscus aponeurus* | *Searsia natalensis* |
| *Celosia trigyna* | *Hibiscus fuscus* | *Searsia pyroides* |
| *Cenchrus sphacelatus* | *Hoffmannanthus abbotianus* | *Senecio hadiensis* |
| *Chenopodium opulifolium* | *Hypoestes aristata* | *Setaria pumila* |
| *Clematis brachiata* | *Hypoestes forskaolii* | *Sida ovata* |
| *Clematis simensis* | *Ipomoea indica* | *Solanecio sp* |
| *Clerodendrum johnstonii* | *Justicia elliotii* | *Solanum aculeastrum* |
| *Clutia abyssinica* | *Kalanchoe spp.* | *Solanum incanum* |
| *Coleus igniarius* | *Lannea spp.* | *Solanum nigrum* |
| *Coleus meyeri* | *Lantana trifolia* | *Solanum spp.* |
| *Commelina spp.* | *Lantana ukambensis* | *Sparrmannia ricinocarpa* |
| *Conyza pyrrhopappa* | *Lantana viburnoides* | *Sporobolus spp.* |
| *Crassocephalum sp* | *Lasiosiphon glaucus* | *Stephania abyssinica* |
| *Crotalaria agatiflora* | *Leonotis nepetifolia* | *Tagetes minuta* |
| *Crotalaria incana* | *Leonotis ocymifolia var. raineriana* | *Themeda triandra* |
| *Croton macrostachyus* | *Leucas deflexa* | *Urtica massaica* |
| *Cucumis spp.* | *Leucas glabrata* | *Vachellia drepanolobium* |
| *Cyathula orthacantha* | *Lipotriche scandens* | *Vachellia lahai* |

| | | |
|---|---|---|
| *Cyathula polycephala* | *Lippia javanica* | *Verbena officinalis* |
| *Cyathula uncinulata* | *Lippia rehmannii* | *Verbena spp.* |
| *Cyathula uniculata* | *Marsdenia abyssinica* | *Vernonia galamensis* |
| *Cynodon dactylon* | *Meiosperma bracteatum* | *Vernonia spp.* |
| *Cynoglossum coeruleum* | *Momordica foetida* | *Vernonia syringifolia* |
| *Cyperus rigidifolius* | *Nelsonia spp.* | *Withania somnifera* |
| *Cyphostemma lentianum* | *Neonotonia wightii* | *Zehneria scabra* |
| *Datura stramonium* | *Nicoteba betonica* | |
| *Diospyros abyssinica* | *Nuxia congesta* | |

Table 5.S4. Species browsed by rhino. (i) stands for invasive species.

| Species | Bites | Total |
|---|---|---|
| *Achyranthes aspera* | 149 | 398 |
| *Lantana trifolia* | 90 | 127 |
| *Abutilon longicuspe* | 57 | 166 |
| *Pavonia urens* | 54 | 152 |
| *Schoenoplectiella confusa* | 39 | 47 |
| *Abutilon mauritianum* | 38 | 119 |
| *Lippia javanica* | 36 | 228 |
| *Hibiscus fuscus* | 27 | 111 |
| *Tagetes minuta* (i) | 26 | 308 |
| *Sida cuneifolia* | 24 | 46 |
| *Lantana ukambensis* | 20 | 128 |
| *Aeschynomene schimperi* | 19 | 28 |
| *Bidens pilosa* | 18 | 104 |
| *Ocimum gratissimum* | 17 | 189 |
| *Solanum incanum* (i) | 17 | 367 |
| *Amaranthus hybridus* | 15 | 93 |
| *Meiosperma bracteatum* | 14 | 164 |
| *Pavonia urens irakuensis* | 13 | 60 |
| *Cyperus imensus* | 12 | 12 |
| *Gutenbergia cordifolia* (i) | 12 | 272 |
| *Indigofera arrecta* | 12 | 41 |
| *Ludwigia stolonifera* | 12 | 18 |
| *Nicoteba betonica* | 12 | 39 |
| *Baccharoides lasiopus* | 11 | 37 |
| *Gymnosporia senegalensis* | 9 | 145 |
| *Hibiscus aporeneus* | 9 | 41 |
| *Clausena anisata* | 8 | 30 |
| *Crotalaria vallicola* | 7 | 27 |
| *Cyathula polycephala* | 7 | 90 |
| *Chenopodium opulifolium* | 6 | 33 |
| *Commelina africana* | 6 | 8 |
| *Helichrysum schimperi* | 6 | 28 |
| *Hibiscus calyphyllus* | 6 | 8 |

| | | |
|---|---|---|
| *Hypoestes forskaolii* | 6 | 163 |
| *Sida ovata* | 6 | 96 |
| *Gymnanthemum auriculiferum* | 6 | 85 |
| *Pavonia burchellii* | 5 | 54 |
| *Hibiscus aponeurus* | 4 | 99 |
| *Vachellia xanthophloea* | 4 | 142 |
| *Aspilia mossambicensis* | 4 | 72 |
| *Vernonia galamensis* | 4 | 30 |
| *Capparis tomentosa* | 3 | 37 |
| *Clutia abyssinica* | 3 | 68 |
| *Coleus meyeri* | 3 | 14 |
| *Jasminum fluminense* | 3 | 3 |
| *Lantana viburnoides* | 3 | 14 |
| *Phyllanthus fischeri* | 3 | 17 |
| *Solanum aculeastrum* | 3 | 60 |
| *Sphaeranthus bullatus* | 3 | 26 |
| *Trichodesma zeylanicum* | 3 | 3 |
| *Bidens schimperi* (i) | 2 | 122 |
| *Coleus igniarius* | 2 | 22 |
| *Crotalaria incana* | 2 | 46 |
| *Cyathula orthacantha* | 2 | 20 |
| *Hypoestes aristata* | 2 | 76 |
| *Justicia betonica* | 2 | 39 |
| *Leucas bracteosa* | 2 | 65 |
| *Leucas deflexa* | 2 | 84 |
| *Vangueria madagascariensis* | 2 | 48 |
| *Amaranthus graecizans* | 1 | 16 |
| *Arundinaria alpina* | **1** | **5** |
| *Clematis simensis* | 1 | 37 |
| *Eleusine jaegeri* (i) | **1** | **28** |
| *Euphorbia tirucalli* | **1** | **18** |
| *Gomphocarpus fruticosus* | 1 | 9 |
| *Gorteria beguinotii* | 1 | 22 |
| *Kalanchoe lanceolata* | 1 | 19 |
| *Leonotis nepetifolia* | 1 | 35 |
| *Lippia rehmannii* | **1** | **10** |
| *Nepeta azurea* | 1 | 13 |
| *Ocimum lamiifolium* | 1 | 9 |
| *Phytolacca dodecandra* | 1 | 1 |
| *Searsia natalensis* | 1 | 18 |
| *Senecio hadiensis* | 1 | 29 |
| | | |

# Chapter 6 – General discussion

## 6.1 Motivation for the thesis

Black rhinos are umbrella species and play a key role in shaping landscapes and influencing vegetation dynamics through their feeding habits and interactions, they are therefore, essential in maintaining ecological balance, promoting biodiversity, and supporting the health of ecosystems (Augustine and McNaughton, 2006; Bergstrom, 1992; Wigley et al., 2014). In 1996, the black rhino was listed as a Critically Endangered species, in 2020 there were reported to be 1044 Eastern black rhinos (583 mature individuals) in the wild (Emslie, 2020). Despite its population gradually increasing, the growth rates are below 5% per annum, the minimum target accepted internationally to maintain genetic diversity (du Toit, 2006; Emslie et al., 2009). Previous conservation efforts focused on establishing protected areas, increasing security, using anti-poaching patrols and fencing (Brett, 1993). However, food availability and quality and genetics constrains are major contributors which need consideration if current populations are to be sustained and potentially grow. (Brooks and Adcock, 1997; Buk and Knight, 2010; Mills, 2006; Muya and Oguge, 2000; Omari, 2009).

To sustain viable rhino populations, it is essential to manage habitats within the ecological carrying capacity (ECC), optimizing breeding performance, minimizing death rates, and ensuring browse availability (Omari 2009, Knaini 2009). This is particularly important in small populations which are more vulnerable to environmental changes (Heywood et al., 1995). The habitat changes naturally over time and geographically, and habitat that was suitable for black rhino might become unsuitable (Amiyo, 2006; Reid et al., 2007). Studies on habitat preferences are vital to improve habitat quality and ensure appropriate management of the protected areas (Hazarika and Saikia, 2012; Omari, 2009; Reid et al., 2007). As the habitat changes, the rhino diets are also expected to be different when compared to old studies in the same site or between protected areas. Therefore, the need for site-specific feeding ecology studies using appropriate methods is paramount. Geospatial approaches such as habitat suitability models using satellite imagery and machine learning algorithms (e.g., Random Forest, MaxEnt) provide finer-scale spatial insights compared to traditional approaches (Breiman, 2001; Eisfelder et al., 2012; Kramer-Schadt et al., 2013; Yang and Prince, 2000). These methods allow for the prediction of rhino distribution by integrating various environmental factors namely vegetation types, water sources, and human disturbance data, which are critical in understanding habitat preferences and identifying potential new habitats for rhino populations (Garzón et al., 2006).

These studies can also be used to predict rhino distribution based on habitat usage using modelling to help identify suitable habitat which may not yet be occupied (Buk and Knight, 2010; Lush et al., 2015). Similarly, monitoring land cover changes using satellite imagery (e.g. through time-series satellite data), helps detect areas where habitat quality is degrading, enabling timely management interventions to maintain or enhance habitat suitability for rhinos and other wildlife (Borges et al., 2022). These insights are critical for guiding targeted conservation actions, such as mapping and creating wildlife corridors, prioritizing areas for habitat restoration, managing human-wildlife conflicts, and planning reintroduction programs to expand rhino habitat

The Ngorongoro Conservation Area (NCA), located in northern Tanzania, is a protected area that forms part of the Serengeti ecosystem and became a United Nations Educational, Scientific and Cultural Organisation (UNESCO) World Heritage Site, in 1979, for exceptional natural and cultural values (UNESCO, 2010). The density and diversity of wildlife in the NCA is of global importance for biodiversity conservation and economically important for Tanzania. The primary aim of this thesis was to critically evaluate the NCA’s capacity to sustain its growing Eastern black rhino population, thereby contributing valuable insights to conservation management in the region. The thesis is structured into four distinct chapters. I started by determining what was the best combination of satellites and seasons to map the main land cover types in the NCA (Chapter 2, Borges et al., 2020). Mapping the extent and the composition of savannah environments is challenging but essential to improve monitoring capabilities, prevent biodiversity loss and ensure the provision of ecosystem services. The outcome of the Chapter provided a high accuracy medium resolution land cover map, with the nine main vegetation types.

The recommendation on best performing season (short-dry season) from Chapter 2 was then applied in Chapter 3 (Borges et al., 2022) to identify and quantify the major land cover changes occurring in the NCA. Land cover changes threaten the wellbeing of livestock, the livelihoods of resident pastoralists and of the wildlife dependent on these grazing areas (Niboye, 2010; Swanson, 2007). Some of the land cover changes may be occurring naturally and caused by herbivory, climate change, rainfall patterns and vegetation succession, but many are linked to human activity, specifically, management policies, tourism development and the increase in human population and livestock (Homewood et al., 2001; Masao et al., 2015; Niboye, 2010). This study provides, for the first time, much needed and highly accurate information on long-term land cover changes in the NCA that can support the sustainable management and conservation of this unique UNESCO World Heritage Site (UNESCO, 2010). Additionally, it further highlights the importance of using remote sensing to monitor and assess changes in vegetation cover and habitat quality over time.

In Chapter 4 I identified potential black rhino habitat, for the wet and dry seasons and assessed how human activities impact habitat quality within the NCA. Additionally, I investigated how using field data combined with remote sensing provides more accurate predictions than solely using a land cover map (Chapter 2) and human disturbance data.

In Chapter 5, I investigated black rhino feeding preferences in the NCA and how it varies with season and region. Areas that experienced extensive land cover changes (e.g. Lerai Forest) and have been previously used by black rhino, and areas that were identified in Chapter 4 as suitable (e.g. between Olmoti Crater and NC) were studied in more detail (Borges et al., 2022; Goddard, 1968). Suitable areas, as identified by remote sensing, have a higher potential of supporting future populations, however, it is still essential to survey the vegetation to ensure there is preferable browse available for rhino.

This comprehensive approach, which combines mapping and quantifying land cover changes, assessing habitat suitability, and understanding dietary preferences, demonstrates how geospatial approaches directly support conservation goals. The integration of these techniques provides insights that are essential for sustaining and increasing the Eastern black rhino population in the Ngorongoro Conservation Area by enabling targeted conservation actions and effective management strategies.

## 6.2 Remote Sensing Applications in Savanna Management

Savannahs are heterogeneous environments with an important role in supporting biodiversity and providing essential ecosystem services. Due to extensive land use/cover changes and subsequent land degradation, the provision of ecosystems services from savannahs has increasingly declined over recent years (Schneibel et al., 2017; Symeonakis and Higginbottom, 2014). To monitor these changes effectively, specific geospatial tools, such as Sentinel-1, -2 and Landsat are used often. For 50 years, the Landsat archive has been the workhorse for vegetation and land cover mapping and monitoring, mainly due to its unparalleled archive. More recently, Sentinel-2 data with improved spatial and spectral resolution have also been successfully employed to map African savannah vegetation characteristics (Zhang et al., 2019). However, optical data come with their limitations, such as the presence of cloud coverage and the difficulty in discriminating between woody vegetation and grassland (Symeonakis et al., 2018). To address these inherent problems, a number of studies have combined Synthetic Aperture Radar (SAR) data (e.g., from the Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar, ALOS PALSAR; or Sentinel-1) with optical data to improve classifications, as SAR sensors are insensitive to cloud cover, discriminate woody vegetation effectively, and are, therefore, particularly helpful for savannah environments (Higginbottom et al., 2018; Mathieu et al., 2013; Naidoo et al., 2016; Symeonakis et al., 2018; Zhang et al., 2019). Techniques like regression-based unmixing and trend break analysis are applied to these datasets to distinguish between subtle changes in vegetation types and to detect shifts in land cover trends over time, providing unique insights into savanna dynamics (EnMAP-Box Developers, 2019; Verbesselt et al., 2010). Understating vegetation dynamics and ongoing land cover change processes in protected areas is to improve monitoring capabilities and prevent biodiversity loss and ensure long-term survival of wildlife (Borges et al., 2022; Harris et al., 2020).

The NCA supports the largest black rhino population in Tanzania and in recent years this population increased to approximately 70 individuals (Kohi and Lobora, 2019). Currently, there is emerging evidence of a decrease in the quality and quantity of preferable browse and, consequently, a decrease in suitable habitat for black rhino (Amiyo, 2006; Makacha et al., 1979; Niboye, 2010). Unsuitable habitats and limited browse promote competition for resources and emigration of rhinos out of the Crater and the NCA (Makacha et al., 1979). In this context, remote sensing approaches, such as those employed here, are essential tools for monitoring these changes and informing management decisions. By applying such approaches, we can accurately track habitat quality and detect areas of degradation or regrowth, which are crucial for understanding the availability of suitable browse for rhinos (Chapter 4). Additionally, these have broader applicability across various ecosystems and regions and have been successfully applied in other studies, as in Abera et al. (2022), to monitor habitat quality and land degradation in different environments, including wetlands and forests.

### 6.2.1 Mapping savannah habitats

In Chapter 2 there are three relevant findings concerning the optimization of land cover mapping and rhino habitats. Firstly, the use of Sentinel-2 imagery during the short-dry season, occurring between January and February, proved remarkably effective, demonstrating a 5% improvement over other single-season Sentinel-2 models and comparable performance to multisensory models. This was the first time that this season was used to map savannah landscape using remote sensing data. Seasonality plays a crucial role in remote sensing as it is influenced by cloud cover and affects vegetation reflectance properties, with the short-dry season providing clearer distinctions between woody and herbaceous vegetation.

The findings from Chapter 2 are particularly relevant due to their transferability, as demonstrated by the successful application of these geospatial analysis techniques in subsequent research. For instance, the recommendations from Chapter 2 were utilized in Chapter 3 to create fractional maps of each land cover type, further validating their applicability in different contexts. Additionally, the findings were extended to a 2022 (Abera et al., 2022) study focused on woody cover changes in East Africa, where similar geospatial analysis methods, including the use of satellite imagery and non-parametric modelling techniques, were employed to assess vegetation dynamics over time. This further illustrates the broader applicability and transferability of the approach across different regions and environmental conditions, reinforcing the importance of seasonality in geospatial analysis and its relevance for diverse ecological studies.

The short-dry season was then used to create fractional maps of each land cover type in Chapter 3. Second, while tri-seasonal imagery has some advantages, there is a substantial increase in data preprocessing and our study suggested that combining data from the dry and short-dry seasons may suffice unless specific vegetation types require tri-seasonal mapping.

Lastly, the findings align with the consensus that multisensor approaches provide more accurate results, particularly in mono-temporal models. However, in the presence of multiseason data, combining more than one sensor may be unnecessary and potentially counterproductive for certain land cover types, such as 'Shrubland.' Additionally, multisensor approaches involve complex preprocessing steps which can be computationally intensive and may present trade-offs between accuracy and processing costs.

The best performing model—using a combination of Sentinel-2 and Sentinel-1 data from the dry and short-dry seasons— was then used in Chapter 4 with the fuzzy approach and measurements relating to impacts. Additionally, our derived land cover map could help monitor black rhino habitat quality and identify new locations within the NCA which the population could expand into. Previously, the only detailed land cover survey in the NCA was completed in 1972, before several major management policies were introduced that brought about significant environmental changes (Herlocker and Dirschl, 1972; Mills, 2006; Niboye, 2010).

### 6.2.2 Land cover changes in the Ngorongoro

Over the last 50 years, African savannahs have undergone considerable land cover changes, including forest degradation, spread of invasive plant species, and woody encroachment (Amiyo, 2006; Higginbottom et al., 2018; Ludwig et al., 2019; Mills, 2006; Symeonakis et al., 2018; Venter et al., 2018). In Chapter 3, I demonstrate a Landsat-based monitoring strategy incorporating regression-based unmixing for the accurate mapping of the fraction of the different land cover types. Additionally, I combined linear regression and the BFAST trend break analysis technique for mapping and quantifying land cover changes. I used Landsat data of the short-dry season as recommended in Chapter 2 and although Sentinel-2 provides a higher resolution, Landsat has the long-term data that is required to identify the more subtle changes (Senf et al., 2020; Souverijns et al., 2020; Suess et al., 2018).

I identified the two dominant land cover change: the degradation of highland forest into bushland, and a transition from grassland to shrubland in the Serengeti Plains. In the NCA highlands, forest degradation is of particular concern, as these forests provide ecosystem services to the Maasai through the provision of fuel wood, traditional medicinal plants, and forage for livestock (Swanson, 2007). Additionally, forests provide shelter for wildlife and regulate water resources (Swanson, 2007). In the Serengeti plains, woody encroachment and invasive species can reduce rangeland carrying capacity, directly affecting wildlife and the Maasai livestock (Venter et al., 2018). To address these issues, understanding the spatial distribution of human activities such as livestock density and settlement expansion is crucial for assessing habitat changes. These factors, alongside climate change, shifting rainfall patterns, and herbivory, likely contribute to the observed land cover changes and underscore the need for targeted management strategies (Homewood et al., 2001; Masao et al., 2015; Niboye, 2010).

### 6.2.3 Implications for the NCA

In the context of conservation efforts within the NCA, these findings offer critical insights into the management and preservation of its diverse ecosystems. Firstly, the provision of a much-needed and highly accurate medium-resolution land cover map for the NCA's main land cover types stands as an important contribution. This will play a crucial role in supporting sustainable management practices and informing targeted conservation initiatives within the area.

Moreover, the identification of specific areas undergoing land changes holds profound significance for black rhino conservation and other wildlife species within the NCA. Remote sensing approaches allow for continuous monitoring of these changes with high temporal resolution, providing detailed insights into shifts in habitat composition. Recognizing these shifts in habitat composition is essential for implementing effective conservation strategies that address the requirements of critically endangered species and safeguard their habitats.

Considering these findings, it is imperative to develop a proactive fire management plan tailored to areas affected by encroachment, such as the Crater floor, and those undergoing vegetation regeneration. Employing remote sensing imagery can enhance fire management by providing data on vegetation health and dryness, which are critical for predicting and managing fire risk. By implementing targeted fire management strategies, conservation efforts can mitigate the adverse impacts of habitat changes, promote ecosystem resilience, and contribute to the long-term conservation goals of the NCA and its diverse wildlife populations.

Additionally, integrating remote sensing data with field observations can further refine conservation strategies. Combining these data sources allows for a more accurate understanding of habitat conditions and variability within the NCA. This integrated approach ensures that management practices are based on accurate, real-time information, ultimately improving the effectiveness of future interventions.

## 6.3 Implications for rhinos

Although the NCA was investigated as whole, to assess habitat cover and change, I was particularly interested in two specific areas; the Oldupai area because it once supported a rhino population, and the montane region between Olmoti and the Ngorongoro Crater which, the results in Chapter 2 indicated suitable vegetation to support black rhino.

### 6.3.1 Montane areas around the Ngorongoro Crater

The area between Olmoti and the Ngorongoro Crater is comprised of forest and bushland cover (Chapter 2). The vegetation was described as *Crotalaria-Gymnanthemum* montane bushland and is dominated by *Gymnanthemum auriculiferum, Pavonia urens irakuensis*, and *Clutia abyssinica,* all of which were browsed by rhino (Chapter 5). This habitat also features moist evergreen forests like *Nuxia congesta* and sporadic occurrences of *Bersama abyssinica* (Herlocker and Dirschl, 1972). Several vines, creepers, and other herbaceous and woody species also thrive in abundance, providing ideal forage and cover (Herlocker and Dirschl, 1972; Gadiye, 2016).

Although, over the last decades, the area has experienced loss of forest and particularly of large trees, the bushland cover, which is more favourable for rhino, has increased (Chapter 3). Forest areas, although useful for shelter and breeding, do not usually provide much browse reachable by rhino. Considering the composition of the vegetation in the area, the increase in bushland would most likely support more rhino as there would be more resources for browsing (Goddard, 1968; Herlocker and Dirschl, 1972; Gadiye, 2016).

The rim and surrounding areas were highlighted as suitable habitat for black rhino in Chapter 4 and 5. It is particularly good because most of the vegetation is evergreen, not severely impacted by seasons (Chapter 4), and has a constant supply of water throughout the year. In addition, it is isolated enough from human activities, namely tourism, but still benefits from the removal of human settlements (Chapter 4). Chapter 4 recommended that suitable areas should be surveyed to determine if rhino browse is available and the relevant data was analysed in Chapter 5. I found that the species preferred by rhino are widely available but there is also a range of other species that are known to be palatable to black rhino (Gadiye, 2016).

The combination of browsing material, habitat type, water availability, breeding areas, shelter, and distance from humans, suggests that the rim, specifically the region between Olmoti and the Ngorongoro Craters could be premium habitat for black rhino. However, it is also important to note that monitoring through direct observation in such a dense habitat would be very challenging. Ideally, the rhinos in this area would be fitted with trackers, so anti-poaching patrols could locate them easily with minimal disruption to the animals while ensuring the safety of the rangers.

### 6.3.2 Oldupai Gorge area

In the 1960s, there was a resident population of 69 rhinos in the Oldupai area but after heavy poaching, during the 1970s and 80s, it disappeared (Kiwia, 1989; Moehlman et al., 1996; Oates and Rees, 2013). Historically, the Gorge was part of a corridor between the Ngorongoro and the Serengeti National Park. Rhinos used to migrate from the Crater to the Rim, towards Balbal and through Oldupai Gorge, to Ndutu and to the Serengeti (Deogratius Maige 2023 *pers. comm.).* In Chapter 2, the Gorge area was identified as mostly grassland, shrubland and woodland which agrees with Herlocker and Dirschl (1972) findings. In Chapter 3 I found that the area experienced encroachment of shrubland and an increase in woodland cover between the South and the Western portions of the Gorge. Assuming, that these changes include species that are palatable, an increase in woody cover would be beneficial for black rhino (Hitchins, 1969).

The area surrounding Oldupai Gorge remains mostly unsuitable throughout except for a few patches (Chapter 4), however the habitat characteristics associated with rhino presence identified the area as a potential site for reintroductions (Chapter 5). This apparent discrepancy underscores the importance of integrating remote sensing techniques with detailed fieldwork. While presence/pseudo-absence data and remote sensing imagery were employed in Chapter 4 to identify suitability, it's essential to acknowledge the data limitations, such as resolution and spectrally similar vegetation types. Field-based studies offer additional detail that cannot be captured by remote sensing alone (Chapter 5).

The ideal habitat for rhino comprises lower vegetation density and browse availability but higher shrub cover, suggesting that rhinos prefer sites with browse that is actually available below 1m of height which explains why Oldupai was flagged in Chapter 5. Additionally, the species that were consumed by rhinos in the past are still present. During the dry season, Oldupai becomes much drier and there is barely any water available (Goddard 1968). Rhinos are water-dependent but in the past they consumed *Euphorbia tirucalli, Sansevieria ehrenbergii* and *Cissus quadrangularis* to fulfil their water requirements (Goddard, 1968).

Despite the presence of browse, most of the Oldupai area was only seasonally suitable and even then, does not seem as ideal the areas between Olmoti and the Ngorongoro Craters or most of the Rim. There is a heavy presence of livestock in the area and it is bisected by the road which connects the NCA to the Serengeti. When human disturbances were removed from the model (settlements and cattle) the suitability of the area increased. However, the road was not removed (even during the simplified human disturbances) as there is no realistic alternative to its presence as is the only viable route to the Serengeti. Additionally, I worked under the assumption that the habitat is suitable in areas that are similar the ones where black rhinos currently reside. Most of the rhinos are 'kept' in the Crater for protection and if they try to leave, they are often brought back to ensure their safety. It could be that if this was not the case, they would expand to other areas.

## 6.4 Limitations of study

EO data limitations: The Landsat 7 satellite's Enhanced Thematic Mapper Plus (ETM+) sensor has a known limitation due to the failure of its Scan Line Corrector (SLC) in 2003, causing gaps and stripes in the imagery, resulting in approximately 22% of data loss in each scene. However, this limitation can be effectively managed by combining Landsat 7 data with imagery from other sources to fill in the gaps, as was done in this study. In Chapter 3, specifically in Figure 3.9, gaps were filled using data from images taken on different dates, which is why some of the stripes remain visible. This approach ensures the continued usability of Landsat 7 data despite the SLC failure.

The resolution of freely available remote sensing data, such as Landsat (30m) and Sentinel-2 (10m), also remains as one of the main limitations. Moderate resolution data limits the ability to detect small-scale habitat features that are often essential for habitat mapping, such as individual species, small water sources, or narrow migration pathways. The inability to accurately capture these fine-scale features can result in underestimating or misclassifying important habitat areas. Other datasets, such as Pléiades (0.5m) or SPOT (1.5m) have a much higher resolution, but the costs associated with acquiring this data are much higher. PlanetScope data has a higher resolution of 3 meters but limited spectral layers (Symeonakis et al., 2019). Higher-resolution datasets would enable more precise habitat mapping, improving the detection of specific forage species and other critical habitat elements. For time series studies using Sentinel-2 would be beneficial due to its higher resolution but since it has only been in orbit from 2016, it has a limited temporal scope (Symeonakis et al., 2019). Additionally, single Landsat images were used rather than composites due to restrictions accessing the university campus during the pandemic. Composites would provide data with fewer cloud gaps and therefore more accurate analysis. However, the Landsat images available for the NCA provided enough quality for the study and decreased processing time.

Spatial Specificity: The study's focus on the Ngorongoro Conservation Area may limit the generalizability of findings to other rhino habitats, and extrapolation to different regions may require caution. However, our methods can be replicated in other locations, which would provide more site-specific information.

Field work limitations: Our field season lasted 7 months, covering both wet and dry seasons. This was due to the pandemic followed by delays associated with research permits. Repeating it over multiple years would provide a broader scope of the browsed species. In addition, the identification of species browsed by rhinos may not cover the entire spectrum of potential food sources, leaving gaps in understanding the full dietary preferences. Another limitation of our field work was that it was solely based on bite identification on each plant. Combining this type of data with other more accurate methods, such as DNA metabarcoding would provide higher quality results.

## 6.5 Recommendations for further research

Based on the findings of the study and the identified challenges and opportunities for rhino conservation in the Ngorongoro, the following recommendations outline key areas for further research to advance our understanding and management of rhino populations and habitats:

- Combine the feeding study with DNA metabarcoding techniques to obtain the full spectrum of plants consumed by rhino. Metabarcoding will allow the identification of grasses (if present), as well as other herbs and shrubs that are difficult to identify using rhino bites.

- Utilise camera trapping methodologies to assess movement patterns and habitat use across different areas within the NCA, aiding in the identification of key habitats and potential corridors for rhino populations.
- Incorporate finer-resolution remote sensing data, such as Unmanned Aerial Vehicles (UAVs) or LiDAR, to improve the spatial detail of habitat maps. These technologies can provide more precise data on vegetation structure, canopy height, and ground cover, which are crucial for identifying microhabitats and fine-scale features important for rhino conservation. Combining these high-resolution datasets with advanced geospatial modelling approaches, including machine learning and artificial intelligence, could enhance the accuracy of habitat suitability models and predict potential habitat changes more effectively.
- Continue long-term monitoring efforts to track changes in habitats, using this research as baseline data to evaluate the effectiveness of conservation interventions, adapt management strategies and to understand the potential impacts of Maasai community relocation on land cover changes.
- The accuracy of the produced models that forecast potential changes in rhino habitats can be tested in the future and be used to validate future predictive models to assess their accuracy and reliability under different scenarios or conditions.

## 6.6 Conclusion

Overall, this research not only advances ecological knowledge but also provides actionable information for on-the-ground conservation strategies, making it an important contribution to both the academic field and practical wildlife conservation efforts. This thesis significantly contributes to the broader understanding of geospatial science in ecology and conservation, particularly through the development and application of advanced remote sensing and spatial analysis techniques.

This research highlights the importance of geospatial science by demonstrating how the integration of Sentinel-1 and Sentinel-2 data across multiple seasons can optimize land cover mapping in heterogeneous environments like the Ngorongoro Conservation Area (NCA). The findings underscore the value of combining different types of remote sensing data to achieve higher accuracy in land cover classification, particularly in challenging savannah landscapes. The identification of optimal black rhino habitats further showcases the practical application of these geospatial techniques, offering targeted information for potential reintroductions, translocations, and management strategies that ensure the preservation of key habitats throughout the year.

This thesis also provides critical insights into the vegetation dynamics within the NCA, employing regression-based unmixing and trend break analysis to map and quantify land cover changes. The detailed mapping of fractional cover for various land cover types—such as grassland, bushland, forest, and woodland—demonstrates the intellectual contribution of this work to geospatial science. By accurately tracking changes in vegetation, such as the encroachment of shrubland into grazing areas, this research provides essential data that promotes sustainable management practices and highlights the role of human activities in driving these changes.

The study's findings emphasize the necessity of combining remote sensing data with ground-truthing, vegetation surveys, and local knowledge to produce the most accurate and reliable results. This multidisciplinary approach is crucial for making informed conservation decisions, particularly for critically endangered species such as the black rhino. Additionally, the research shows that relying solely on remote sensing data can be unreliable, as it often overlooks crucial field variables. The methods developed here, although applied specifically to the NCA and its black rhinos, are replicable and can be adapted to other species and sites. The vegetation changes and invasive species distribution identified in this thesis can directly inform the development of fire and invasive species management programs, which have the potential to improve vegetation quality throughout the NCA.

As the NCA undergoes significant policy changes, this thesis provides foundational data that can support these transitions while ensuring that conservation efforts are grounded in robust scientific methodologies. The intellectual contribution of this work lies not only in its application to rhino conservation but also in its advancement of geospatial science as a critical tool for ecological research and conservation planning.

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## 6.8 Appendix 2 - Publications

Chapters 2 and 3 appear below, as their final versions in published papers.

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SHORT COMMUNICATION

African Journal of Ecology WILEY

# A learning network approach to resolve conservation challenges in the Ngorongoro Conservation Area

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## 1 | INTRODUCTION

The Ngorongoro Conservation Area (NCA) is a protected area and UNESCO World Heritage Site and part of the Serengeti-Ngorongoro Biosphere reserve in northern Tanzania. It is famous for its large volcanic caldera, unique cultural heritage, early hominid fossils and significant wildlife populations. NCA has been managed as a multiple land-use area since 1959, a designation intended to foster a harmonious coexistence between indigenous residents and wildlife (Goldstein, 2004).

The NCA has international conservation prominence due to its populations of black rhinoceros (*Diceros bicornis michaeli*), African elephant (*Loxodonta africana*), and a wide range of herbivore and large predator species (Homewood et al., 2004). It supports one of the largest mammal migrations on earth, with estimates of greater than 1,000,000 wildebeest (*Connochaetus taurinus*), 260,000 plains zebra (*Equus quagga*) and 460,000 Thompson gazelle (*Eudorcas thompsoni*) (Campbell & Borner, 1995; Lembo et al., 2011). The area is also home to a large human population made up of several ethnic groups and diverse cultural traditions, including Hadzabe hunter-gatherers, and

Datooga and Maasai pastoralists (McCabe, 2003). These features attract nearly 50% of all international tourists who visit Tanzania (Melita, 2015), making the NCA by far the largest single contributor to the national economy relative to all other conservation areas in the country (accounting for 38% of park revenue in Tanzania; Busiweek, 2018). As a result, the NCA is considered a priceless and irreplaceable reserve for nature and nature's contribution to people.

Despite its enormous conservation, cultural and economic standing, there are considerable challenges in maintaining the NCA as a sustainable system for nature and people into the future. One of these challenges relates to the volume of tourists now visiting the area. Tourism has increased from approximately 50,000 visitors in 1960 to 647,773 in 2013 (Melita, 2015; Melita & Medlinger, 2013) and approaching one million more recently (Slootweg, 2016). While this rise in paying visitors has brought about significant economic benefits, stimulating considerable infrastructure development, it has also increased disturbance in and around the caldera, swelling the demand for water and natural resources. This has led to the assertion that tourism growth is incompatible with conservation objectives in the NCA (Charnley, 2005).

At the same time, unpalatable invasive plant species have spread extensively within the NCA and dominate more than half of the caldera floor (Ngondya et al., 2019), reducing rangeland quality for many wildlife species and livestock (Foxcroft et al., 2006; Ngondya et al., 2016, 2019). The resident human population has also grown dramatically from approximately 10,000 people in 1954 (displaced from adjacent areas set aside for the Serengeti National Park) to 87,851 in 2013 (Galvin et al. 2015, Masao et al., 2015) and currently approaching 100,000 (Manzano & Yamat, 2018). Associated with the expansion of the human population, livestock numbers within the NCA have increased during the same period, fostering the greater incidence and impact of diseases affecting humans, livestock and wildlife (Homewood, 2008). However, livestock populations have risen considerably less steeply than the human population (Ghosh & Uddhammar, 2013), causing a negative impact on livelihoods and well-being of the people in the NCA (McCabe, 2003). The total livestock units (TLUs) per person, a measure of food productivity for tropical pastoralists, fell from around 12.5 TLU/person in 1960 to 2.02 in 2009 (Galvin et al. 2015), well below the benchmark minimum for pastoralist food provision (~6 TLU/person). Concomitant with these changes, there is mounting evidence to show that populations of some wildlife species (i.e. gazelle species, wildebeest, kongoni (*Alcelaphus buselaphus cokii*), waterbuck (*Kobus ellipsiprymnus*) and eland (*Taurotragus oryx*) have declined in the Ngorongoro caldera (Estes et al., 2006, Moehlman et al., 2020). These species preferred the short grasslands as maintained through prescribed burning. Since the practice of burning was banned from 1975, grasslands supported taller grass stands benefitting Cape buffalo (*Syncerus caffer*, Fyumagwa et al., 2007) and elephant populations, while plains zebras have remained stable (Moehlman et al., 2020).

Mirroring a larger pattern of lifestyle change in traditional pastoral communities across Africa (Homewood, 2008), Maasai people have adapted to a more sedentary lifestyle with modern houses, increasing their reliance on garden crops and on food provided by the NCA Authority. Although it has been suggested that small-scale agriculture could be developed alongside wildlife populations in the NCA (e.g. Boone et al., 2006), it is prohibited at present and there is a complicated history associated with human rights and legal permission to farm in the NCA, which has been permitted, restricted or banned at different points in time (Goldstein, 2004; McCabe, 2003). However, were sustainable agriculture to be permitted in the NCA, the enterprise would necessarily be limited in scale due to its incompatibility with wildlife conservation. In addition, the expansion of cultivation in the NCA could clash with the tourism ideal, which perceives a benefit from the absence of development in the area (Slootweg, 2016).

While conditions for wildlife, livestock and people within the NCA have deteriorated, tourism intensity and its associated revenue have increased, thus creating a unique challenge for managers. The result is that there is no clear single causative agent or solution to improve conditions simultaneously for people, wildlife and tourism. Likewise, different stakeholders may have divergent objectives: a potential outcome for one stakeholder group may be perceived as undesirable, or even disastrous, by others. Also, the nature of issues may change through time, such as the aspirations of young people for education and jobs in urban areas instead of the pastoral lifestyle, rendering possible solutions conceived in the present ineffectual in the future. Situations like this, with uncertain, contradictory and changing requirements, have been referred to as 'wicked problems' (Rittel & Weber 1973), and it has been suggested that this may be typical of complex conservation challenges involving multiple stakeholders (DeFries & Nagendra, 2017). While there is a long history of conservation management in the NCA, in the context of similar challenges across east Africa (Reid et al., 2014), the situation continues to defy a long-term solution and has been described as a wicked problem of the utmost severity (Balint et al., 2011).

Here, we conceptualise challenges in the NCA into four categories, and we assess them for their wickedness (Table 1). Of primary importance is the sustainable livelihood and welfare of people. Specific issues include education and healthcare provision, nutrition and food sustainability, and grazing and water access for livestock. The challenge is multifarious because of human population growth, along with conflicts of interest between land use for agriculture (currently not permitted), livestock grazing and wildlife conservation. Also, there is a contradiction between romanticising the 'traditional' way of life for people in the NCA that tourists perceive versus improving living standards with modern homes and associated technologies. Another challenge is the preservation of biodiversity in the NCA. While some aspects of ecology in and around the caldera have been well studied (e.g. Sinclair et al., 2015), fundamental aspects of NCA biology outside of the caldera are less well understood, especially relating to climate change (but see Moehlman et al., 2020 for the caldera), the impact of tourism, and the interaction between humans, cattle and wildlife. The conflict of interest here is between the effects that residents and visitors have on the environment versus the economic value of increased tourism. Invasive plants are another

**TABLE 1** Synthesis of principle management challenges in the NCA, management questions arising from them and reasons for wickedness

| Management challenge | Management questions | Reasons for wickedness |
|---|---|---|
| Sustainable livelihood and welfare for local people | How can food sustainability and improved nutrition be achieved? How can education and prospects for young people be improved? How can cultural tourism be developed? How to mitigate livestock grazing, water access and cultivation rights with conservation? | • Human population growth and immigration<br>• Differences in social values<br>• Political sensitivity<br>• Divergence of objectives amongst stakeholders<br>• Cultivation, land-use change and degradation<br>• Grazing of cattle owned by non-NCA residents<br>• Development insults the tourist aesthetic |
| NCA biodiversity | Can continuous biodiversity monitoring be achieved? How resilient are crater ecosystem services? How best to mitigate and monitor poaching risk? | • The economic value of tourism and tourism growth<br>• Potential competition between livestock and wildlife for forage and water<br>• NCAA has limited jurisdiction and resources outside the NCA to implement strategies<br>• Increased tourism depletes water resources<br>• Climate change |
| Invasive plant species | What impact do invasive plants have on NCA biodiversity? How best to prioritise and manage invasive plant ecology in the NCA? | • Scale of the problem is large and uncertain<br>• Reduces available forage for wildlife and livestock<br>• Complex causality from invasion source points<br>• Long seed bank lag time |
| Healthy livestock populations and zoonotic disease | How to manage and monitor risk of anthrax, Peste des Petits Ruminants, foot and mouth, rabies, rift valley fever, Brucellosis and other diseases? | • Increase in cattle population increases zoonosis risk<br>• Increased cost of veterinary support<br>• Epidemiology of outbreaks |

Abbreviation: NCA, Ngorongoro Conservation Area

priority area, reducing rangeland quality and quantity available to wildlife and cattle. While there is awareness of the negative impacts of invasive plants (Foxcroft et al., 2006; Ngondya et al., 2017), the scale of the problem is alarming and is increasing. A final area of great concern is that of livestock and wildlife health and zoonoses. With a history of dramatic outbreaks of diseases, such as Peste des Petits Ruminants, anthrax, and foot and mouth disease, there is a looming threat to both wildlife and human welfare, exacerbated by changing land use. Meanwhile, tick-borne infections have become more common in both wildlife and livestock since the spread of taller grasses in recent decades (Fyumagwa et al., 2007).

## 2 | THE NCA: A FRAMEWORK FOR THE FUTURE

Processes where research and management are not closely intertwined with local communities are now considered ineffectual for nature conservation, especially in rangeland ecosystems (Reid et al., 2014). A prominent alternative approach is that of adaptive management, which emphasises knowledge creation through the scientific method (Walters & Holling, 1990) and which is favoured, perhaps unsurprisingly, by ecological scientists. However, while popular and conceptually satisfying, application of adaptive management to conservation challenges suffers inherently from a lack of spatial or temporal replication, undermining the scientific method (Sutherland, 2006). There is also a lack of evidence as to whether it has actually been widely implemented, and disagreement as to whether it is successful as a method to solve conservation problems (Reid et al., 2014; Westgate et al., 2013). A combination of adaptive management with community-based conservation, where the social and economic developments of local people are linked with the responsibility to carry out conservation goals, leveraging local ecological and traditional knowledge while building capacity, is now widely considered the way forward. While there is some evidence that community-based conservation projects tend to be successful when designed to achieve social and economic outcomes along with biological ones (Oldekop et al., 2016), there is often a fundamental conflict between sustainability of development and the preservation of nature (Berkes, 2004).

We propose a solution for the NCA that imparts responsibility and acknowledges expertise amongst stakeholder groups (Table 2). This solution is inspired by the continual engagement model (Reid et al., 2009), with an emphasis on knowledge sharing, where all principal stakeholders in the NCA are represented. These stakeholders are (a) the Ngorongoro Pastoral Council, representing NCA residents; (b) tourism industry workers from outside the NCA; (c) NCA Authority and government managers, who have direct fiscal and operational responsibility; and (d) natural scientists, social scientists and conservation organisations, both local and global, concerned with conservation of the natural resources of the NCA and human welfare. We propose a learning network solution that is characterised by knowledge exchange between stakeholders (e.g. Balint et al., 2011) and informed by continuous scenario-based assessment of outcomes (e.g. Game et al., 2014; Mason et al., 2018). For instance, a locally based wildlife manager should monitor

**TABLE 2** Conventional versus learning networks approach (adapted from Mason et al., 2018)

| Conventional | Learning networks | Application to NCA project |
|---|---|---|
| *Top-down decision-making* | *Distributed decision-making* | |
| Management decisions are made in a top-down process | Management decisions are contributed by different stakeholders | Aspects of management (e.g. monitoring, key species, invasive species, grazing) led by a local manager which takes day to day decisions within agreed parameters (legal, ethical) |
| *Standard practice* | *Creative practice* | |
| Standard management practices, applied elsewhere for other problems, are used | Creative management practices, suited to the specific problems, are developed | Utilise local knowledge and practices from NCA residents, evaluate ideas from similar projects worldwide, facilitate communication between project themes |
| *Restricted expertise* | *Diverse expertise* | |
| Management is guided by restricted expertise | Management is guided by the learning network. Challenge conventional 'best practice'. Maintain flexibility in terms of how objectives are achieved. Encourage discussion, dissent and diversity in the learning network | Establish learning network amongst NCA stakeholders. Develop a forum for the open discussion continuous knowledge exchange of management actions and outcomes |
| *Passive management* | *Predictive management* | |
| Management interventions are adapted over time as the system is altered | Management interventions are guided by continuous evaluation of scenario-based predictions | Management practice based on competing scenarios. For example, evaluate which management actions for forest regeneration will have the widest beneficial impact and what is the scope of potential costs? Preparation must be made to completely change strategies rather than an inflexible approach |
| *Conventional evidence* | *Pattern-based evidence* | |
| Management is informed by evidence from single processes | Management is informed by pattern recurrence in complex, interactive processes | Evidence-based review of existing research outcomes to inform scenario modelling (e.g. forest regeneration, rangeland management, long-term monitoring) |
| *Strategy-focused* | *Outcome-focused* | |
| Management strategy constrained by objectives | Focus on outcomes, strategy is flexible | Define a discrete set of specific desired outcomes for scenario modelling |
| *Objective success* | *Trade-offs in objectives* | |
| Focus only on management successes | Trade-offs in management success are acknowledged | Evaluate outcomes and trade-offs amongst scenario alternatives. |
| *Avoid sharing failures* | *Sharing failures* | |
| Management failures are not shared with stakeholders | Management failures are shared transparently with stakeholders | Full disclosure of progress including successes and failures in learning networks |

Abbreviation: NCA, Ngorongoro Conservation Area.

patterns of wildlife and livestock grazing and report, on a predetermined schedule (i.e. bi-monthly), to a committee consisting of representatives of all major stakeholders. This committee, chaired by an individual with no conflict of interest, will then be able to make informed decisions about grazing management, reducing the chances of interaction and pathogen transfer between wildlife and livestock. This would allow for continuous engagement between stakeholders in the decision-making processes and for flexible management that can cope with changes in the parameters, such as those related to climate change. We believe this can be effective through generating consensus amongst stakeholders through the discussion of acceptable trade-offs between competing management objectives.

Many of the conservation and human welfare challenges in the NCA have been acknowledged and studied in the past. Yet, ongoing intensification of population growth and tourism pressures has created a unique situation at present, aggravated by the geographical, biophysical and political circumstances that have created it. While there has been a long history of conservation management in the NCA, the nature of continuous change requires continuous adaptation drawn from all-inclusive stakeholder insights. Our goal here, as representatives of each major group of stakeholders, was to propose a new process in the NCA and to document a consensus to engage in it. Therefore, we call for the immediate institution of a process of continual engagement (sensu Reid et al. 2009) and learning amongst stakeholders based on the learning networks approach leading to a decision for action to secure the future of the NCA. Addressing conservation and development challenges in the Ngorongoro Conservation Area will necessitate creativity, persistence and long-term commitment. Our aim here was not to convey a simple solution to the huge challenge of reconciling wildlife and human conflict in the light of climate change and other land pressures imposed on the NCA, but instead to communicate a consilience amongst stakeholders on both the nature of a resolution and the will to work together to achieve it. We believe this is possible if we can echo and implement the famous words of Tanzania's first President Julius Nyerere: ‘In accepting the trusteeship of our wildlife we solemnly declare that we will do everything in our power to make sure that our children's grand-children will be able to enjoy this rich and precious inheritance’ (Arusha Manifesto in Watterson, 1961).

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## CONFLICT OF INTEREST

The authors declare there are no conflicts of interest.

## DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analysed in this study.

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MDPI

Article

# Sentinel-1 and Sentinel-2 Data for Savannah Land Cover Mapping: Optimising the Combination of Sensors and Seasons

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**Abstract:** Savannahs are heterogeneous environments with an important role in supporting biodiversity and providing essential ecosystem services. Due to extensive land use/cover changes and subsequent land degradation, the provision of ecosystems services from savannahs has increasingly declined over recent years. Mapping the extent and the composition of savannah environments is challenging but essential in order to improve monitoring capabilities, prevent biodiversity loss and ensure the provision of ecosystem services. Here, we tested combinations of Sentinel-1 and Sentinel-2 data from three different seasons to optimise land cover mapping, focusing in the Ngorongoro Conservation Area (NCA) in Tanzania. The NCA has a bimodal rainfall pattern and is composed of a combination savannah and woodland landscapes. The best performing model achieved an overall accuracy of 86.3 ± 1.5% and included a combination of Sentinel-1 and 2 from the dry and short-dry seasons. Our results show that the optical models outperform their radar counterparts, the combination of multisensor data improves the overall accuracy in all scenarios and this is particularly advantageous in single-season models. Regarding the effect of season, models that included the short-dry season outperform the dry and wet season models, as this season is able to provide cloud free data and is wet enough to allow for the distinction between woody and herbaceous vegetation. Additionally, the combination of more than one season is beneficial for the classification, specifically if it includes the dry or the short-dry season. Combining several seasons is, overall, more beneficial for single-sensor data; however, the accuracies varied with land cover. In summary, the combination of several seasons and sensors provides a more accurate classification, but the target vegetation types should be taken into consideration.

**Keywords:** Sentinel-2; Sentinel-1; radar; seasonality; savannah landscapes

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## 1. Introduction

Savannahs are heterogeneous landscapes combining grassland, open canopy trees and shrubs. These ecosystems occur in tropical and subtropical climate zones, mainly in the Americas and Australia, as well as in Africa, where they cover half of the land surface [1]. Savannah ecosystems are important for biodiversity and the global carbon cycle and provide essential ecosystem services for some of the world's poorest communities [2–6]. In recent years, the provision of ecosystems services from savannahs has increasingly declined due to extensive land use/cover changes and subsequent land degradation [5,6]. Woody vegetation encroachment or densification, attributed to climate change and altered rainfall patterns, can have negative impacts on carbon storage, biodiversity, grazing capacity, and tourism [7–13]. Additionally, management policies (e.g., fire management), herbivore pressure, and invasive plant species directly impact savannah dynamics [8,9,14].

Savannahs in southern and eastern Africa are similar in their ecological structure and function, sharing similar fauna and flora [15,16]. However, there are key differences in conservation land management. Southern Africa adopted a proactive approach, using fences, culling, fire, and large-mammal translocation programs [16]. Conversely, East Africa's protected areas are often unfenced and follow a 'hands-off' approach allowing wildlife to roam freely and intervening as little as possible [17]. In this region, around 20% of the land is officially protected [18]; however, due to population growth driving demand for crop and rangeland, pressure on the savannah is increasing. Sustainable ecosystems require an understanding of how savannahs work and how losses of function can be mitigated or prevented through informed management decisions [16]. Therefore, to improve monitoring capabilities, prevent biodiversity loss and ensure savannah ecosystem services, it is essential to produce high-resolution, up-to-date and highly accurate land cover information [19,20].

Over small areas, traditional methods of land cover mapping, e.g., ground-based surveys and aerial photographs, are able to provide information on the dynamics of savannah vegetation structure and distribution. However, to portray the spatial patterns of vegetation change over larger areas, these techniques are time consuming, limited in extent and expensive, and therefore, inefficient [19,20]. In the last five decades, satellite Earth observation (EO) data are increasingly used to map and monitor vegetation cover and its characteristics [21–23]. The use of EO technologies with open-access data archives provide the opportunity to study inaccessible areas and to assess the vegetative cover and its evolution through time [19]. Mapping savannah vegetation, however, is challenging due to varying degrees of vegetation cover, high background soil signal and the spectral similarities between land cover types [10,24,25]. In East Africa, in particular, high cloud coverage represents an additional challenge [26,27].

For almost 50 years, the Landsat archive has been the workhorse for vegetation and land cover mapping and monitoring, mainly due to its unparalleled archive. More recently, Sentinel-2 data with improved spatial and spectral resolution have also been successfully employed to map African savannah vegetation characteristics [10]. However, optical data come with their limitations, such as the presence of cloud coverage and the difficulty in discriminating between woody vegetation and grassland [28]. To address these inherent problems, a number of studies have combined Synthetic Aperture Radar (SAR) data (e.g., from the Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar, ALOS PALSAR); or Sentinel-1, with optical data to improve classifications, as SAR sensors are insensitive to cloud cover, discriminate woody vegetation effectively and are, therefore, particularly helpful for savannah environments [10,28–31].

In addition to multisensor approaches, previous studies examined the effect of single season and biseasonal data on classification accuracies [28,29,32]. Biseasonal data provide improved accuracies in savannah land cover mapping [28,29,32]. If a single season approach is chosen, the dry-season is preferred due to lower cloud cover and higher contrasts between woody and grassland components [29,32]. However, when the mapping of herbaceous vegetation is of interest, using dry season data only can be suboptimal, as most of the vegetation is dry. In areas where bimodal rainfall patterns occur, using data from the short-dry season, which takes place after the short rains, may be beneficial. To our knowledge, land cover classification performance using short-dry season data has never been studied before but could be particularly useful due to the availability of cloud free data and herbaceous vegetation being photosynthetically active [33].

Regardless of the sensors or seasons used, most studies focussing on African savannah consider either a distinction between woody and non-woody vegetation or represent woody vegetation as a gradient [10,28–30]. However, such information might not always be meaningful as it might obscure important differences between ecologically distinct land cover types. Considering the amount and types of data currently available, there is an opportunity to develop meaningful, detailed classifications of the savannah environment. Furthermore, recent advancements in computing power, cloud computing (e.g., Google Earth Engine) and the development of machine and deep learning algorithms (e.g., random forests (RF) and support vector machines (SVMs)), have given rise to new approaches in mapping and monitoring land cover, e.g., spectral-temporal variability metrics [28,34] or image compositing [35]. These new approaches have proven to be robust in characterising savannah landscapes [6,25,28,29,33,36–38]. Within this context, the aim of this study is to create a detailed, high-resolution and highly accurate land cover map of a montane savannah system: the Ngorongoro Conservation Area (NCA) in Tanzania. We used different combinations of optical (Sentinel-2) and radar data (Sentinel-1) from different seasons (wet, dry and the short-dry season) and compared the classification accuracies to address the following research questions:

1. Can Sentinel-1 and Sentinel-2 seasonal imagery be used to accurately map savannah land cover types at the regional scale?
2. Can the combination of optical and radar data improve classification accuracies?
3. How does the combination of data from different seasons influence the accuracy of the classification?

## 2. Study Area

The NCA, located in northern Tanzania, is a protected area and a World Heritage Site that forms part of the Serengeti ecosystem. It covers an area of around 8283 km$^2$ and includes the famous Ngorongoro Crater, the world's largest inactive, intact and unfilled volcanic caldera [39,40]. The NCA boarders Loliondo Game Controlled Area to the North, Serengeti National Park to the West, Lake Eyasi to the Southwest, the area between Lake Eyasi, Lake Manyara and Manyara National Park to the South and agricultural communities to the Southeast (Figure 1b,c). The temperature ranges between 7 and 15 °C in the wet season and 11–20 °C in the dry season [41]. Annual rainfall ranges from 450 mm/year in the lowlands to 1200 mm/year in the highlands [42] There is a distinctive variation in rainfall patterns, consisting of two wet seasons from March until May and October to December, and two dry seasons from January to February and from June to October ([43], Figure 1a). Considering the typical pattern of bimodal seasons, for 2018/2019 February was particularly wet (Figure 1a).

The NCA is composed of more than 15,000 km$^2$ of savannah habitat [44] and is included in the Greater Serengeti Ecosystem (GSE), where the great African wildebeest migration takes place [39,44]. The NCA vegetation ranges between highland plains, savannah woodland, forest and savannah grasslands [45]. The northwest part, bordering with the Serengeti National Park, comprises savannah grassland plains and some woodland areas. Within the Ngorongoro Crater itself, the vegetation comprises mostly of short-to-medium grasses, wetlands, and a soda lake, Lake Magadi. Southwest of the lake is the Lerai Forest, which is degrading and gradually disappearing [46]. Lerai Forest was dominated by mature *Acacia xanthophloea* trees, which have not been replaced by young *Acacia* trees [41]. A combination of factors, such as high herbivore pressure, high salinity, water availability and encroachment of invasive species, could explain the forest's dieback [41,45,46]. In the past, Lerai Forest was regularly used by black rhinos for shelter, browsing and breeding [41,46]. Due to vegetation changes or the presence of other herbivores, black rhinos are now rarely seen in this area [41,46].

The NCA is managed by the NCA Authority (NCAA) as a 'multiple land-use area' to promote biodiversity conservation and the interests of the resident Maasai pastoralists [14,47]. In the last 50 years, the NCA followed a 'hands-off' management approach. For instance, fire regimes, traditionally implemented by the Maasai and used to improve pasture, control bush encroachment, and reduce tick populations, were banned in 1974 [41]. This measure is thought to have contributed to woody encroachment, grassland growth and the spread of invasive plant species, which consequently favour species like elephant (*Loxodonta africana*) and buffalo (*Syncerus caffer caffer*) [14,41,46]. Fire was used in 2003 to control invasive plant species as it has been identified as an important step towards active management. However, an official fire management programme has not been implemented yet [41]. Cultivation was also banned in 1974 when the Maasai pastoralists were relocated out of the Ngorongoro Crater [42]. Nonetheless, in order to support the Masaai communities living within the NCAs boundaries, the cultivation ban was partially lifted in 1992, allowing the cultivation of 1 acre per household [41,42]. Nowadays, the NCAA is looking into more active management approaches to tackle some of the 'wicked' problems that the NCA is facing [48], e.g., inbreeding of endangered species such as black rhino (*Diceros bicornis michaeli*), changes in habitat suitability, food security and the spread of invasive species. However, there is a lack of empirical data on these issues that could be used to support and advise decision making.

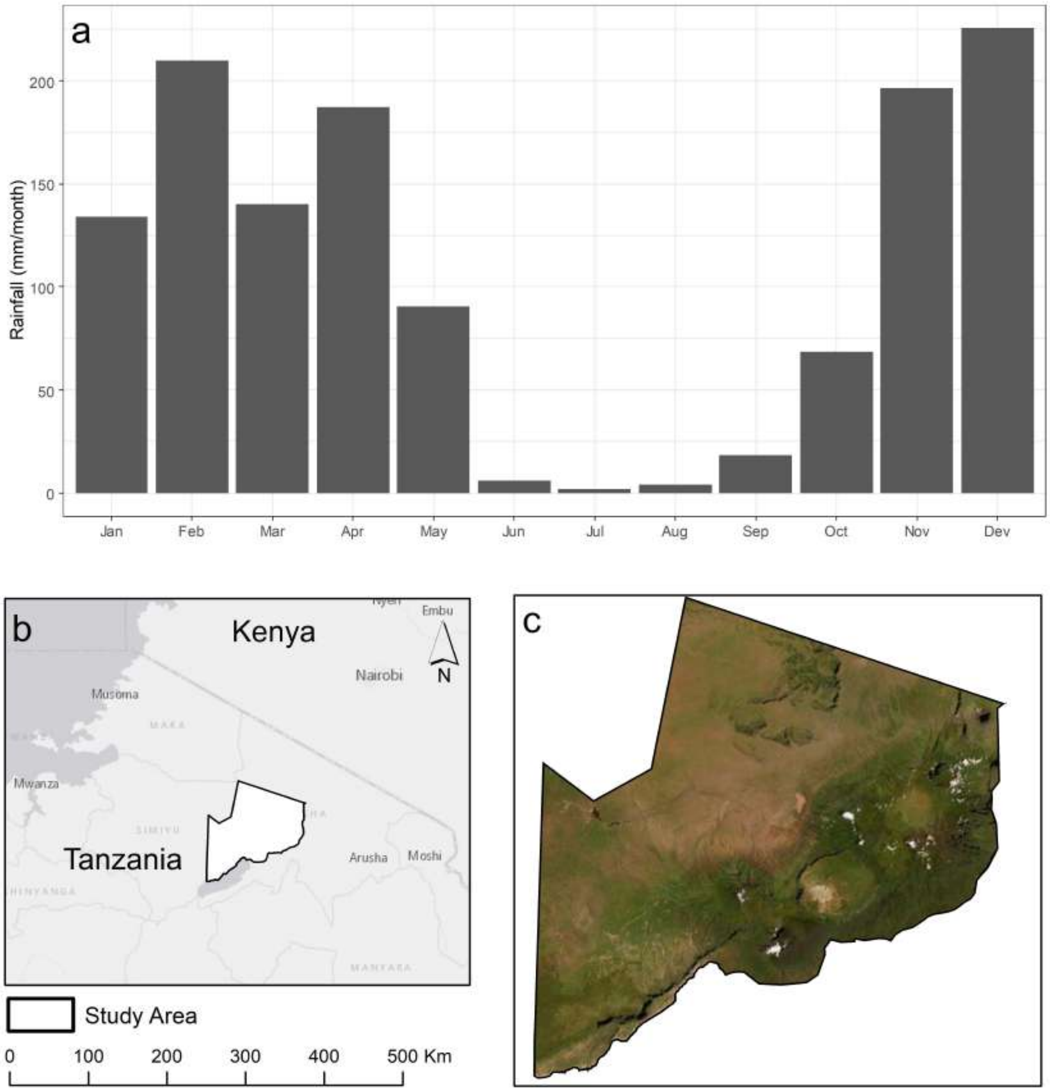

**Figure 1.** (**a**) ECMWF (European Center for Medium-Range Weather Forecasts) Re-Analysis (ERA) rainfall average in the study area for 2018/2019, (**b**) location of the study area in East Africa, (**c**) Ngorongoro Conservation Area, Tanzania from Google Earth (Digital Globe).

Herlocker and Dirschl [45] carried out the first detailed land cover study in the NCA in 1960s and distinguished eight land cover types: (1) Montane heath; (2) Bamboo forest; (3) Evergreen forest; (4) High woodlands; (5) Low woodlands; (6) Medium grasslands; (7) Short grasslands; (8) Sand dune grasslands. Here we combined the nomenclature and descriptions of Herlocker and Dirschl (1972; [45]) and Pratt and Gwyne (1966) [49], which enabled the identification of nine land cover types:

- Bareland: areas with minimal plant cover that include bare rock, sand, alpine snow and ice, saline or alkaline flats or riverine deposits. These areas often experience extreme environmental conditions, such as low rainfall, high winds, high salinity and toxic or infertile soils that prevent vegetation from developing.

- Bushland: areas of woody plants, bushes or trees, with a closed shrub canopy between 3 and 6 m in height. The closed canopy of bushland thicket has little grazing value and makes it challenging for large animals to navigate through [49].
- Cropland: areas where natural vegetation has been removed or modified and replaced by other types of vegetation that requires human activity to maintain it in the long term. Cropland fields may be fallow at certain times during the year.
- Forest: areas with closed canopy trees of one or more storeys, rising from 7 to ≥40 m in height. Bushes and shrubs dominate the ground making it difficult for animals to travel through it.
- Grassland: areas dominated by grasses <25 to 150 cm tall, sometimes with herbs, scarred trees or shrubs, with a high grazing value for both wildlife and livestock. Areas may contain some woody cover and may be almost bare during the dry season and during drought episodes.
- Montane heath: areas with medium-sized woody vegetation (<1 m) that can be shrubs, grasses, ferns and mosses. Montane heath occurs in environments ≥1600 m in altitude, usually on mountains, but also on hills with lower and more variable temperatures and rainfall.
- Shrubland: areas with medium sized woody vegetation (<6 m in [49]), generally open canopy, surrounded by grassland or dry land. Some occasional trees and bushes are present depending on location.
- Water: areas that can be lakes, rivers, ponds or reservoirs, which vary with season.
- Woodland: tree-covered area with trees as tall as 20 m and an open canopy surrounded by grassland and sometimes shrub but not thicket. These areas are sometimes dominated by only a few species of trees.

## 3. Materials and Methods

We combined SAR (Sentinel-1) and optical (Sentinel-2) data from three different seasons (dry, wet and short-dry seasons) and compared the outcomes to optimise land cover mapping in savannahs. Sentinel-2 data were obtained and processed in the Framework for Operational Radiometric Correction for Environmental monitoring (FORCE) software version 2.0 and three Best Available Pixel composites were created for each targeted season [35]. The NDVI bands were also calculated and added. The Google Earth Engine computing platform was used to acquire, process and calculate the textural metrics for Sentinel-1 data for the three target seasons [50,51]. Training data were collected based on our knowledge of the area and Google Earth (Digital Globe) imagery. The land cover classifications were produced using random forests (RF; [52]) and validated with a two-stage random sampling procedure according to best practice guidelines [53]. Figure 2 is a flowchart of our methodological framework.

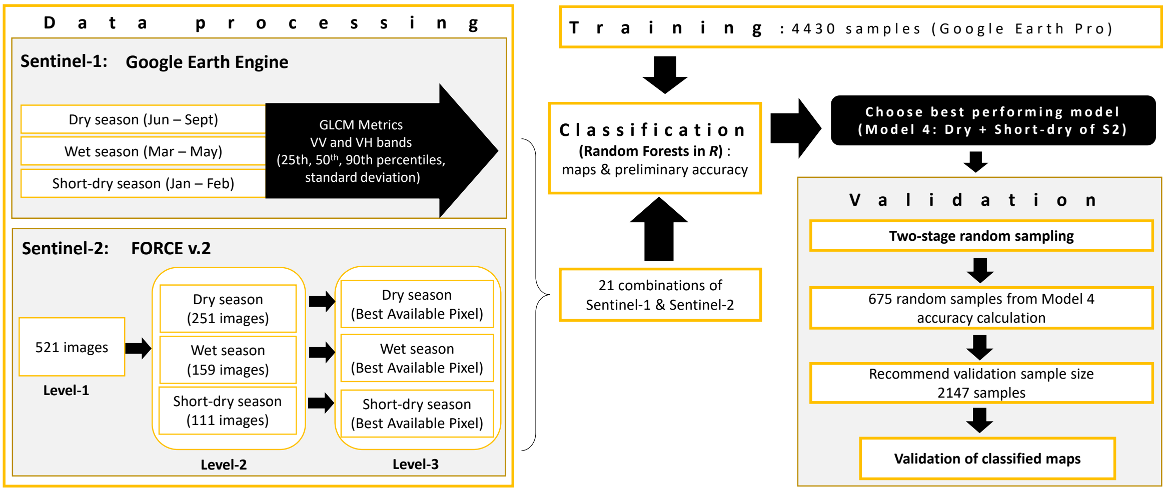

**Figure 2.** Methodological framework. Google Earth Engine: Gorelick et al. [50]; FORCE (i.e., Framework for Operational Radiometric Correction for Environmental monitoring): Frantz et al. [35].

### 3.1. Data

#### 3.1.1. Sentinel-2

Sentinel-2 is an Earth Observation mission from the European Space Agency's (ESA) Copernicus

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Sentinel-2 is an Earth Observation mission from the European Space Agency's (ESA) Copernicus Programme. It consists of two satellites, Sentinal-2A and Sentinel-2B, launched in 2015 and 2017, respectively [10]. Sentinel-2 carries a Multi-Spectral Instrument (MSI) that images 13 spectral bands in the visible, near infrared and shortwave infrared spectral range (SWIR) at 10–60 m spatial resolution. The combination of Sentinel 2A and 2B provides a 5-day revisit rate. Sentinel-2 imagery are freely available and accessible through the Copernicus API Hub.

We obtained all Sentinel 2 images that intersected our study area between 1 January 2019 and 30 September 2019, with less than 75% cloud cover, resulting in 521 images (Table 1). All image processing was in the Framework for Operational Radiometric Correction for Environmental monitoring (FORCE) software version v.2.0 [35]. Firstly, Level 1C images were downloaded from the Copernicus API hub. Secondly, the raw images were processed to Level 2 using the FORCE L2PS module, applying: atmospheric and topographic correction, cloud and cloud shadow masking, data cubing, and downscaling of the 20 m bands using the ImproPhe algorithm [54–56].

**Table 1.** Seasonal temporal windows and number of Sentinel images used in each season.

| Season | Start Date | Target Date | End Date | N° of Images |
|---|---|---|---|---|
| Short-dry | 1 January 2019 | 27 January 2019 | 28 February 2019 | 111 |
| Wet | 1 March 2019 | 17 April 2019 | 31 May 2019 | 159 |
| Dry | 1 June 2019 | 17 September 2019 | 30 September 2019 | 251 |

Next, we produced three Best Available Pixel Composites using the L3PS module. The temporal windows were chosen according to the general climatological patterns in the study area but also the specific rainfall dynamics for the year of study (i.e., 2019): March to May for the wet season; June to September for the dry season, and January to February for the short-dry season (Table 1). These composites score all available observations within the temporal window selecting the optimal observation based on nonparametric quality scoring. The final products included three composites with 10 bands each to which a normalised difference vegetation index (NDVI) band was then calculated and added.

### 3.1.2. Sentinel-1

Sentinel-1 is an Earth Observation mission from ESA's Copernicus Programme consisting of two satellites, Sentinal-1A and Sentinel-1B, launched in 2014 and 2016, respectively [10]. Sentinel-1 carries a C-band Synthetic-aperture radar (SAR), which is unaffected by clouds and has been successfully employed in savannah environments for mapping land cover characteristics [10,57]. In comparison to the ALOS PALSAR 2 L-band, the C-band is a shorter wavelength with a shallower penetration into open savannah vegetation [31]. The C-band is better at detecting leaves and grasses and therefore more useful for canopy and cropland studies [31]. The L-band is a long wave band more suitable for closed canopy forested environments as it successfully detects woody vegetation [31].

The Google Earth Engine (GEE) computing platform [50,51] was used to process the Sentinel-1 data and to calculate the metrics from the VV and VH bands (25th, 50th, and 90th percentiles and standard deviation). The temporal windows used were the same as for the Sentinel-2 processing. The final products consisted of three composites, one for each season, with eight bands each.

### *3.2. Classification Strategy*

#### 3.2.1. Training Samples and Classification

The training data were collected based on our knowledge of the area and high-resolution Google Earth (Digital Globe) imagery acquired between 2013 and 2019. A total of 4430 training points were used (306 for 'Bareland'; 397 for 'Bushland'; 320 for 'Cropland'; 370 for 'Forest'; 1093 for 'Grassland'; 337 for 'Montane heath'; 580 for 'Shrubland'; 301 'Water' and 726 for 'Woodland').

Classifications were carried out in the *R* statistical Software Environment, using the 'RStoolbox' and 'randomforest' packages [58,59]. The land cover maps were created using the 'SuperClass' function [58] and random forests (RF; [52]). RF is a nonparametric machine learning classifier, that combines decision trees with bootstrapping and aggregation [28,52,60,61]. It has been proven to be more time effective and highly accurate in comparison to traditional approaches, such as maximum likelihood, and support vector machines (SMV) [60,61]. RF was implemented using the 'SuperClass' function, which takes as an input, the training data and the corrected Landsat image [58]. Specifically in African savannahs, RF classification has successfully been applied in southern Africa [29,36–38] and eastern Africa [62,63].

#### 3.2.2. Modelling Framework: Season and Sensor Combinations

In order to determine the best sensor and seasonal combinations to map savannah landscapes, we developed 21 models consisting of combinations of three seasons using Sentinel-1 and 2 imagery (Table 2).

**Table 2.** The 21 combinations of the models tested.

| Sensor | Data Included | Model |
|---|---|---|
| Sentinel-2 (S2) | Dry season S2 | 1 |
| | Short-dry season S2 | 2 |
| | Wet season S2 | 3 |
| | Dry + short-dry seasons S2 | 4 |
| | Dry + wet seasons S2 | 5 |
| | Wet + short-dry seasons S2 | 6 |
| | All seasons S2 | 7 |
| Sentinel-1 (S1) | Dry season S1 | 8 |
| | Short-dry season S1 | 9 |
| | Wet season S1 | 10 |
| | Dry + short-dry seasons S1 | 11 |
| | Dry + wet seasons S1 | 12 |
| | Wet + short-dry seasons S1 | 13 |
| | All seasons S1 | 14 |
| Sentinel-1 and Sentinel-2 combinations (S1 and S2) | Dry season S1 and S2 | 15 |
| | Short-dry seasons S1 and S2 | 16 |
| | Wet season S1 and S2 | 17 |
| | Dry + short-dry seasons S1 and S2 | 18 |
| | Dry + wet seasons S1 and S2 | 19 |
| | Wet + short-dry seasons S1 and S2 | 20 |
| | All seasons S1 and S2 | 21 |

#### 3.2.3. Validation and Accuracy Assessment

The final classified maps were validated using a two-stage random sampling procedure as recommended the best practice guidelines [53]. First, an initial sample of 675 points (75 per class) was randomly obtained from the classified map with the preliminary higher overall accuracy (Model 4 in Table 2). The accuracy was calculated together with the size of the area covered by each land cover class from the same map (Model 4 in Table 2). The second stage used this information as a basis for identifying a suitable validation sample size. The final validation samples were 2147 in total, covering seven classes: 82 for 'Bareland'; 218 for 'Bushland'; 103 for 'Forest'; 1262 for 'Grassland';

56 for 'Montane heath'; 184 for 'Shrubland'; 242 for 'Woodland'. The area covered by the 'Water' and 'Cropland' classes was too small and, therefore, they were not considered in the validation process.

Following the validation, the accuracy assessment was determined by calculating the following statistics: the overall accuracy, user's accuracy and producer's accuracies. A nonparametric McNemar's test was carried out to determine if there were statistically significant differences between the classifications performance [64].

## 4. Results

### 4.1. Sentinel-2 and Sentinel-1 Seasonal Imagery to Map Savannah Land Cover Types

The multisensor and multiseason model, incorporating Sentinel-1 and Sentinel-2 data for both the dry and the short-dry season (Model 18) was the best preforming model, with an overall accuracy of 86.3 ± 1.5% (Figures 3 and 4). A land cover map produced from this model is shown in Figure 3, with the associated confusion matrix and accuracy statistics in Table 3. Adjusting the mapped areas, using stratified area estimation, identified 'Grassland' as the predominant land cover type covering 60% of the study area (5631 ± 106 km$^2$), followed by 'Woodland' (1205 ± 90 km$^2$), 'Shrubland' (922 ± 111 km$^2$) and 'Bushland' (842 ± 63 km$^2$). Smaller classes comprised the remaining 8% of the NCA, with 'Forest' accounting for 5% (507 ± 44 km$^2$), and 'Bareland' and 'Montane heath' combined covering 3% (276 ± 30 km$^2$).

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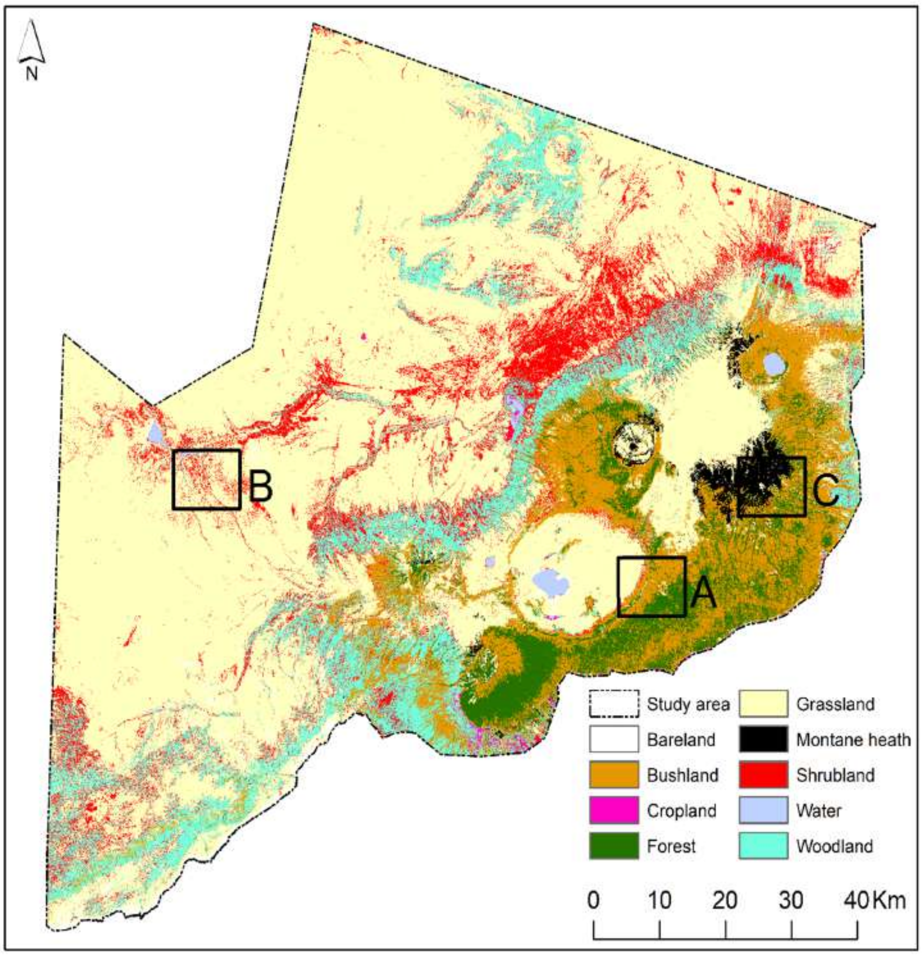

**Figure 3.** Output of the best performing model incorporating Sentinel-1 and Sentinel-2 data for both the dry and the short-dry season (i.e., Model 18). Locations A–C are the example subsets that appear in the results.

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**Producer's accuracy** 0.70 0.92 0.84 0.95 0.84 0.49 0.73

Models 4, 7, 16, 20 and 21 all achieved accuracies greater than 85%, using different season and sensor combinations (Table 2, Table S1, Figure 4). These five models, and the best-performing model, were able to map the majority of the savannah vegetation types, with the exception of 'Shrubland' (Figures 5 and 6, Table S2), with comparable accuracies.

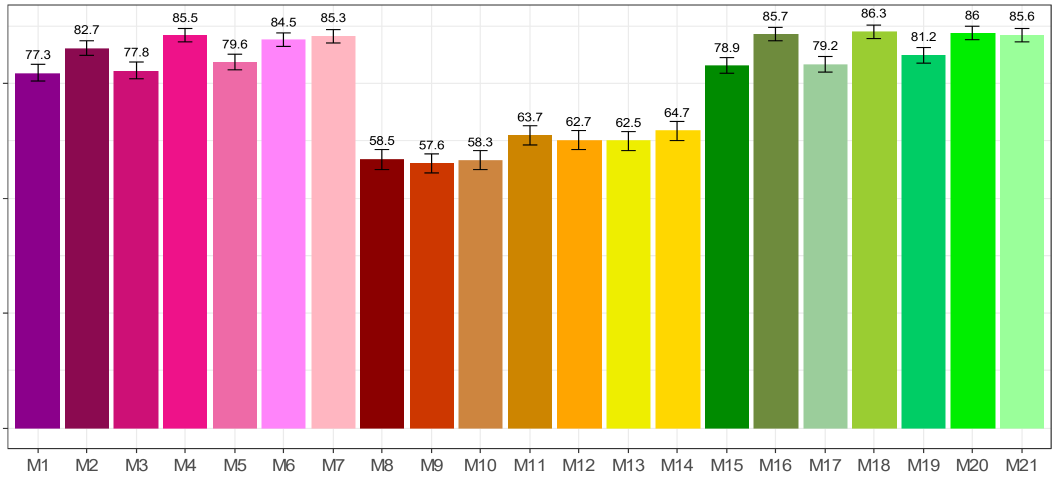

**Figure 4.** The overall accuracies and confidence intervals for the 21 model combinations tested. M1 to M7 include Sentinel-2 models; M8 to M14 include Sentinel-1 models and M15 to M21 include Sentinel-1 and -2 models. Coding of model combinations in Table 2.

**Table 3.** Confusion matrix for the best performing model incorporating Sentinel-1 and Sentinel-2 data for both the dry and the short-dry season (i.e., Model 18).

| | | **Reference** | | | | | | | | **User's Accuracy** |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **Ba** | **Bu** | **Fo** | **G** | **Mh** | **Sh** | **Wo** | **Total** | |
| **Mapped** | Bareland (Ba) | 73 | 0 | 0 | 8 | 0 | 1 | 0 | 82 | 0.89 |
| | Bushland (Bu) | 0 | 205 | 22 | 9 | 2 | 17 | 16 | 271 | 0.76 |
| | Forest (Fo) | 0 | 7 | 78 | 0 | 0 | 1 | 0 | 86 | 0.91 |
| | Grassland (G) | 4 | 3 | 0 | 1203 | 2 | 65 | 19 | 1296 | 0.93 |
| | Montane heath (Mh) | 0 | 1 | 0 | 1 | 51 | 1 | 2 | 56 | 0.91 |
| | Shrubland (Sh) | 4 | 1 | 0 | 31 | 1 | 77 | 31 | 145 | 0.53 |
| | Woodland (Wo) | 0 | 1 | 0 | 9 | 0 | 22 | 173 | 205 | 0.84 |
| | Total | 81 | 218 | 100 | 1261 | 56 | 184 | 241 | 2141 | |
| | **Producer's accuracy** | 0.70 | 0.92 | 0.84 | 0.95 | 0.84 | 0.49 | 0.73 | | |

In all models, the most reliably mapped class was 'Grassland', with maximum producer's and user's accuracies of 96% and 92%, respectively, achieved by Model 21 (Figures 5 and 6). The accuracy of the remaining six classes varied considerably in several models. 'Shrubland', for instance, was mapped poorly by all models, with a maximum user's and producer's accuracy of 59% and 54%, respectively, achieved by Model 16. The 'Forest' class was mapped accurately by Sentinel-2 or multisensor models (e.g., Models 7 and 18). However, Sentinel-1-only models were unable to map it successfully scoring a maximum user's accuracy of 38% and producer's accuracy of 33% achieved by Model 11 (Figures 5 and 6). The remaining classes, namely 'Bushland', 'Woodland', 'Shrubland' and 'Montane heath' were also mapped more accurately by Sentinel-2 and multisensor models than by the Sentinel-1-only models.

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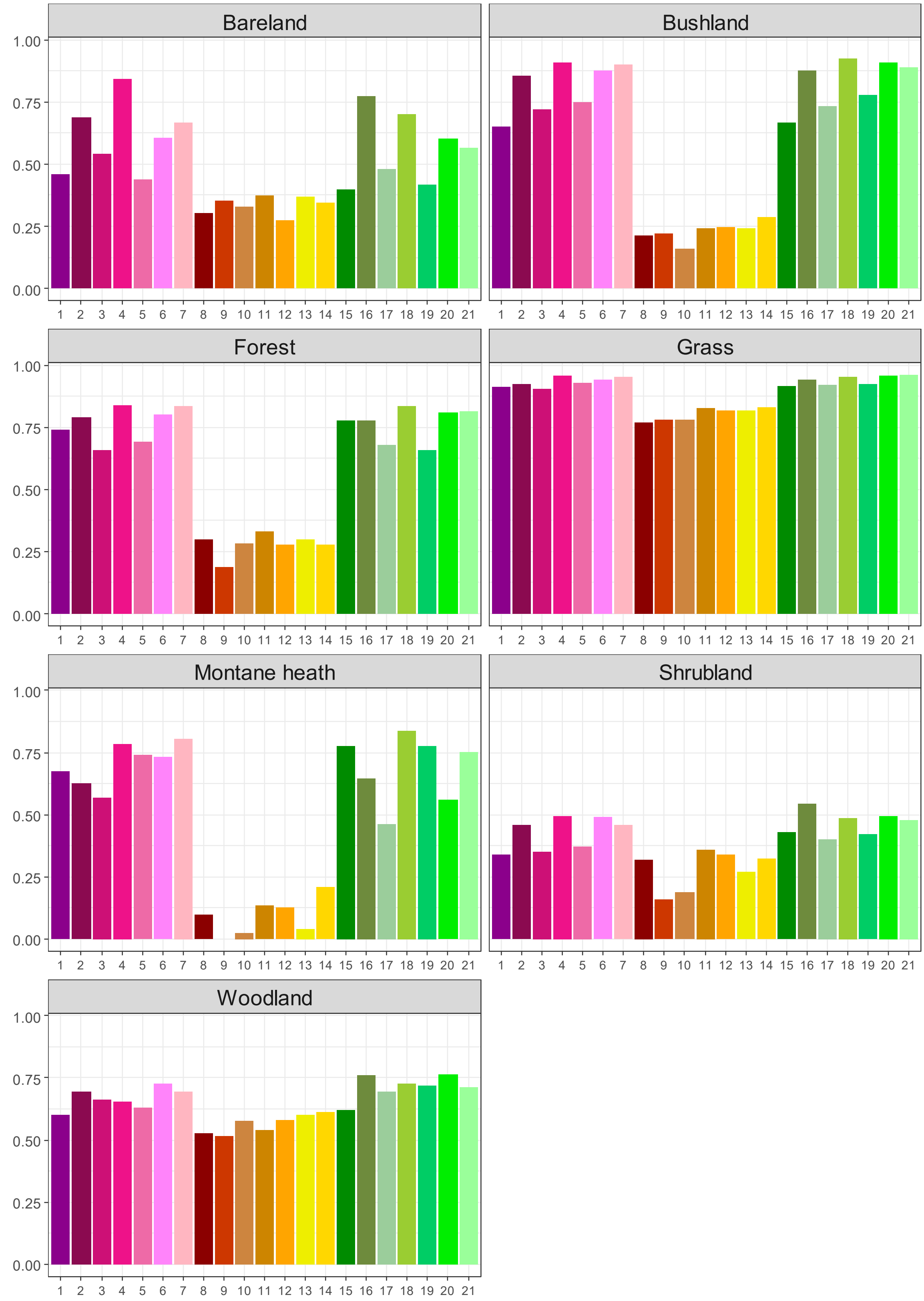

**Figure 5.** Producer's accuracy for different land cover types and models. Coding of model combinations in Table 2.

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*Remote Sens.* **2020**, *12*, x FOR PEER REVIEW 11 of 21

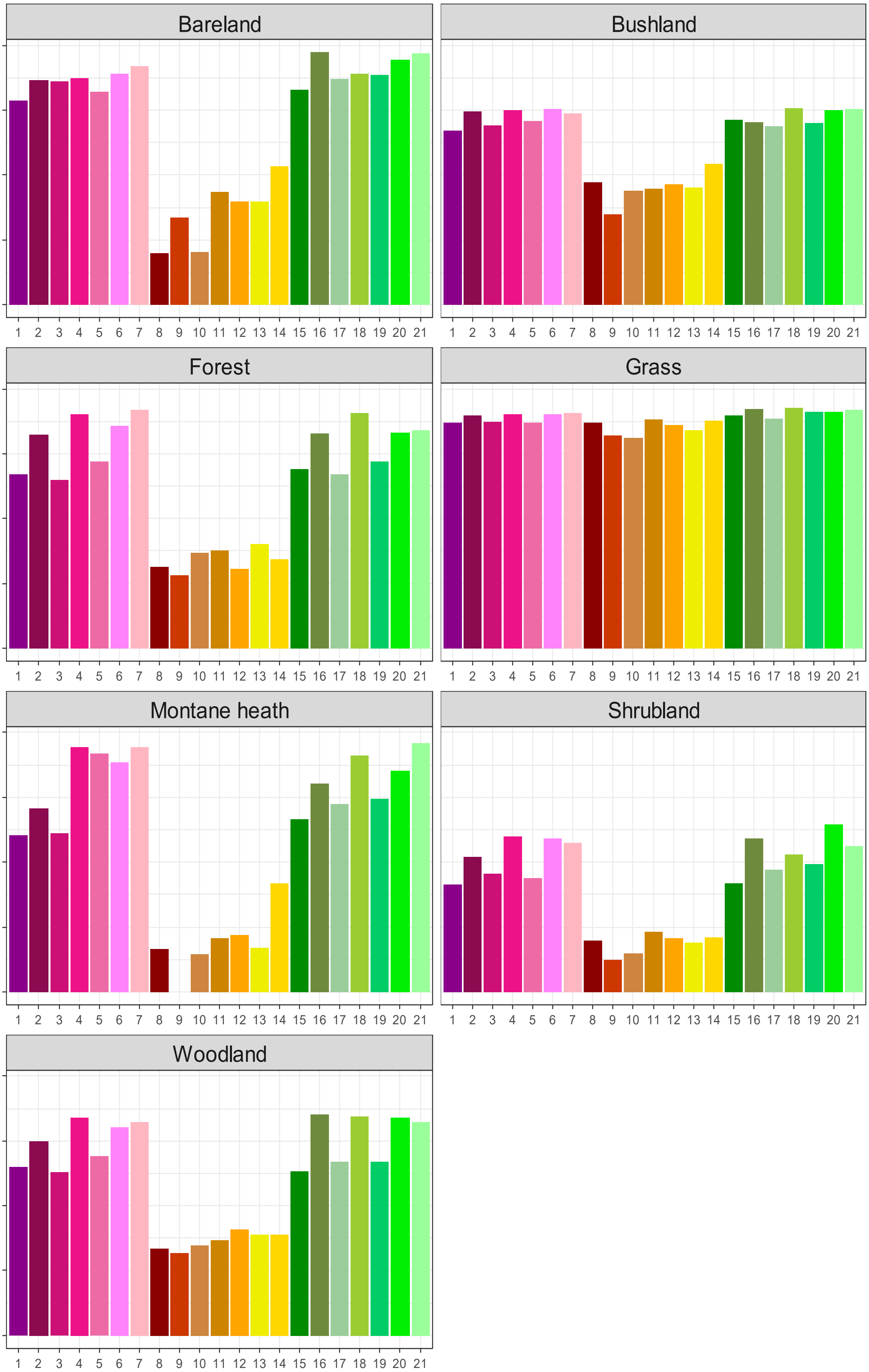

**Figure 6.** User's accuracy for different land cover types and models. Coding of model combinations in Table 2.

## 4.2. The Role of C-Band SAR

Comparing the two different sensors, Sentinel-2 models outperform the Sentinel-1 ones, in all combinations and land cover types (Figure 4). Sentinel-1 models have much lower overall accuracies and fail to distinguish most land cover types well, especially 'Montane heath', which goes completely undetected in Model 9 (Figures 5 and 6). In terms of the spatial configuration of the classified land cover maps, those produced by the Sentinel-1 models also show a higher degree of confusion between 'Woodland', 'Bushland' and 'Forest', and tend to overestimate 'Shrubland' (Figure 7(A4, B4 and C4)). 'Grassland' was the only land cover type that Sentinel-1-only models were able to identify with higher accuracies (>76.8%; Model 10; Figures 5 and 6). When combining Sentinel-2 and Sentinel-1 data, all models scored higher overall accuracies when compared to their single sensor counterparts (Figure 4). For example, the overall accuracy of Model 2 (i.e., Sentinel-2-only, short-dry season) increased from 82.7% (±1.6%) to 85.7% (±1.5%) after the Sentinel-1 data were added (Figure 4; McNemar test: $p < 0.05$).

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Comparing the two different sensors, Sentinel-2 models outperform the Sentinel-1 ones, in all combinations and land cover types (Figure 4). Sentinel-1 models have much lower overall accuracies and fail to distinguish most land cover types well, especially 'Montane heath', which goes completely undetected in Model 9 (Figures 5 and 6). In terms of the spatial configuration of the classified land cover maps, those produced by the Sentinel-1 models also show a higher degree of confusion between 'Woodland', 'Bushland' and 'Forest', and tend to overestimate 'Shrubland' (Figure 7(A4, B4 and C4)). 'Grassland' was the only land cover type that Sentinel-1-only models were able to identify with higher accuracies (>76.8%; Model 10; Figures 5 and 6). When combining Sentinel-2 and Sentinel-1 data, all models scored higher overall accuracies when compared to their single sensor counterparts (Figure 4). For example, the overall accuracy of Model 2 (i.e., Sentinel-2-only, short-dry season) increased from 82.7% (±1.6%) to 85.7% (±1.5%) after the Sentinel-1 data were added (Figure 4; McNemar test: $p < 0.05$).

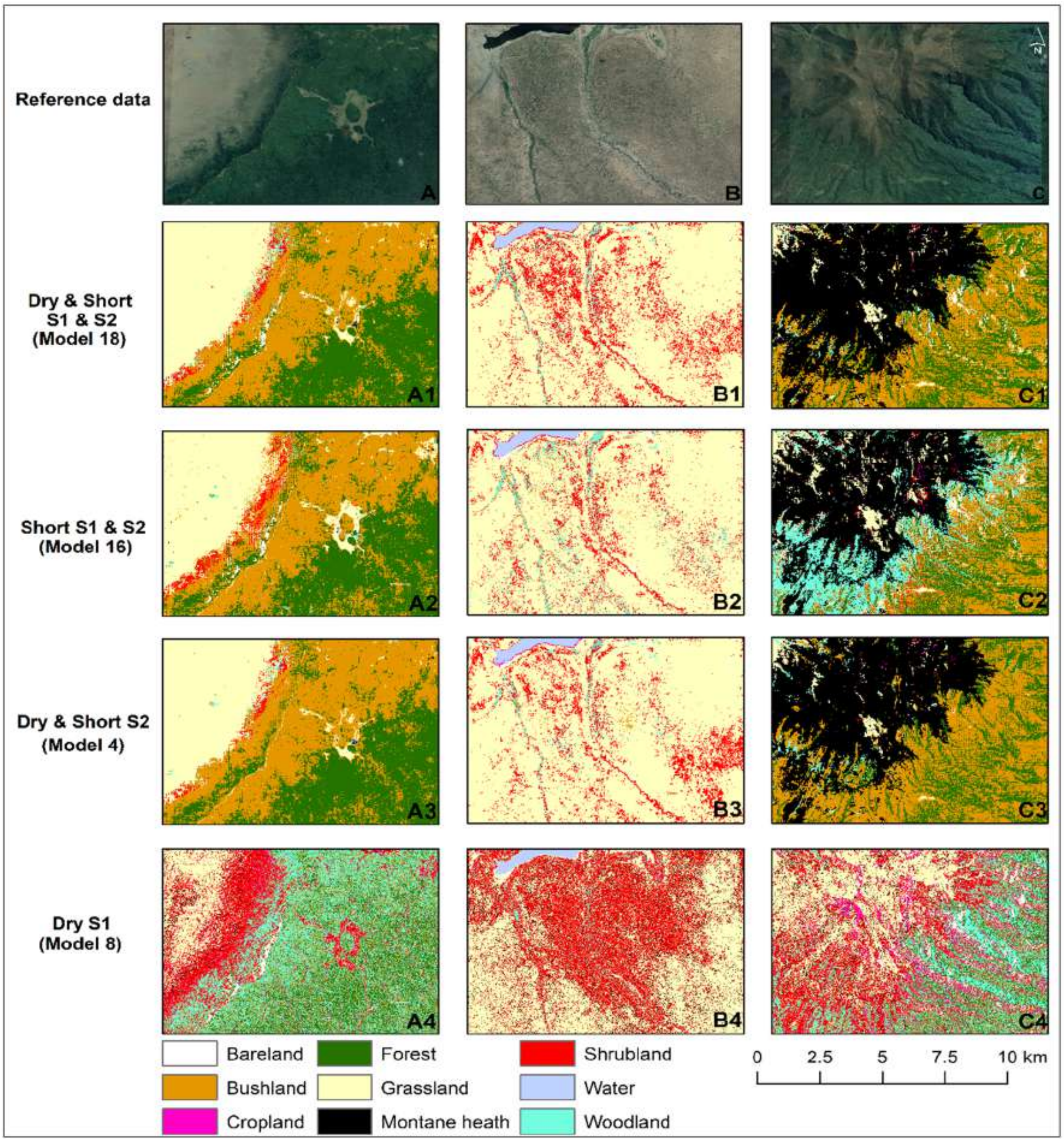

**Figure 7.** Example subsets of the study area: (**A**–**C**): very-high resolution imagery; (**A1**–**C1**): land cover maps from Model 18; (**A2**–**C2**): land cover maps from Model 16; (**A3**–**C3**): land cover maps from Model 4; (**A4**–**C4**): land cover maps from Model 8. Coding of model combinations in Table 2.

Figure 7. Example subsets of the study area: (A–C): very-high resolution imagery; (A1–C1): land cover maps from Model 18; (A2–C2): land cover maps from Model 16; (A3–C3): land cover maps from Model 4; (A4–C4): land cover maps from Model 8. Coding of model combinations in Table 2.

*Remote Sens.* **2020**, *12*, x FOR PEER REVIEW 13 of 21

For single season models, adding radar data improved accuracies for nearly all land cover types, with few exceptions (Figures 5 and 6). For instance, adding Sentinel-1 data to the short-dry single season (Model 2), increased the accuracy for most land cover types, except for the user's accuracy of 'Bushland' and producer's accuracy for 'Forest' (Figures 5 and 6). For multiseason models, adding Sentinel-1 data only improved the overall accuracy slightly (Figure 4), and visually the land cover maps are very similar (Figure 7(A1–C1,A3–C3)). For instance, the overall accuracy for Model 4 (i.e., Sentinel-2, dry and short-dry seasons) increased slightly from 85.5% (±1.5%) to 86.3% (±1.5%) after the Sentinel-1 data were added; however, this increase is within the respective confidence interval and is statistically insignificant (Figure 4; McNemar test: $p > 0.05$). Moreover, adding the SAR data to Model 4 decreased the producer's accuracy for 'Bareland', 'Grassland', 'Forest' and 'Shrubland' and decreased the user's accuracy for 'Shrubland' and 'Montane heath' (Figures 5 and 6). This decrease in the per-class accuracies for some land cover types occurs in other models, too: when adding Sentinel-1 data to Model 7 (which combines all three seasons; Figures 5 and 6), a decrease in the producer's accuracy for 'Bareland', 'Bushland', 'Forest' and 'Montane heath' and a decrease in the user's accuracy for 'Forest' and 'Shrubland' is observed.

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### 4.3. The Role of Season

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Unlike their Sentinel-1 counterparts, Sentinel-2 single season models with data from the short-dry season out-performed dry or wet mono-season ones (Figures 4 and 8). Additionally, all single season models, using dry or wet season imagery, produced very similar overall accuracies (e.g., Model 1 obtained 77.3% and Model 3 obtained 77.8% (McNemar test: $p > 0.05$); Figures 4 and 8). Both Sentinel-2 and multisensor models incorporating the short-dry season, on its own or with other seasons, performed better than other combinations (Figures 4 and 8; McNemar test: $p < 0.05$). In Sentinel-2-only models, combining the short-dry season with either the wet or dry seasons, improved all land cover classes, except for the producer's accuracy for 'Bareland' in Model 6 and 'Woodland' in Model 4, which performed better with the short-dry season on its own (Figures 5 and 6). Regarding the SAR-only models, season does not seem to have a clear effect on overall accuracies (Figures 4 and 8). However, when optical and SAR data were combined, the models that incorporated the short-dry season, obtained overall accuracies >85.6%—this included the best performing model (Model 18; Figures 4 and 8).

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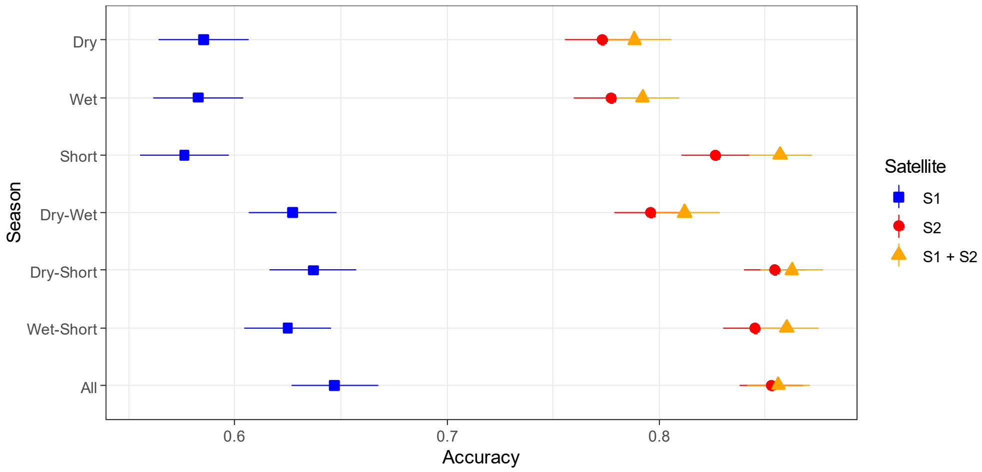

**Figure 8.** Overall accuracy results for the 21 models according to sensor and season combinations.

**Figure 8.** Overall accuracy results for the 21 models according to sensor and season combinations.

Combining imagery from more than one season increased model accuracy (Figures 4 and 8). For Sentinel-2-only models, using only the dry and short-dry seasons produced accuracies of 77.3 ± 1.8% and 82.7 ± 1.6%, respectively, while a combination of both, increased the accuracy by 2.8% (to 85.5 ± 1.5%; Figures 4 and 8; McNemar test: $p < 0.05$). In addition, this combination obtained similar results to the best performing model (Figure 7(A1–C1,A3–C3)). For Sentinel-1-only models, the dry and short-dry

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season models produced accuracies of 58.5% (±2.1%) and 57.6% (±2.1%), respectively; when combined this rises to 63.7 ± 2.1% (Figures 4 and 8; McNemar test: $p < 0.05$).

The models that combined more than one season scored lower commission and omission errors for most land cover classes (Figures 5 and 6). For Sentinel-2-only models, the combination of dry and short-dry seasons (i.e., Model 4), increased the accuracy for most land cover types, with the exception of the producer's accuracy of 'Woodland' (Figures 5 and 6). In addition, the combination of wet and short-dry season (Model 6) increased the accuracy for nearly all land cover types, except for the producer's accuracy of 'Bareland' (Figures 5 and 6). On the other hand, for multisensor models, combining more than one season increased overall accuracies slightly but these varied depending on the land cover type. For instance, the combination of dry and short-dry season data in multisensor models (Models 15 and 16) decreased the user's accuracy for 'Bareland' by 8%, of 'Shrubland' by 6%, of 'Woodland' by 1% and of 'Bushland' by 5%. Producer's accuracy also decreased for 'Bareland' (7%), 'Shrubland' (6%) and 'Woodland' (3%; Figures 5 and 6). Despite the statistics, there are areas where the opposite holds true, as in the case of the mountains northeast of the Crater (Figure 7C). In that area the inclusion of the dry season data corrected the wrongly classified 'Woodland' for 'Bushland' (Figure 7(C1,C2)).

Interestingly, the combination of all three seasons did not significantly improve the overall accuracy for most of the models (McNemar test: $p > 0.05$). However, this combination performed better than the combination of data from the dry and wet seasons (Figures 4 and 8; McNemar test: $p < 0.05$). Nonetheless, the three-season models seem to be beneficial for the mapping of specific land cover classes (Figures 5 and 6). Considering only the Sentinel-2 models, the three-season combination increases the user's accuracy for 'Forest', 'Bareland' and 'Grassland' and increases the producer's accuracy for 'Montane heath', when compared to single- or biseason combinations (Figures 5 and 6).

## 5. Discussion

### *5.1. Can Sentinel-2 and Sentinel-1 Seasonal Imagery Be Used to Accurately Map Savannah Land Cover Types at the Regional Scale?*

To improve habitat monitoring, preserve biodiversity and sustain ecosystem services, the provision of moderate-resolution land cover maps across savannah environments is essential. Mapping savannahs is a challenging task, due to varying vegetation densities, high background soil signal, and the spectral similarities between the dominant land cover types [10,24,25]. Our results demonstrate that imagery from the Sentinel constellation (optical and C-band SAR) has good utility for mapping complex savannah systems at moderate resolution. Our best performing model—using a combination of Sentinel-2 and Sentinel-1 data from the dry and short-dry seasons—achieved an overall accuracy of 86.3 ± 1.5%. This compares favourably with other studies in savannah environments (e.g., [10,28,29,37]). The land cover type most accurately mapped was 'Grassland' obtaining a maximum producer's and user's accuracy of 96% and 92%, respectively, achieved by Model 21 (three seasons). This is consistent with previous research (Figures 5 and 6, [28]). On the other hand, the performance of 'Shrubland' was relatively poor, scoring a maximum user's accuracy of 59% and producer's accuracy of 54%, achieved by Model 16 (Figures 5 and 6). A study carried out by Mishra (2014; [37]) found that lower vegetation density/height, such as 'Shrubland', performed poorly at finer scales. Spectral similarities, similar ecological composition and the fact that 'Shrubland' vegetation is highly variable and difficult to identify using Google Earth imagery, can also explain the confusion between 'Shrubland', 'Woodland' and 'Grassland' [65]. To investigate the reliability of mapping savannahs using Sentinel imagery that comes with an undisputed spatial resolution advantage compared to Landsat or MODIS, we examined the role of different sensor and season combinations on mapping accuracies.

### *5.2. Can the Combination of Optical and Radar Data Improve Classification Accuracies?*

Our results show models using solely Sentinel-1 data underperformed their Sentinel-2 counterparts, for all seasons and all land cover types (Figure 4). The best Sentinel-2 only model (dry and short-dry season) produced an 85.5% overall accuracy compared to 64.7% for the best Sentinel-1 only model (all seasons): a nontrivial difference (McNemar test: $p < 0.05$). This agrees with both Lopes et al. (2019; [66]) and Higginbottom et al. (2018; [29]) who compared optical with radar imagery in West and South Africa, respectively. This could be attributed to SAR-only models incurring errors caused by incidence angle variation, speckle, geolocation accuracy and moisture content [29]. The results from Naidoo et al. (2016; [30]) who mapped woody vegetation cover in southern African savannahs show the opposite result, but they employed longer wavelength L-band data (ALOS PALSAR), which are more sensitive to the dense woody vegetation structure [25,28,29].

The SAR-only models were able to successfully identify only the 'Grassland' land cover type (accuracies above 76.8%). 'Montane heath' on the other hand, obtained accuracies as low as 0% in Model 9 and was often confused for 'Grassland', likely due to textural similarities between the two land cover types and their lack of dense or woody plants. Interestingly, the woody classes also scored low accuracies in the SAR-only models, with open 'Woodland' achieving a maximum of 57.5% (Model 10), 'Bushland' 47.2% (Model 8) and closed 'Forest' 37% (Model 10) (Figures 5 and 6). The relatively large number of woody classes in our study area and the land cover nomenclature we adopted might explain the confusion between them, as previous research shows that combining such classes can improve mapping accuracy from SAR data [67,68]. In addition, Huttich et al. (2011; [69]) suggested that using inter-annual metrics of over one or two years could increase accuracies of 'Shrubland' and 'Grassland' classes. Our results also show that SAR only models overestimated 'Shrubland', specifically in low vegetated areas (Figure 7(A4–C4)). This can be attributed to the high surface roughness that produces similar signals for trees and shrubs [10,70]. Zhang et al. (2019; [10]) and Urban et al. (2020; [70]), also showed that radar data overestimate the presence of woody vegetation, for the Sahel and South Africa, respectively.

Previous research recommends combining SAR with optical data for improved land cover mapping [10,28,67]. Our results show that the combination of Sentinel-2 and Sentinel-1 data achieves higher overall accuracies when compared to single sensor models. Model 2 (Sentinel-2, short-dry season), scored an overall accuracy of 82.7%, increased by 3% when Sentinel-1 data were added (Figure 4; McNemar test: $p < 0.05$). The addition of SAR data increased the accuracies for most vegetation types, with the UA for 'bushland' and PA of closed 'forest' being the only two exceptions. These results are consistent with previous research carried out by Laurin et al. (2013; [67]) and Symeonakis et al. (2018; [28]), finding that combining SAR and optical data also decreased the omission and commission errors for all land cover types. Zhang et al. (2019; [10]) suggested adding SAR to optical data as they can correct errors particularly in highly productive areas (e.g., wetlands, irrigated fields and perennial grasses) which can be misclassified as trees.

Our findings agree with the emerging consensus that multisensor approaches to land cover mapping perform best. However, we found the benefits of multisensor approaches were most evident in mono-temporal models. For instance, adding SAR data to Model 4 (Sentinel-2 data, dry and short-dry seasons), improved its overall accuracy by only 0.8% (Figure 4; McNemar test: $p > 0.05$). This slight increase is within the confidence interval of both models (Models 4 and 18) and produce a very similar spatial configuration of the mapped land cover classes (Figure 7(A1–C1,A3–C3)). Our results, therefore, support those of Higginbottom et al. (2018; [29]), who found that the multisensor approach was only marginally beneficial (≈1%), and at fine scales (30m) the addition of PALSAR data to Landsat may reduce accuracies. Chatziantoniou et al. (2017; [71]) achieved similar results to ours, suggesting that although SAR data are solely impacted by wind, droughts might also influence the data quality thereby negatively affecting the overall classification accuracy. Therefore, if multiseason data is available, combining more than one sensor might be unnecessary and even counterproductive for specific land cover types (e.g., 'Shrubland').

### 5.3. How Does the Combination of Data from Different Seasons Influence the Accuracy of the Classification?

Savannah mapping studies generally use data from the dry season, due to significantly lower cloud contamination and heightened contrasts between woody and grassland components [29,32]. We found only small differences in accuracy, less than 1%, between wet and dry season models, for Sentinel-2 and multisensor scenarios (Figures 4 and 8; McNemar test: $p > 0.05$), which agrees with Symeonakis et al. (2018; [29]). Interestingly, Sentinel-2 imagery from the short-dry season, which occurs between January and February was highly effective, preforming comparably to the multisensor models and outperforming the other single season Sentinel-2 models by 5% (Figure 8). The short-dry season, which occurs right after the short rains (from October to December), is characteristic of East Africa and, to our knowledge, this is the first study to examine its utility in mapping savannahs. This season is particularly useful for land cover mapping due to it having cloud free data and being wet enough for herbaceous vegetation to be photosynthetically active, which is not the case during the dry season [33]. In the Ngorongoro Conservation Area (NCA), during the short-dry season the grasses in the North-West of the NCA starts to emerge, attracting the great wildebeest migration. Moreover, this season is dry enough to provide noticeable differences in the spectral characteristics of woody and herbaceous vegetation [30].

We found that models combing dry and wet season imagery outperform their single season counterparts in all scenarios (Figure 8). However, compared to other model combinations, Sentinel-2-only and multisensor models were improved by including the short-dry season data (Figure 8). The dry season (Model 1) and the short-dry season model (Model 2) produced an overall accuracy of 77.3% and 82.7%, respectively. Once combined, the overall accuracy increased to 85.5% (≈2.8%, McNemar test: $p < 0.05$), which is very close to the best performing model (Figure 4; McNemar test: $p > 0.05$). This agrees with Haro-Carrión and Southworth (2018; [32]) and Symeonakis et al. (2018; [28]), who also reported higher accuracies when combining biseasonal data. Adding multiseason data provides additional spectral information and, if available, should be preferred for successfully distinguishing between spectrally similar savannah vegetation classes [32].

Multiseason models generally scored higher overall accuracies; however, multisensor models were less improved. For instance, the increase in the overall accuracy from the combination of Models 15 and 16, which include multisensor data for the dry and short-dry seasons, was ≈0.6% ($p > 0.0.5$). This agrees with Symeonakis et al. (2018; [28]) who reported the same increase of 0.6% in the overall accuracy for their multisensor dry season model by combining sensors and seasons. Regardless of the impact on the overall accuracy, our results show that adding more than one season to multisensor models solved misclassification problems in specific areas within the NCA (Figure 7). For instance, in the mountains northeast of the Crater (Figure 7C), Model 16 overestimated the open 'Woodland' cover: by adding the dry season data, the classification was improved (Figure 7(C1,C2)). These errors in the spatial configuration of the mapped classes can go unnoticed, as the calculation of accuracy statistics is carried out over a limited number of locations compared to the much larger total number of pixels of the study area.

Most multiseason mapping studies consider only the wet and dry seasons or a combination of the two. Our results show that the triseasonal models performed better than the wet and dry season models (McNemar test: $p < 0.05$) and improved the accuracies for several specific land cover types (e.g., closed 'Forest' and 'Grassland' achieved 92% and 90.6%, respectively, in Model 7). However, the overall accuracy did not increase significantly when compared to other biseasonal models. For example, Model 21 (three seasons) achieved an overall accuracy of 85.6%, which is higher than Model 19 (dry and wet; 81.2%, McNemar test: $p < 0.05$), but (insignificantly) lower than Model 18 (dry and short-dry; 86.3%, McNemar test: $p > 0.05$) (Figures 4 and 8). These results contrast with Hüttich et al. (2011; [69]) who found that increasing the length of the observation period and interseasonal data increases the accuracy of the classification. However, the scholars also mention that highly dynamic classes, such as 'Grassland' and 'Bareland', benefit when longer time series are used which our results support. Whilst there are benefits from using triseasonal imagery, it must be noted that the amount of data and time required for preprocessing also increases significantly. Unless triseasonal data provide improvements for mapping specific vegetation types of interest, using a combination of the dry and short-dry seasons should suffice.

### *5.4. Implications for Biodiversity Monitoring/Ecosystem Monitoring Challenges in the Area*

This study has demonstrated that Sentinel imagery can reliably map land cover in the Ngorongoro Conservation Area (NCA), and the wider Serengeti region. The NCA is globally important for biodiversity conservation due to the presence of iconic megafauna, such as the Eastern black rhino and African elephant. It is among the best locations in the world to see black rhino in the wild, attracting thousands of tourists every year. The NCA supports the largest black rhino population in Tanzania and in recent years this population increased to 56 individuals [72]. Currently, there is emerging evidence of a decrease in the quality and quantity of preferable browse and, consequently, a decrease in suitable habitat for black rhino [14,41,73]. Unsuitable habitats and limited browse promote intra- and interspecific competition for resources and emigration of rhinos out of the Crater and the NCA [73]. Our derived land cover map could help monitor black rhino habitat quality and identify new locations within the NCA which the population could expand into. In addition, land cover maps can infer rhino home ranges and support antipoaching efforts in the NCA. Previously, the only detailed land cover survey in the NCA was completed in 1972 [45], before several major management policies were introduced that brought about significant environmental changes, e.g., the displacement of pastoralists from the Ngorongoro Crater [14,46]. Therefore, our accurate and up-to-date land cover map could have considerable conservation implications for the NCA, in general, and the black rhino population, in particular, as it provides information essential for the development of sustainable management strategies.

## 6. Conclusions

Savannahs are heterogeneous environments providing essential ecosystem services to communities. Currently, they are threatened by extensive land use/cover changes and subsequent land degradation. Mapping these environments is challenging but essential in order to improve monitoring capabilities, prevent biodiversity loss and ensure savannah ecosystem service provision. In this study, we tested how combinations of imagery from different seasons and sensors affects the accuracy of land cover maps for the NCA and provide guidance for future attempts to monitor and understand savannah landscapes. We conclude that the combination of Sentinel-1 and 2 data from the dry and short-dry seasons successfully maps most of the land cover types in the NCA, with 'Shrubland' remaining a challenge. Additionally, we found that if SAR data are unavailable, multiseason Sentinel-2 data provide a good alternative, whilst if no multiseasonal data can be used, a combination of SAR and optical data can be used to accurately map savannah environments with similar results to the best performing model. Finally, we advise that the short-dry season should be preferred over the wet and dry seasons for both multisensor combinations and optical data. In conclusion, we provide much needed and highly accurate, medium resolution land cover maps for the NCA, which will support sustainable management and conservation.

**Supplementary Materials:** The following are available online at http://www.mdpi.com/2072-4292/12/23/3862/s1, Table S1: Overall accuracy of the models tested, Table S2: User's and producer's accuracy of all land cover types and models tested.

**Author Contributions:** Conceptualisation, J.B. and E.S.; Formal analysis, J.B.; Methodology, J.B., T.P.H. and E.S.; Project administration, E.S. and M.J.; Supervision, E.S. and M.J.; Validation, J.B., T.P.H. and E.S.; Writing—original draft, J.B., T.P.H. and E.S.; Writing—review and editing, M.J. All authors have read and agreed to the published version of the manuscript.

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ORIGINAL RESEARCH

# Landsat time series reveal forest loss and woody encroachment in the Ngorongoro Conservation Area, Tanzania

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## Abstract

The Ngorongoro Conservation Area (NCA) of Tanzania, is globally significant for biodiversity conservation due to the presence of iconic fauna, and, since 1959 has been managed as a unique multiple land-use areas to mutually benefit wildlife and indigenous residents. Understating vegetation dynamics and ongoing land cover change processes in protected areas is important to protect biodiversity and ensure sustainable development. However, land cover changes in savannahs are especially difficult, as changes are often long-term and subtle. Here, we demonstrate a Landsat-based monitoring strategy incorporating (i) regression-based unmixing for the accurate mapping of the fraction of the different land cover types, and (ii) a combination of linear regression and the BFAST trend break analysis technique for mapping and quantifying land cover changes. Using Google Earth Pro and the EnMap-Box software, the fractional cover of the main land cover types of the NCA were accurately mapped for the first time, namely bareland, bushland, cropland, forest, grassland, montane heath, shrubland, water and woodland. Our results show that the main changes occurring in the NCA are the degradation of upland forests into bushland: we exemplify this with a case study in the Lerai Forest; and found declines in grassland and co-incident increases in shrubland in the Serengeti Plains, suggesting woody encroachment. These changes threaten the wellbeing of livestock, the livelihoods of resident pastoralists and of the wildlife dependent on these grazing areas. Some of the land cover changes may be occurring naturally and caused by herbivory, rainfall patterns and vegetation succession, but many are linked to human activity, specifically, management policies, tourism development and the increase in human population and livestock. Our study provides for the first time much needed and highly accurate information on long-term land cover changes in the NCA that can support the sustainable management and conservation of this unique UNESCO World Heritage Site.

## Introduction

African savannah environments provide essential ecosystem services to communities, sustain endemic biodiversity and play a critical role in regulating carbon cycles (Liu et al., 2015; McNicol et al., 2018; Poulter et al., 2014; Schneibel et al., 2017). In recent years, the provision of ecosystem services from many savannah regions has progressively declined due to agricultural expansion, woodland degradation, invasive species, bush encroachment, climate change and management policies, all of which can place wildlife and communities at risk (Schneibel et al., 2017; Symeonakis & Higginbottom, 2014; Tsalyuk et al., 2017).

The Ngorongoro Conservation Area (NCA) in Northern Tanzania is a designated United Nations Educational, Scientific and Cultural Organisation (UNESCO) World Heritage Site for exceptional natural and cultural values (UNESCO, 2010). It is part of the world's largest intact savannah systems, the Greater Serengeti Ecosystem, which includes the Serengeti National Park and the Maasai Mara, where one of Africa's largest animal migrations takes place (Masao et al., 2015; Swanson, 2007). The NCA also supports the largest population of the critically endangered Eastern Black Rhinoceros *Diceros bicornis michaeli* in Tanzania (Amiyo, 2006; Goddard, 1968; Mills et al., 2006). The density and diversity of wildlife in the NCA is of global importance for biodiversity conservation and economically important for Tanzania. For instance, in 2016 over 1 million tourists visited the NCA, generating revenue of approximately $70 million (Slootweg, 2016, 2017). The NCA is also unique as it operates as a multiple land-use model designed to protect not only wildlife but also the lifestyle of the resident Maasai pastoralists (Niboye, 2010).

The NCA vegetation is composed of a combination of highland forests around the Ngorongoro Crater, savannah woodland and shortgrass plains (Herlocker & Dirschl, 1972). Over the last 50 years, African savannahs have undergone considerable land cover changes, including forest degradation, spread of invasive plant species, and woody encroachment (Amiyo, 2006; Higginbottom et al., 2018; Ludwig et al., 2019; Mills et al., 2006; Symeonakis et al., 2018; Venter et al., 2018). In the NCA highlands, forest degradation is of particular concern, as these forests provide ecosystem services to the Maasai through the provision of fuel wood, traditional medicinal plants, and forage for livestock (Swanson, 2007). Additionally, upland forests provide shelter for wildlife and regulate water resources (Swanson, 2007). Meanwhile, in the grassland plains, woody encroachment and invasive species can reduce rangeland carrying capacity, directly affecting wildlife and the Maasai livestock (Venter et al., 2018).

Land cover changes in the NCA are driven by a combination of local and global drivers (Homewood et al., 2001; Masao et al., 2015; Niboye, 2010). Firstly, the Maasai community within the NCA increased from roughly 8000 in 1959 to almost 100 000 in 2018, with an accompanying livestock population of approximately 800 000 in 2018 (Lyimo et al., 2020; Manzano & Yamat, 2018). Population growth has led to the expansion of settlements, livestock bomas and demand for water resources (TAWIRI & NCAA, 2020). In addition, tourism, grazing pressure, climate change and management decisions also seem to be contributors to change (Homewood et al., 2001; Masao et al., 2015; Niboye, 2010). Many of these changes have led to the decline in habitat quality (Amiyo, 2006; Estes et al., 2006; Niboye, 2010). Less suitable habitats with limited opportunities for browsing and grazing encourage inter- and intraspecific competition for resources, threatening wildlife populations and their distribution, and subsequently raising concerns of biodiversity loss and increasing human-wildlife conflicts (Amiyo, 2006; Kija et al., 2020; Makacha et al., 1979; Niboye, 2010). In addition, for the Maasai pastoralists these changes threaten the quantity and quality of pasture resources for livestock and consequently food security. Previous small-scale studies have mentioned ongoing land cover changes within the NCA, but the large-scale dynamics remain poorly understood (Boone et al., 2006; Homewood et al., 2001; Masao et al., 2015). The research available for the NCA is mostly based on field surveys and aerial photography, which provide highly detailed information at the species level but do not offer large-scale, holistic coverage (Amiyo, 2006; Herlocker & Dirschl, 1972).

Over the last five decades, Earth-observation (EO) data have increasingly been used to map and monitor land cover (Adole et al., 2016; Woodcock et al., 2008; Wulder et al., 2012). In particular, the Landsat archive provides open-access, long-term data, with 30-metre spatial resolution and six spectral bands that are well suited for vegetation mapping. However, savannah landscapes are challenging to map due to their heterogeneous and complex characteristics, incorporating a mixture of woody vegetation (trees, bushes and shrubs), different grass species and bare land (Borges et al., 2020; Ludwig et al., 2019; Mathieu et al., 2013; Settle & Drake, 1993; Symeonakis et al., 2018; Venter et al., 2018). Mapping and monitoring change in savannah environments is even more challenging, as most changes occur gradually and incrementally, resulting in subtle spectral changes that are difficult to detect using imagery with a moderate spatial resolution. Recently, the combination of synthetically generated mixed samples with machine learning regression methods has proved effective for mapping fractional cover in complex environments (Okujeni et al., 2013; Senf et al., 2020; Suess et al., 2018). Meanwhile, the development of time-series methodologies has facilitated a more ecologically meaningful quantification of landscape change detection. These time-series approaches exploit the higher observation densities that are now available, to detect changes in either spectral bands, vegetation indices or derived layers such as class probabilities or fractional coverage. (Schneibel et al., 2017; Schwieder et al., 2016; Souverijns et al., 2020).

There is a pressing need to quantify the extent and magnitude of land cover changes within the NCA, to identify vulnerable areas and prevent potential threats to habitats and livelihoods. The NCA's multiple-use approach, which attempts to reconcile biodiversity protection and the needs of local people, is a notoriously challenging task (Harris et al., 2020). Moreover, in the context of protected area management, an improved understanding of land cover dynamics is imperative for sustainable development, to support effective land use planning, conserve and manage biodiversity and ensure the long-term survival of wildlife and the prosperity of resident human communities.

The main aim of the paper is to support the sustainable management of the NCA by developing an Earth-observation-based approach for monitoring multi-faceted land cover changes occurring over the past 35 years. We employ the approach of Okujeni et al. (2013) to produce near-annual fractional cover maps for nine constituent land cover classes of the NCA. To identify the various change processes, we employ two pixel level time-series analyses. Firstly, we employ monotonic linear trend analysis to detect long-term changes in land cover (Herrmann et al., 2005; Higginbottom & Symeonakis, 2014). Secondly, we used the Breaks For Additive Season and Trend (BFAST) piece-wise linear regression method to detect possible breakpoints, specifically for upland forest cover (Grogan et al., 2016; Lewińska et al., 2020; Morrison et al., 2018; Schmidt et al., 2015; Wu et al., 2020). We use the linear trend analysis to detect long-term, incremental land cover changes, such as shrub encroachment and grassland decline. Meanwhile, BFAST is well-suited to identifying abrupt shifts and reversals in trends that may be obscured by monotonic analysis, such as deforestation and regrowth (Verbesselt, Hyndman, Zeileis, et al., 2010).

## Study area

The NCA covers an area of around 8283 km$^2$ (Swanson, 2007, Fig. 1). It contains the largest, intact volcanic caldera in the Ngorongoro Crater and has highly abundant and diverse wildlife (Estes et al., 2006, Fig. 1C). Annual rainfall ranges from 450 mm/year in the lowlands to 1200 mm/year in the highlands (Boone et al., 2007; Fig. S1). Rainfall follows a bimodal pattern, characteristic of East Africa, comprising two wet seasons: the main between March and May, and a shorter one between November and December (Pellikka et al., 2018). During the dry season, temperature ranges between 11 and 20°C, while in the wet season it ranges between 7 and 15°C (Amiyo, 2006).

# Materials and Methods

## Landsat image acquisition and processing

We acquired and processed Landsat Collections Level 1 Tier 1 imagery from 1985 to 2020. Based on our previous study, we selected images from the short dry season (January–April), which enables the highest separability of the land cover types (Borges et al., 2020). For the 35-year study period, we obtained 26 images with cloud cover less than 75%, acquisition dates ranged from 9 January to 28 April (Fig. 2). No suitable images were available for 1986, 1988, 1991–1994 and 1996–1999. The Landsat collections are pre-processed for atmospheric corrections using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) routine (Masek et al., 2006). Cloud masking was provided by F-mask (Schmidt et al., 2013). We topographically corrected the images using a Sun Canopy Sensor (Gu & Gillespie, 1998) and C-correction approach (Teillet et al., 1982). The Normalised Difference Vegetation Index (NDVI; Tucker, 1979) was calculated using the standard equation and added to the spectral bands, NDVI is useful in savannahs that do not feature dense forest canopies (Prince & Tucker, 1986). We used the Google Earth Engine cloud-computing environment for all Landsat processing (Gorelick et al., 2017; Moore & Hansen, 2011).

## Fractional cover mapping

Our approach focusses on the generation of near-annual fractional land cover maps, where each pixel represents the 0%–100% coverage of the constituent land cover types. The production of fractional land cover maps requires predictive models quantifying the relationship between the input satellite imagery products and the target classes as *fractions*. Previous studies have generated fractional training data by the manual interpretation or classification of imagery with a finer spatial resolution than the input predictive layers; however, this is a time-consuming exercise (Baumann et al., 2018). More recently, Okujeni et al. (2013) developed an approach to generate mixed samples from pure spectra representing 100% class coverage, producing synthetic samples of mixed fractions for the desired land cover types. This synthetic training data can be combined with modern machine learning models and has proved highly effective in a range of settings (Okujeni et al., 2013; Senf et al., 2020; Suess et al., 2018).

Here, we expand on the methodology developed by Okujeni et al. (2013). First, we developed a spectral library for a land cover schema of the NCA. We focussed on ecological meaningful land cover types comprised of mixed vegetation communities which are spectrally separable. Second, we generated synthetically mixed training data using the approach proposed by Okujeni et al. (2013). Finally, we input these synthetic samples into a Random Forest regression model. To guide our analysis, we employed a land cover map of the NCA

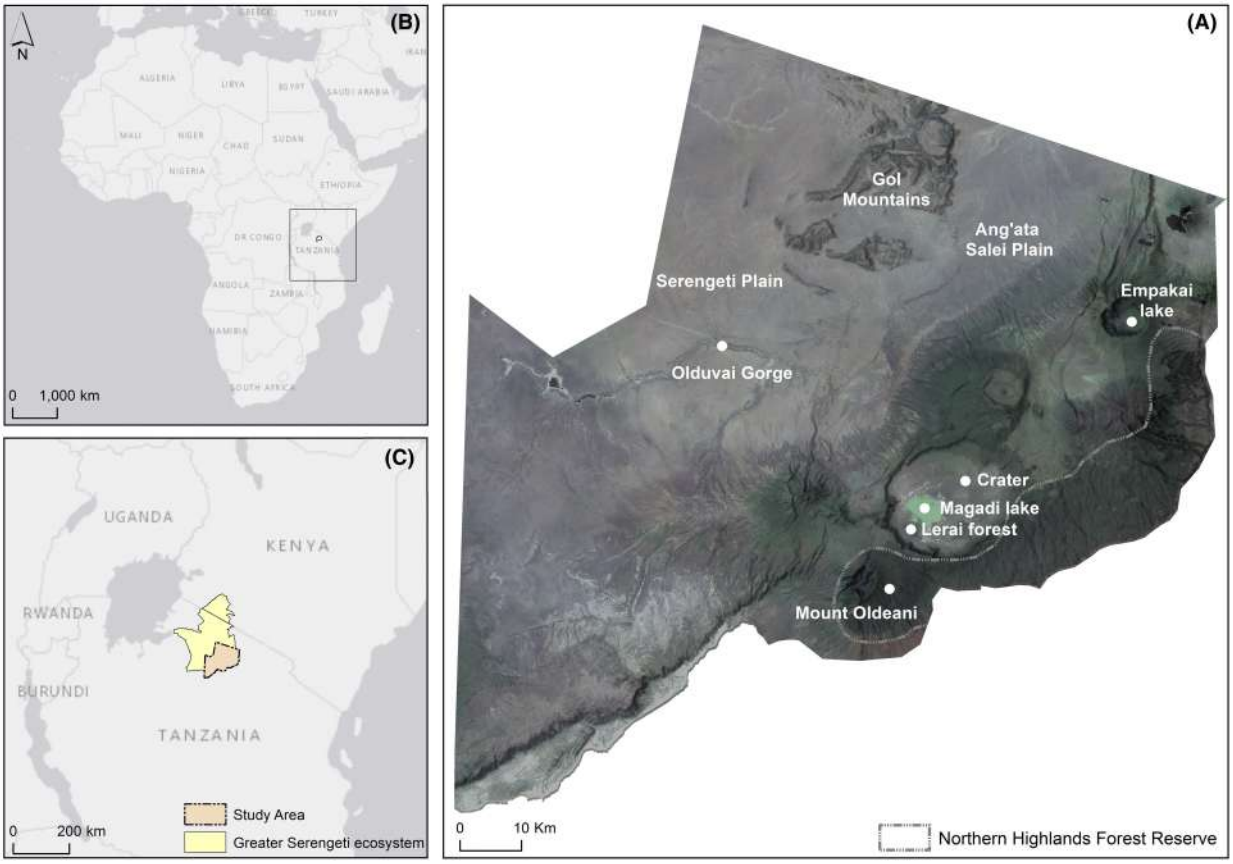

**Figure 1.** The Ngorongoro Conservation Area (A) and its location within Africa (B), Tanzania and the Greater Serengeti ecosystem (C).

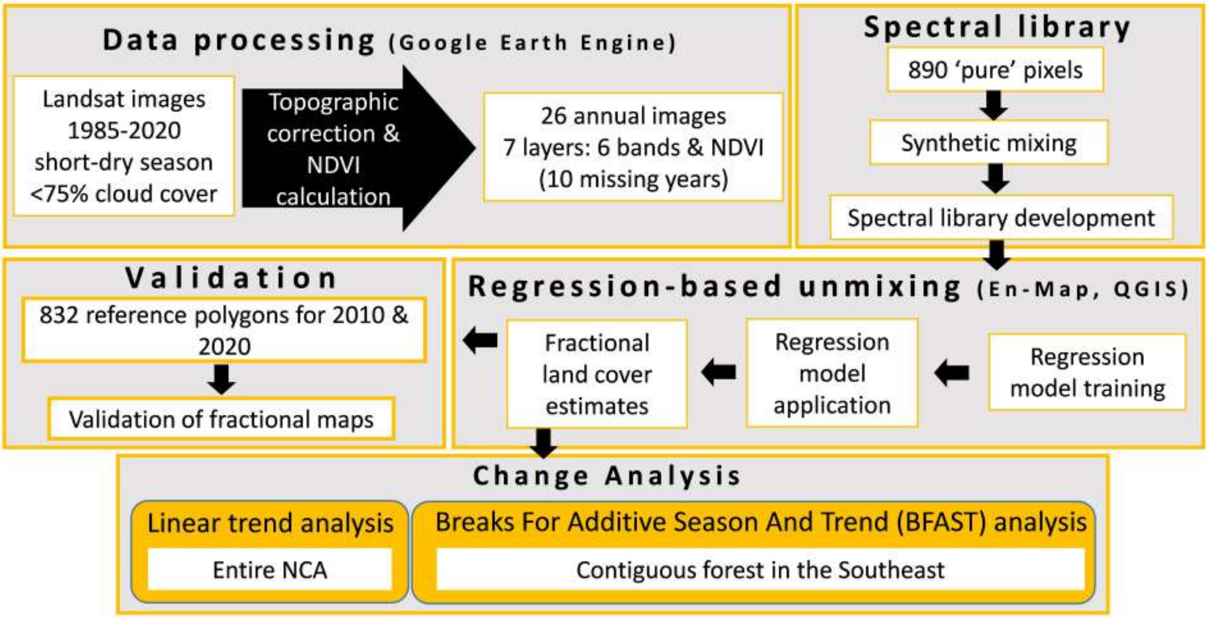

**Figure 2.** Methodological flowchart of our study.

**Table 1.** Description of the nine main land cover types of the NCA, according to Herlocker and Dirschl (1972) and Pratt et al. (1966).

| Land cover types | Description | Examples of land cover |
|---|---|---|
| Bareland | Minimal or no vegetation cover including bare rock, sand, saline or alkaline flats or riverine deposits. |  |
| Bushland | Closed shrub canopy comprising woody plants, bushes or trees, ranging from 3 to 6 m in height. |  |
| Cropland | Natural vegetation has been removed and replaced by other types of vegetation cover that require human activity to maintain it. |  |
| Forest | Closed canopy trees ranging between 7 and 40 m or more in height. The ground is mostly covered by bushes and shrubs making it difficult for animals to move through it. |  |
| Grassland | Grasses that vary between short (<25 cm) and tall (150 cm). In certain areas, herbs, scarred trees, or shrubs can occur. During the dry season and during droughts, it can be almost bareland. |  |
| Montane heath | Medium-sized vegetation (<1 m) including shrubs, grasses, ferns, and mosses, usually at higher altitudes. |  |
| Shrubland | Open canopy with medium-sized woody vegetation (<6 m in Pratt), surrounded by grass or bareland. Some trees and bushes can occur. |  |

(*Continued*)

**Table 1.** Continued.

| Land cover types | Description | Examples of land cover |
|---|---|---|
| Water | Ponds, lakes, rivers and swamps (with little or no vegetation cover). |  |
| Woodland | Open or continuous canopy with trees as tall as 20 m, often surrounded by shrubs, bushes or grass but not thicket. |  |

produced in an earlier study (Borges et al., 2020). This map was based on multi-temporal Sentinel-1 and 2 composites for 2019 with a 10 m spatial resolution. With higher quality input data used in its production and achieving high per-class and overall classification accuracies, we consider this dataset to be the best available and most suitable reference for informing our Landsat-based methodology in the present study.

## Spectral library development

We employed a land cover classification schema based on the detailed surveys of the NCA undertaken in the 1960s by Herlocker and Dirschl (1972) and Pratt et al. (1966). This aligns with our previous work on land cover classification in the area (Borges et al., 2020), and is ecologically relevant both in terms of habitat usage by species and the management of the park. For instance, the highest densities of black rhino occur in bushland areas (Emslie, 2020), but in the NCA they can also be found in shrubland, open grasslands and closed-canopy forest, as such it becomes increasingly important to distinguish between these classes (Gadiye et al., 2016). In total, we assigned samples to nine land cover types, detailed in Table 1.

For the development of the spectral library, we collected 890 polygon samples from across the NCA, covering the nine land cover classes, based on our knowledge of the area, spectral information (Figs. S2 and S3), visualisation of high-resolution imagery within Google Earth Pro and the processed Landsat images (Fig. 2). The samples were distributed as follows: 20 for Bareland; 94 for Bushland; 11 for Cropland; 50 for Forest; 498 for Grassland; 19 for Montane heath; 82 for Shrubland; 13 for Water, and 103 for Woodland. The sample size was proportional based on our earlier land cover map (Borges et al., 2020). Using a proportional sample size accommodates the greater spectral variability within the large classes (e.g. grassland) relative to the smaller more classes (e.g. montane heath). We compared multi-temporal Landsat images and aerial photography to select only pixels that remained unchanged throughout the study period (i.e. pseudo-invariant features). For each Landsat image, we extracted pixel values to produce an independent annual-level spectral library, creating a total of 26 libraries.

## Synthetic mixing

To create fractional training data from our spectral library we used the EnMAP-box (version 3.6; EnMAP-Box Developers, 2019) software to generate synthetic mixture samples (Okujeni et al., 2013; Van der Linden et al., 2015). For each class, we generated 1000 synthetic samples, comprised of different fractional mixtures of all classes. The following processes, described in (Cooper et al., 2020), produced each synthetically mixed sample:

1. We established the likelihood for different multi-class combinations across each pixel and included endmembers according to this weighting. We set a 20% chance for a two classes mixture, 40% for a three classes mixture and 40% for a four classes mixture.
2. From the target class spectral library, one random endmember was pulled.
3. This selected endmember was randomly allocated a mixing fraction between 0 and 1.
4. Additional endmembers were randomly selected from the additional classes and added.

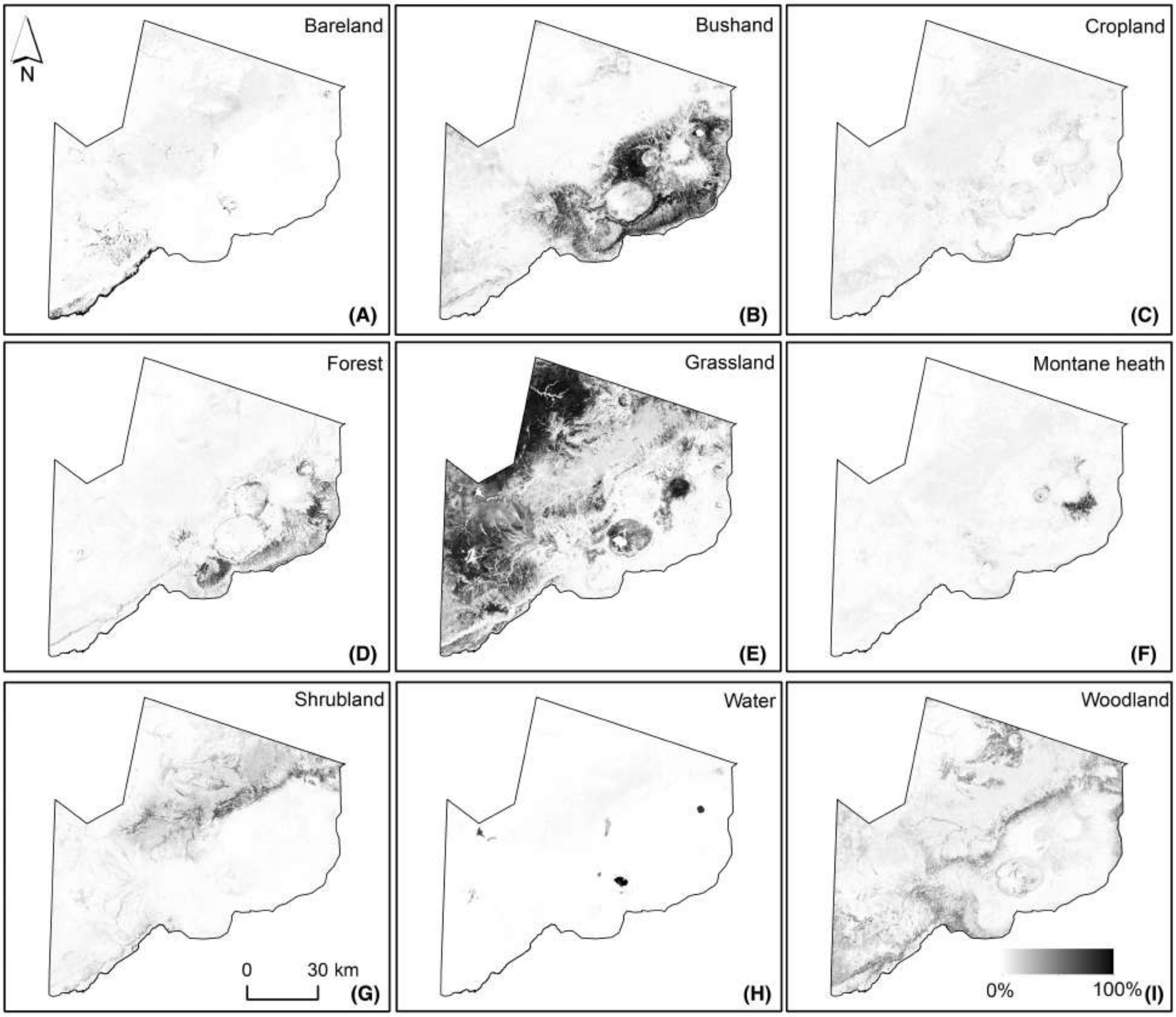

**Figure 3.** Fractional cover maps for the nine main land cover classes of the NCA in the year 2020. (A) Bareland, (B) Bushland, (C) Cropland, (D) Forest, (E) Grassland, (F) Montane heath, (G) Shrubland, (H) Water, (I) Woodland.

5. The newly added endmembers were randomly assigned mixing fraction, with the sum of all fractions equalling one.
6. Synthetically mixed spectra were generated based on linear combinations of the assigned mixing fractions.We repeated this process for every synthetic spectra. Finally, we added the original endmembers to the synthetic samples and assigned mixing fractions of one or zero for spectra belonging to target and non-target classes, respectively.

## Regression-based unmixing

We used a Random Forest regression to map vegetation class fractions (Breiman, 2001). The Random Forest is a non-parametric machine learning model based on ensembles of regression trees, popular for image classification and land cover mapping (Li et al., 2015; Rodriguez-Galiano et al., 2012; Symeonakis et al., 2018).

The regression-based unmixing was carried out in the EnMAP-Box 3.6 (EnMAP-Box Developers, 2019), an open-source QGIS plugin designed for advanced processing workflows of optical remote sensing data (Van der Linden et al., 2015). We repeated the unmixing procedure 10 times and averaged the predictions for each year, produced using the correspondent spectral library. This allowed the inclusion of multiple types of synthetic mixtures into the unmixing process while keeping the training sample size low (Okujeni et al., 2017).

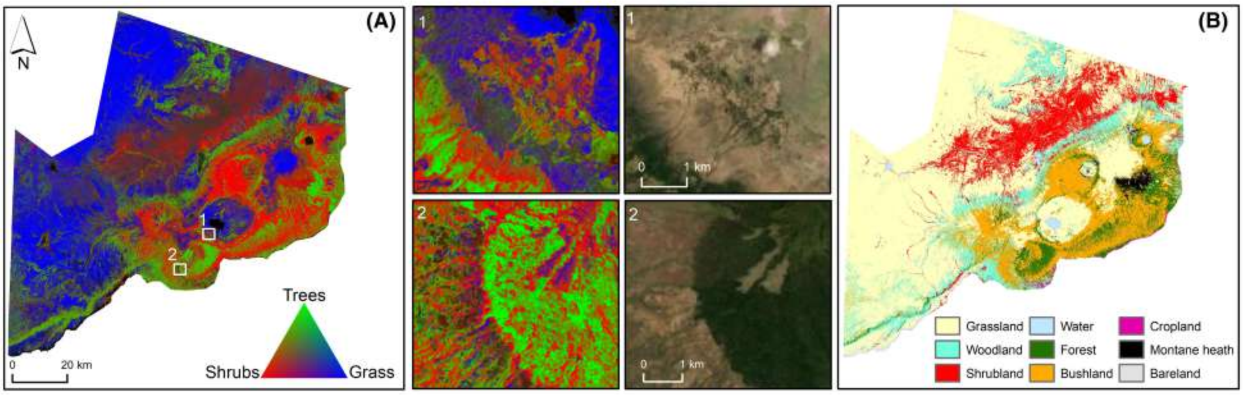

**Figure 4.** (A) RGB composite of the aggregated three main components of savannah landscapes: trees (G, forest and woodland), shrubs (R, bushland and shrubland) and grasses (B) for the year 2020; locations 1 and 2 are example subsets. (B) Land cover ('hard') classification for the year 2020.

**Table 2.** Accuracy of the fractional land covers for the NCA for the years 2010 and 2020.

| Land cover | | Bareland | Bushland | Cropland | Forest | Grassland | Montane heath | Shrubland | Water | Woodland |
|---|---|---|---|---|---|---|---|---|---|---|
| 2010 | MAE | 2.80 | 5.08 | 5.34 | 4.69 | 14.18 | 5.64 | 6.00 | 4.47 | 6.70 |
| | $R^2$ | 0.90 | 0.92 | 0.43 | 0.88 | 0.83 | 0.64 | 0.77 | 0.81 | 0.61 |
| | Bias | −3% | −6% | −8% | −6% | −1% | −8% | −3% | −6% | −8% |
| 2020 | MAE | 2.97 | 6.13 | 6.72 | 6.09 | 13.67 | 5.24 | 6.23 | 1.63 | 6.42 |
| | $R^2$ | 0.89 | 0.91 | 0.33 | 0.84 | 0.82 | 0.76 | 0.76 | 0.95 | 0.73 |
| | Bias | −2% | −10% | −9% | −7% | −1% | −8% | −2% | −10% | −8% |

## Validation of fraction maps

A validation dataset centredon 2010 and 2020 was developed based on visual interpretation of high-resolution imagery in Google Earth Pro (Ludwig et al., 2016). Due to limited Google Earth imagery and uncertain dates for certain images, imagery between 2009 and 2014 was aggregated and compared to the 2010 fraction layers, and imagery between 2015 and 2020 was aggregated and compared to the 2020 layer. Validation of model predictions prior to 2010 was not possible as earlier images had substantially lower resolution or were unavailable. We validated the model predictions by using a stratified random sampling, based on best practise (Olofsson et al., 2014). We collected 416 reference pixels for each epoch, resulting in 832 reference pixels. For each reference pixel, a 10 × 10 grid of 3 m squares (Fig. S4) was used, and the class fractions were estimated by a researcher with local knowledge. For statistical validation, we calculated the bias, the coefficient of determination ($R^2$) and the mean absolute error (MAE) between the reference fractions and predicted fractions.

## Change mapping

To detect changes in the fractional land cover, we employed two complementary time series analyses. Firstly, to detect the general land cover change, we performed a linear regression against time on the annual fractional cover maps of each land cover class (Herrmann et al., 2005). Changes that were statistically ($p > 0.05$) or ecologically (cover in 2020 $< 5\%$) insignificant were masked.

Secondly, to provide more detailed information on changes specifically in the upland forests, we applied the Break For Additive Season and Trend (BFAST) method (Verbesselt, Hyndman, Newnham, et al., 2010). BFAST is a piecewise linear regression approach that combines time-series decomposition with structural breakpoint detection. The statistical basis of BFAST is the decomposition of a time-series into trend, seasonal and residual components; with significant changes in the trend component detected by a moving sum of residuals (MOSUM) test. BFAST was originally developed for NDVI time-series, however, it is not specific for any type of data (Verbesselt, Hyndman, Newnham, et al., 2010) and has been applied to other vegetation indexes, rainfall data or Landsat bands. (Che et al., 2017; Higginbottom & Symeonakis, 2020; Horion et al., 2016; Morrison et al., 2018; Platt et al., 2018). We used the 'BFAST01' implementation of BFAST, which is tailored for non-seasonal (i.e. annual) data, and allowed for a single breakpoint to occur in the time series using a $P < 0.05$ significance threshold. The breakpoints identified by BFAST were then classified into six change types, based on de Jong et al. (2013): (1)

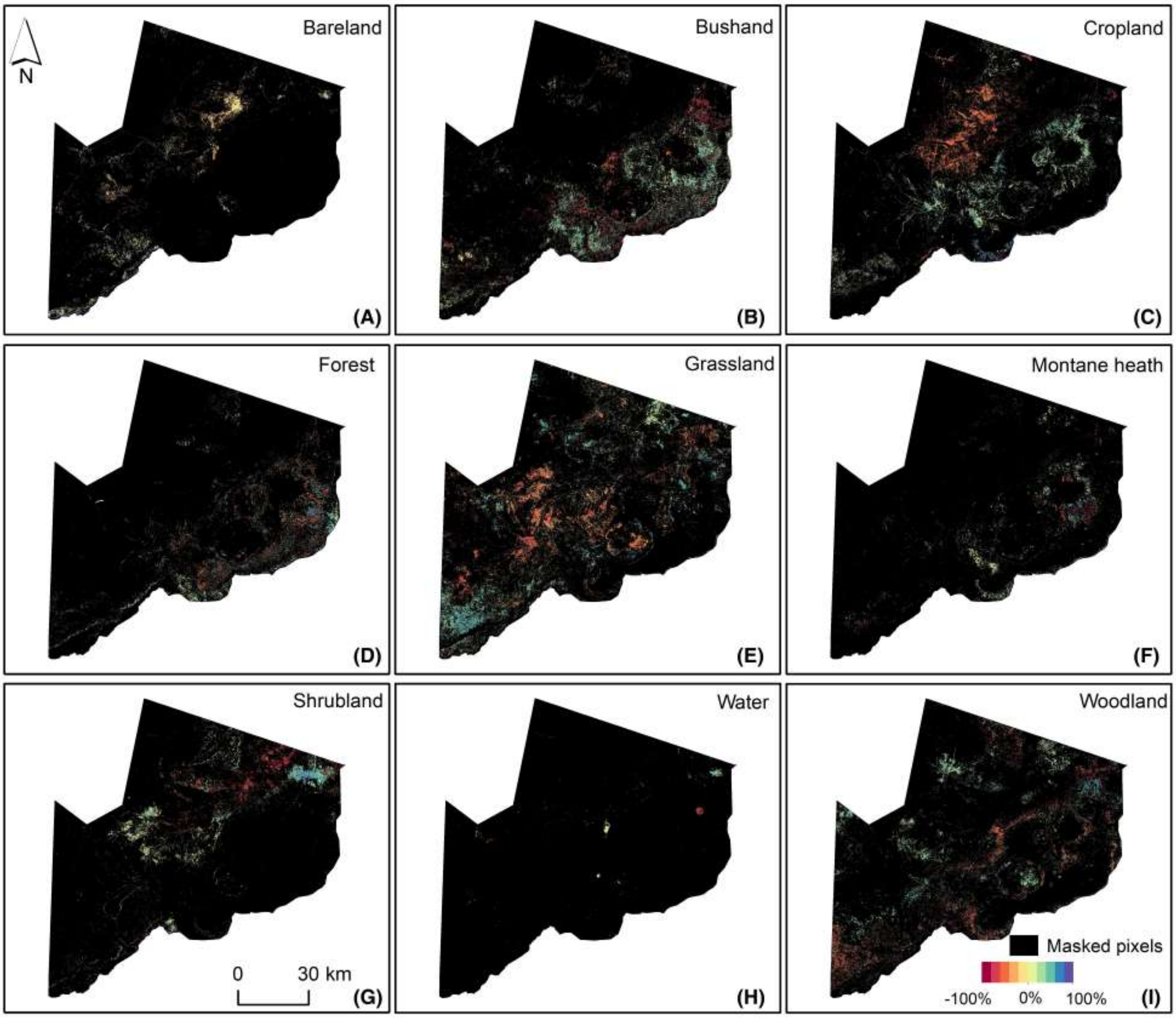

**Figure 5.** Land cover changed according to the linear trend analysis in the NCA between 1985 and 2020 for all land cover classes. (A) Bareland, (B) Bushland, (C) Cropland, (D) Forest, (E) Grassland, (F) Montane heath, (G) Shrubland, (H) Water, (I) Woodland.

*monotonic*: increase, (2) *monotonic*: decrease, (3) *reversal*: increase to decrease, (4) *reversal*: decrease to increase, (5) *interruption*: increase with negative break, and (6) *interruption* decrease with positive break.

Our logic for employing two time-series analyses is as follows: gradual changes (e.g. shrub encroachment, grassland degradation) will be best identified using monotonic trend analysis (Lewińska et al., 2020), whereas BFAST is well suited for identifying sudden changes and reversals that may be obscured within the long-term analysis. However, grasslands and non-woody areas will fluctuate more on an annual basis, due to climatic variation and benefit from a simpler change model. Furthermore, we employ trend analysis over direct comparison of the fractional cover maps to ensure our analysis is robust to variation and noise in the input maps. We expect our annual fractional maps to contain errors and noise which may distort bi-temporal comparisons. This is analogous to post-classification cleaning of hard classification change detections, by removing illogical transitions (e.g. Griffiths et al., 2018) or applying statistical techniques such as Hidden Markov Models (e.g. Abercrombie & Friedl, 2016).

## Results

### Fraction maps

The predicted fractional land cover maps (Fig. 3) successfully distinguished the nine land cover types (Table 1), and a discrete land cover map shown in Figure 4B was estimated from the fractional map of 2020 (Fig. 3). We were able to identify transitional areas with highly heterogeneous land cover (Fig. 3). For instance, most of the NCA is dominated by grassland (Fig. 3), which transitions into shrubland around the centre. The Highland area (Fig. 1A) is dominated by woody classes (bushland, woodland, forest). Figure 4A shows a red-green-blue composite of the land cover layers aggregated into three main components of savannah landscapes: trees (forest and woodland), shrubs (bushland and shrubland) and grasses (grassland). For bushland and forest, there are areas of clear separation (Fig. 4A) but there is also some degree of mixture (Fig. 3). The West side of the NCA mostly comprises grassland (e.g. the Serengeti Plain) with some patchy shrubland around the Ang'ata Salei plain.

Validation statistics for the fractional land cover maps of 2010 and 2020 (MAE and $R^2$) are shown in Table 2 (full statistics in Tables S1 and S2 and scatterplots in Figs. S5 and S6). Most classes performed well, achieving accuracies between $R^2$ 0.61 and 0.95 (Figs. S5 and S6). The lowest absolute errors occurred in the bareland class with an MAE of 2.8 for 2010 and water with an MAE of 1.63 for 2020. Cropland had the highest relative errors with $R^2$ of 0.43 and 0.33 for 2010 and 2020, respectively. Most cross-class confusion occurred in transition ecozones between grassland-bareland and grassland-shrubland. This was expected due to the highly heterogeneous nature of these regions.

## Linear trends

### Linear trends for the NCA

Figure 5 shows the statistically significant ($p < 0.05$) linear trends for each individual and cover type. Areas with <5% cover in the respective class for 2020 were masked. There were notable increases and decreases for all land cover types with most of the change in the ±25% range (Fig. 6) The most common change in the NCA was decreasing forest by ~25% coverage, which affected roughly 900 km$^2$ (Figs. 5 and 6). The second most common change was grassland coverage declining by 25%, which affected roughly 782 km$^2$ (Figs. 5 and 6). A sizeable amount of grassland also experienced a decline of up to 50% (~493 km$^2$), mostly in the Serengeti plains (Figs. 5 and 6).

A majority of forest cover is located in the eastern part of the NCA. Figures 7B and C show a clear reduction in fractional cover, particularly visible around Mount Oldeani, throughout the highlands and on the south-east side of the Crater rim (Fig. 7D). There is also some patchy increase in forest cover, ranging between 25% and 75% cover in the highlands, outside the NCA border near Mount Oldeani and in the montane areas (Fig. 7D).

### Linear trends: the case of Lerai Forest

Contrarily to its name, the Lerai Forest mostly comprises low woodland and bushland with some forest and

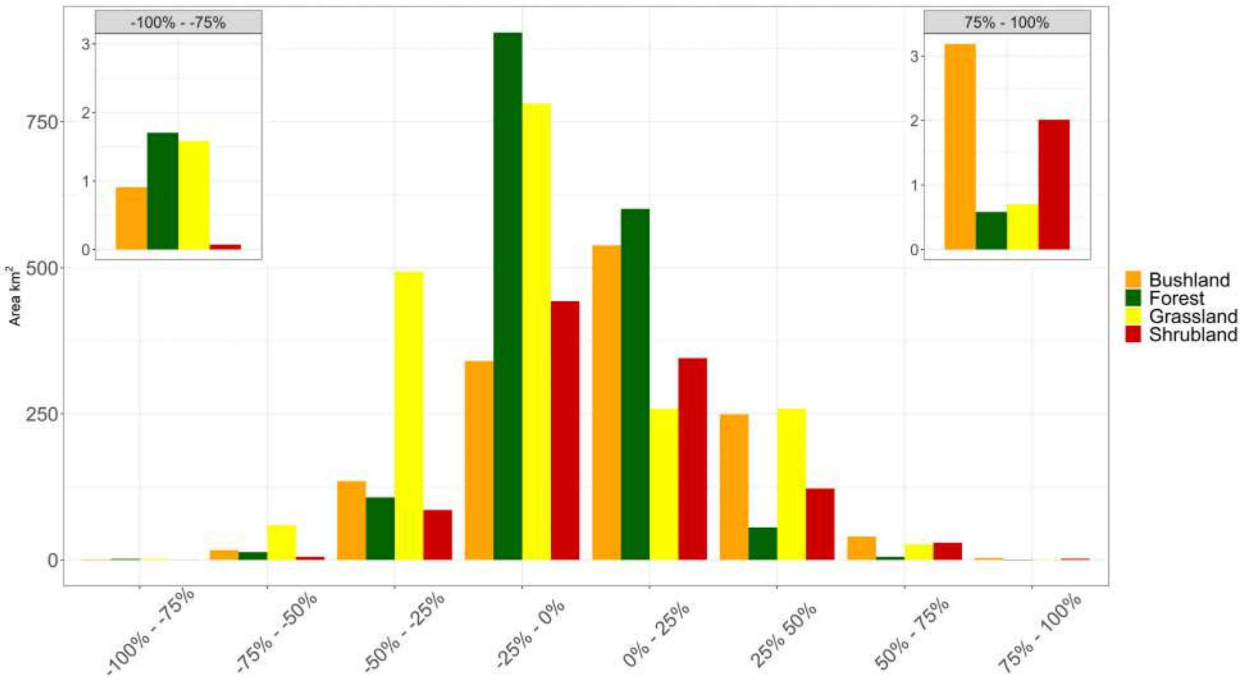

**Figure 6.** Statistically significant ($p < 0.05$) changes in land cover between 1985 and 2020 for forest, bushland, shrubland, and grassland.

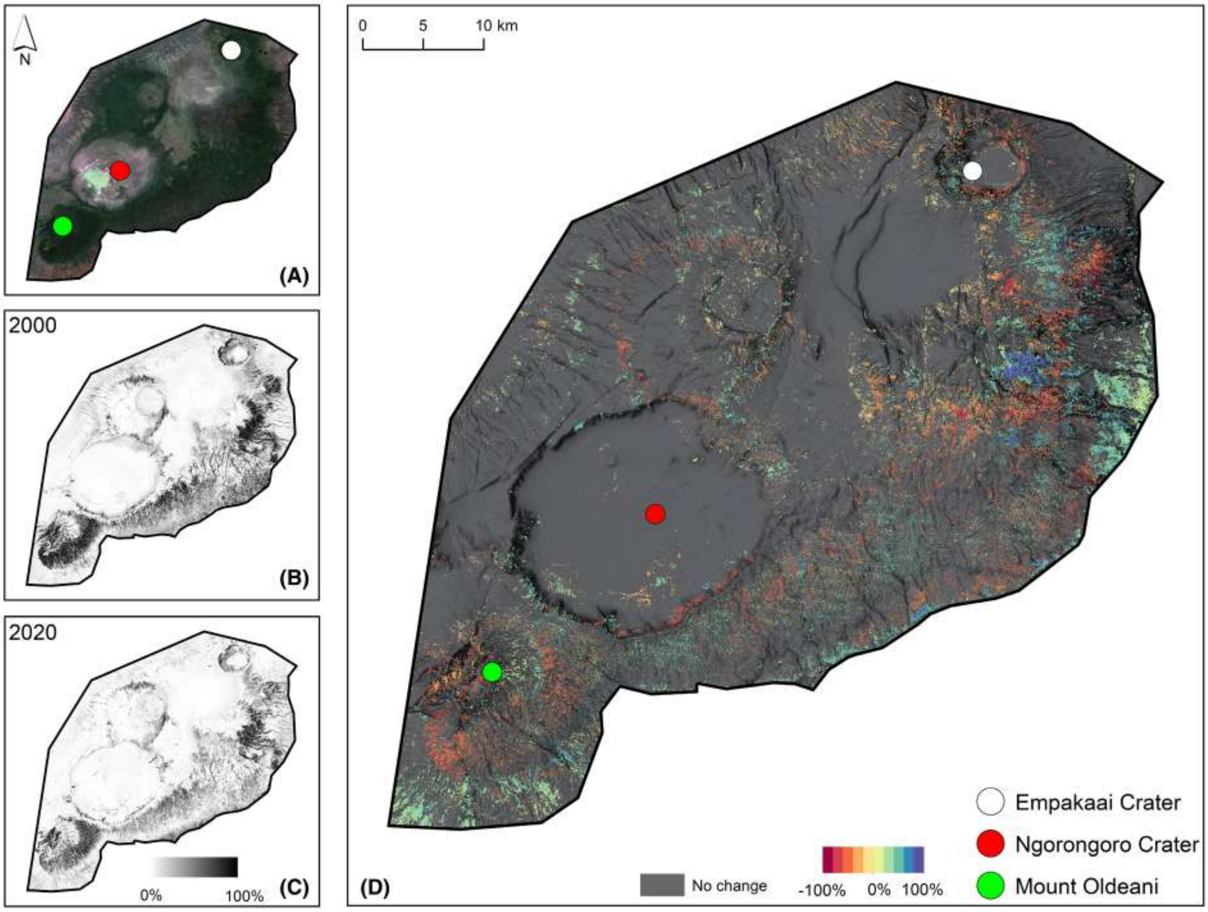

**Figure 7.** True colour composite Landsat image for the year 2000 (A). Fraction of forest cover in the NCA in the years 2000 (B) and 2020 (C). Forest cover change according to the linear trend analysis between 1985 and 2020 in the southeast of the NCA (D).

shrubland. According to our findings, there were both increases and decreases in the fractional cover of forest, bushland and woodland (Figs. 8A and C). The most obvious change in the Lerai Forest was the decrease in bushland cover, ranging between −25% and − 75% (covering 1.6 km$^2$), and the increase in woodland (+25% covering 1 km$^2$; Figs. 8B and C). However, the expansion of woody vegetation, specifically forest and woodland occurred mostly in the southwest side of the Lerai Forest (Fig. 8A and C; Figure S7).

## BFAST trends

### BFAST trends in the NCA

Most of the forest change detected by BFAST consisted of monotonic increases and decreases (Fig. 9A). Forest loss was widespread with some focal points in the rim of the Crater, around Mount Oldeani and Empakai Crater. Throughout the highlands, there was also a reversal where forest cover increased but then started to decrease. These shifts in the vegetation occurred mostly between 2004 and 2009 (Fig. 9B).

### BFAST trends: the case of Lerai Forest

The change map produced using BFAST for the Lerai Forest is shown in Figure 10. In the northeast side of the Lerai Forest, BFAST detected a consistent monotonic decrease in forest cover (Fig. 10). Additionally, a large cluster that experienced a monotonic increase occurred on the southwest side of the Forest (Fig. 10). Although significant, some of those changes were subtle (<25%; Fig. 10, location A2) when compared to others (Fig. 10, location A1). For instance, in location A2 (Fig. 10) there was a consistent increase in cover which remained low. In A1, forest cover increased until 2008, when it started to decrease but the changes were more pronounced than in A2.

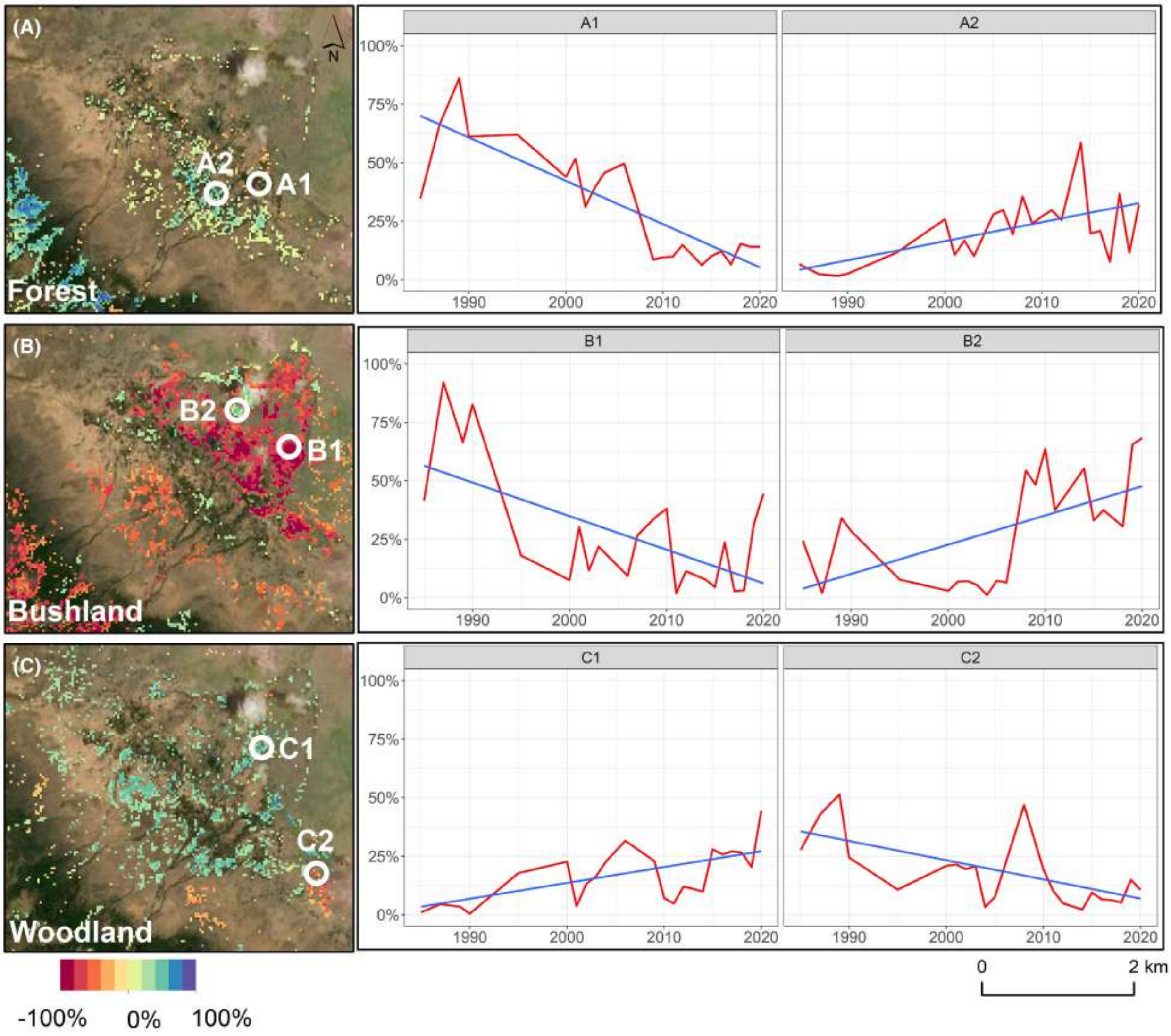

**Figure 8.** (A–C) and respective plots (A1 to C2): linear trend changes in forest, bushland, and woodland in the Lerai Forest (this area is the example Location 1 shown in Fig. 4).

## Discussion

Understanding land cover dynamics is increasingly important to improve habitat monitoring, preserve biodiversity and ensure sustainable development (Reed et al., 2009). Over the last 30 years, the NCA has undergone considerable changes but these remain poorly understood due to lack of robust information and detailed maps. Here, we demonstrate a Landsat-based monitoring strategy, combining synthetic unmixing, machine learning regression and time-series analysis, to quantify sub-pixel change in nine land cover classes. Our fractional cover maps for 2010 and 2020 achieved high accuracies for most land cover types (Table 2, Tables S1 and S2 and Figs. S5 and S6), distinguishing the nine main land cover classes but also identifying transitional areas with heterogeneous vegetation (Figs. 3 and 4A). Out of our nine land cover types, only cropland scored low accuracies ($R^2$ 0.43 and 0.33 for 2010 and 2020, respectively), while the other classes high accuracies ($R^2 > 0.6$, Table 2). Souverijns et al. (2020) and Senf et al. (2020) achieved similar accuracies for comparable land cover types, but Nabil et al. (2020) reported low accuracies for cropland in the Sahel regions. Using fractional cover maps has proven advantageous, as it allows for the detection of more subtle land cover variability and changes that cannot be captured by discrete classifications (Senf et al., 2020; Souverijns et al., 2020; Suess et al., 2018).

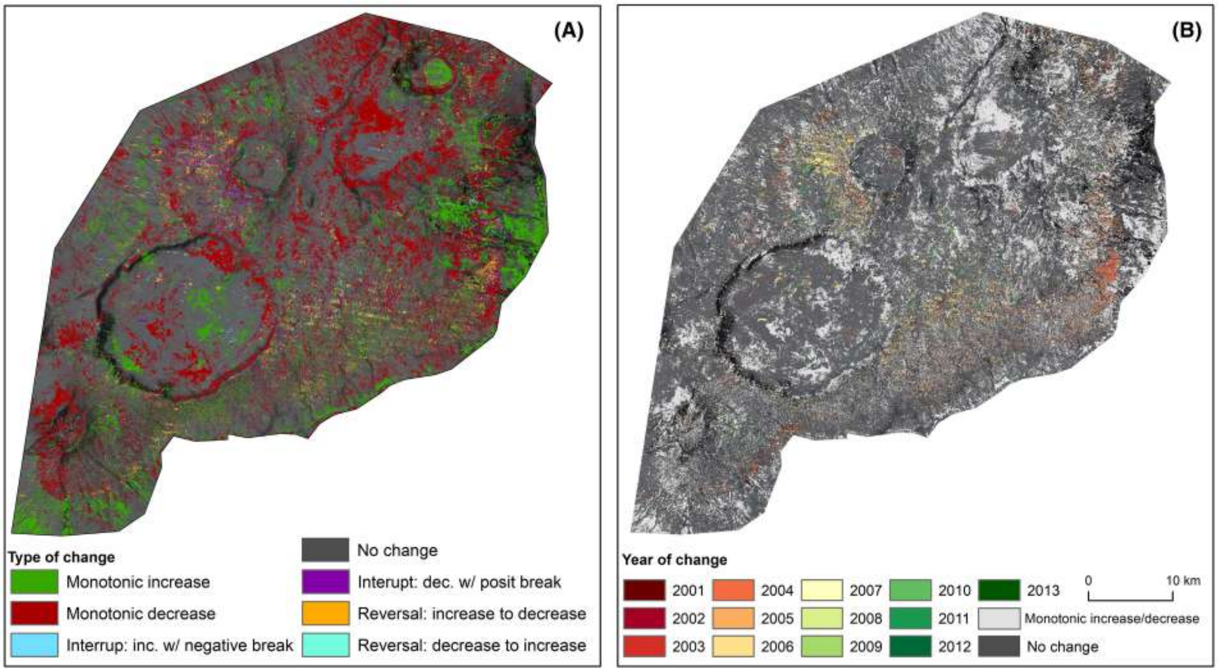

**Figure 9.** (A) BFAST trend analysis results for the southeast side of the NCA showing the type of change in forest cover; (B) the year of change in forest cover.

Between 1985 and 2020, we identified significant land cover changes; in particular, declines in forest and grassland cover (Figs. 5–7). The most common change using the linear trend analysis was a decrease in forest coverage by ~25%, which affected roughly 900 km$^2$ (Fig. 6). BFAST also detected a similar trend in the highlands, with a monotonic decrease in forest throughout the period (Fig. 9A). Contrarily, there was an increase in bushland cover by 25%, covering 440 km$^2$ (Fig. 6). These changes are consistent with field studies that have identified forest conversion into bushland due to the removal of larger trees (Amiyo, 2006; Masao et al., 2015; TAWIRI & NCAA, 2020). A report by the Tanzania Wildlife Research Institute (TAWIRI) and the Ngorongoro Conservation Area Authority (NCAA) in 2020 also found a decrease in forest cover between 1978 and 2018. These changes were linked to human disturbances namely clearing for settlement or cultivation and searching for thatching materials and fuel wood (Kija et al., 2020; Masao et al., 2015; TAWIRI & NCAA, 2020). In addition (Mills, 2006), studied the dieback of *Acacia xanthophloea* (commonly known as fever tree which can reach 25 metres) in Ngorongoro Crater identified natural disturbances, specifically herbivory (mainly by elephants, *Loxodonta africana*), disease and salinity as contributors for the demise of large trees.

Forest degradation has been reported across Africa and is a common indicator of land degradation (Ahrends et al., 2021; Bukombe et al., 2018; McNicol et al., 2018). In addition, forests promote carbon sequestration and therefore, directly affect global carbon budgets and climate change (McNicol et al., 2018; Venter et al., 2018). In the NCA, degradation of forests threatens the availability of good habitat for wildlife species adapted to such particular forest type. Souverijns et al. (2020) mapped 30 years of land cover changes over the Sudano-Sahel and detected forest degradation based on fractional land cover maps. Meanwhile, McNicol et al. (2018), used radar data to study losses in carbon in savannahs, identifying deforestation and degradation proximate to roads and urban areas but gains in remote regions. Our results support those findings and show that Landsat data and fractional cover maps can be used to detect and monitor forest degradation. The use of Landsat to map forest degradation processes is highly beneficial, due to the temporal length of the Landsat archive relative to radar data.

## Serengeti plains

The loss of palatable grasses has been identified as a threat to wildlife, the Maasai pastoralists and the NCA ecosystem as a whole (Amiyo, 2006; Mills et al., 2006). We found that grassland cover decreased in the NCA during the study period (Figs. 5 and 6). Figure 6 shows between 25% and 50% decrease in grassland cover (493 km$^2$ to 782 km$^2$), mostly located in the Serengeti plains (Figs. 5 and 6). In the same area, the increase in

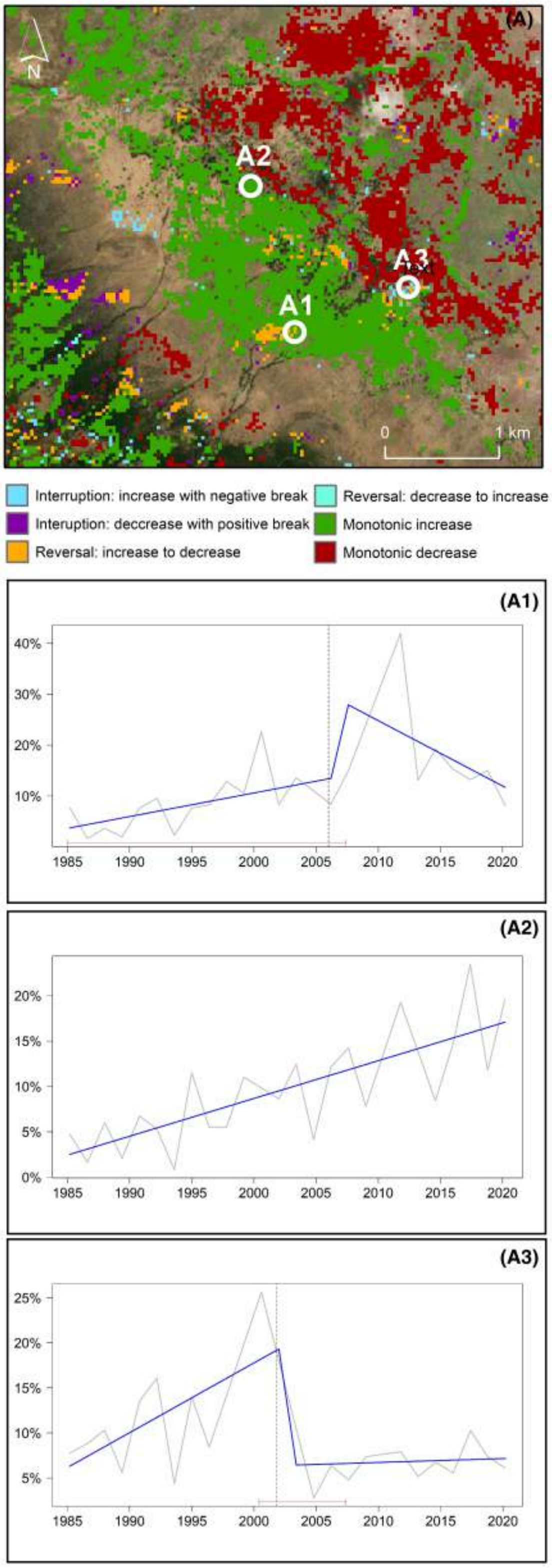

**Figure 10.** Outcome of the trend analysis using BFAST for the Lerai Forest (A). Locations A1–A3 are used as examples of time-series plots at the individual pixel level.

shrubland (~345 km$^2$) and woodland cover (~497 km$^2$) is also visible (Figs. 5 and 6). Previous research reported a decline in grassland and woody encroachment in the NCA which supports our findings (Amiyo, 2006; Masao et al., 2015; Niboye, 2010). The no-burning policy imposed in the 1980s was identified as the main driver for land cover changes, specifically woody encroachment in the NCA (Amiyo, 2006; Homewood et al., 2001). In addition, grazing pressure, by wildlife and livestock, also facilitates the development of woody plant communities by removing fine fuels and reducing fire frequency and intensity (Archer et al., 2017; Smit et al., 2010).

Shrub encroachment, often linked to grassland decline and land degradation, is a serious threat to ecosystem services and biodiversity (Higginbottom & Symeonakis, 2020; Symeonakis et al., 2018). Previous research found an increasing trend of woody cover throughout Africa (Higginbottom et al., 2018; Ludwig et al., 2019; Symeonakis et al., 2018). Venter et al. (2018) reported that encroachment is accelerating over time and that African savannahs are at high risk of widespread vegetation change. Stevens et al. (2016) measured woody cover change between 1940 and 2010 and found similar results in areas with low rainfall (<650 mm). Contrarily to forest degradation, shrub encroachment can have a positive impact on aboveground carbon storage (McNicol et al., 2018). However, the loss of grassland areas raises issues for wildlife, the Maasai pastoralists and their livestock (Niboye, 2010). In the Serengeti plains, densification and encroachment of woody cover can have a negative effect on groundwater recharge, grazing potential (Angassa & Baars, 2000; Stevens et al., 2017), tourism (Gray & Bond, 2013), and is related to increase costs for woody vegetation clearing (Grossman & Gandar, 1989). Woody encroachment into grasslands can potentially be reversed by a combination of management (frequent fires) and climatic events (drought; Roques et al., 2001). In these areas using fire as a management strategy can decrease shrub and invasive species, and has been successfully employed throughout the continent (Sankaran et al., 2005; Venter et al., 2018). Additionally, reducing grazing pressure by decreasing livestock numbers can positively affect grassland areas (Archer et al., 2017). As such, given the infeasibility of reducing livestock numbers, trailing fire management to assess the potential for limiting encroachment and improving rangeland condition may be beneficial.

## Lerai Forest

The earliest records of change in the NCA date back to the 1960s when the dieback of the Lerai forest was first suggested (Amiyo, 2006; Mills, 2006). Our results show contrasting trends: a significant decline in woody cover within the original range of Lerai Forest (Fig. S7) and an overall increase in forest cover in the periphery (Figs. 8A and 10). These results suggest that Lerai Forest is re-establishing outside its original range (Amiyo, 2006). Historically, mature fever trees *Acacia xanthophloea*, which can reach heights up to 25 meters and require high water tables (Homewood et al., 2001), dominated the Lerai Forest, however since their decline they have not been replaced by young *Acacia xanthophloea* trees (Amiyo, 2006). The decrease in groundwater availability, due to a higher influx of tourism and diversion of streams, as well as floods of the salt lake, Lake Magadi, contributed to an increase in soil salinity, which negatively affects vegetation (Amiyo, 2006; Boone et al., 2007; Mills, 2006). Mills (2006) suggested that sodicity (e.g. the accumulation of sodium salt in the soil) can exacerbate salinity-induced drought stress in vegetation, by limiting entry of rainwater into the soil, which was already low due to a reduced rainfall (Fig. S1). Furthermore, sodicity can promote sodium concentrations in trees, which has an additional detrimental effect by attracting elephants and other herbivores (Homewood et al., 2001; Mills, 2006). Management strategies were implemented and in 2006, the stream was diverted back to supplying the Forest (Mills, 2006, Fig. 10, location A1). This increased the freshwater supply to the area and promoted the flushing of salts from the soil (Mills, 2006). The southwest side, closer to the Crater rim, is more fertile and has a lower soil salinity due to its proximity to the stream, which explains the increase in forest and woodland cover (Fig. 8A and C; 10 location A1; Elisante et al., 2013, Mills, 2006). Exclusion of elephants from Lerai was considered in 2006 but was never implemented (Mills, 2006). The dieback in Lerai may be jeopardising the long-term conservation of the black rhinoceros *Diceros bicornis michaeli* population in the caldera (Mills, 2006). Historically, the Lerai Forest was used for shelter and browse by the rhinos and it has been suggested it was also critical for hiding newborn rhinos from predators (Goddard, 1967, 1968). Consequently, the recovery of the Lerai Forest is an essential priority for the success of black rhino population in the NCA (Mills et al., 2006).

## Conclusion

Mapping and quantifying land cover change is important to support habitat monitoring, preserve biodiversity and ensure sustainable development (Reed et al., 2009). Savannah landscapes, such as the NCA, however, are complex heterogeneous combinations of vegetation. Here we demonstrate that a regression-based unmixing with synthetic training data-based approach is effective in the fractional mapping of spectrally similar land cover types. In addition, the combination of linear trend and BFAST time-series analysis provided highly detailed and complimentary insights into land cover change dynamics throughout the 35-year study period. We identified two dominant land change dynamics: the degradation of uplands forest into bushland, and a transition from grassland to shrubland in the Serengeti Plains. These changes threaten the wellbeing of livestock, and consequently the livelihoods of pastoralists but also grazing dependent wildlife. These changes are likely due to a combination of climate change, shifting rainfall patterns, herbivory; and human activities, namely, management policies, tourism and increasing human populations and livestock. In conclusion, we provide much needed and highly accurate information on long-term land cover changes in the NCA, which can support sustainable management and conservation. In addition, our methodological approach can be applied elsewhere to understand savannah landscape changes.

## Conflict of Interest

The authors declare no conflict of interest.

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## Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

**Figure S1** Rainfall in The Ngorongoro between January 1985 and June 2020.
**Figure S2.** Example of spectral data using near-infrared, green and red bands for bushland, forest, montane heath, shrubland and woodland for the year 2020.
**Figure S3.** Example of spectral data using SWIR, red and green bands for bushland, forest, montane heath, shrubland and woodland for the year 2020.
**Figure S4.** Grid used for validation.
**Figure S5.** Validation 2010.
**Figure S6.** Validation 2020.
**Figure S7.** Lerai Forest range: (A) Landsat imagery in December 1985; (B) Landsat imagery in February 2020; (C) CNES/Airbus in January 2020.
**Table S1.** Full validation statistics 2010.
**Table S2.** Full validation statistics 2020.