A thesis submitted to the Department of Environmental Sciences and Policy of Central European University in part fulfilment of the Degree of Master of Science

Quantifying landcover change in the Kruger to Canyons Biosphere Reserve, South Africa: A case study from 2013 to 2019

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June, 2020

Budapest

Erasmus Mundus Masters Course in Environmental Sciences, Policy and Management

MESPOM

This thesis is submitted in fulfilment of the Master of Science degree awarded as a result of successful completion of the Erasmus Mundus Masters course in Environmental Sciences, Policy and Management (MESPOM) jointly operated by the University of the Aegean (Greece), Central European University (Hungary), Lund University (Sweden) and the University of Manchester (United Kingdom).

(3) For bibliographic and reference purposes this thesis should be referred to as:

Irvine, R.M. 2020. *Quantifying landcover change in the Kruger to Canyons Biosphere Reserve, South Africa: A case study from 2013 to 2019.* Master of Science thesis, Central European University, Budapest.

Author's declaration

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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ABSTRACT OF THESIS submitted by:
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for the degree of Master of Science and entitled: Quantifying landcover change in the Kruger to Canyons Biosphere Reserve, South Africa: A case study from 2013 to 2019

Month and Year of submission: June, 2020.

Human land-use decisions are a driving factor in landcover change. The retention of natural landcover is necessary to stop ongoing biodiversity loss. Remote sensing analyses serve an important role in monitoring landcover dynamics that can inform conservation efforts. This study applies remote sensing techniques to understand the landcover changes that take place in the Kruger to Canyons (K2C) Biosphere Reserve in South Africa between 2013 and 2019. As a biosphere reserve, K2C manages its landscape for both biodiversity conservation and sustainable development. Biosphere reserves implement a spatially explicit zonation system, wherein the 'core' zone focuses on conservation while the 'buffer' and 'transition' zones allow for intermediate- and high-intensity human-utilization of the landscape, respectively. This study examines how three priority landcover classes, 'Intact Vegetation,' 'Impacted Vegetation,' and 'Settlement,' change in quantity and spatial distribution across the entire landscape and with regards to the biosphere zonation. It was found that 'Intact Vegetation' remains the predominant landcover type across K2C (65% of the landscape) but is in decline (down 5.5% from 2013). Increases in the 'Settlement' footprint continue (up 2.7% since 2013) and were spatially located primarily in the transition zone. Overall, the greatest quantity of landcover change occurred within the transition zone, while the least was detected in the core. Climatic change may play an increasingly important role in landcover dynamics within K2C and should be incorporated into further studies of the region. Overall, the findings indicate that K2C is successfully maintaining conditions that support its biodiversity conservation goals.

Keywords: biosphere reserve, biodiversity, land-use, landcover change, conservation, remote sensing

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Acknowledgements

Much gratitude is due to the numerous individuals who have offered their support and encouragement to pave the way to the completion of this thesis, and the culmination of my participation in the MESPOM program.

First, thank you to my thesis supervisor, Dr. Brandon Anthony, who has been a constant source of feedback, insight, and encouragement. Your capacity to question critically and listen openly is admirable; the egalitarian spirit with which you engage with colleagues and students alike speaks to your kindness and your professional approach. I have learned so much from being a student in your courses and through this research endeavor. Thank you.

The completion of this thesis would also not have been possible without the support and generosity of Dr. Kaera Coetzer-Hanack, whose research this study is based upon. Kaera has graciously helped answer my numerous methodological questions and has always shared words of encouragement and opportunities to improve. Thank you for your thoughtful answers and genuine engagement with me along the way.

Additionally, I would like to thank all those individuals who have helped with technical and computing hiccups that no amount of mitigation planning could have foreseen being a possibility, yet became reality, due to the surprise of a global pandemic. While each instance may have seemed inconsequential to those who offered help, I would not have been able to complete my work without this support. Credit is due in particular to: the IT staff at CEU and the University of Manchester; Dr. Gail Millin-Chalabi of the University of Manchester; Chaz Sinn; Ceci Maron-Puntarelli; Hana Cleveland.

I would also like to thank all those people who have made participation in the MESPOM program possible, and those who have made it such a fulfilling experience. Thank you to Tyler Henderson, who first planted the seed of an idea that graduate studies abroad were a possibility. To Steve Cotter and Brian Garshellis, whose professional support helped launch me here. To the professors at CEU, whose courses challenged me to develop as an analytical thinker and writer. And notably, thank you to the MESPOM 2018-2020 cohort, who have been a fascinating bunch to get to know and learn alongside, and from. Thank you to Gabriella, Janna, and Ben, for always pushing me academically, and to Bairma and Joel, for their levity and support during times of uncertainty.

Last but not least, deep gratitude to 'my people,' the ones who make being away an adventure worth pursuing because you know you have roots to return to. Thank you to Dr. Tina Irvine, who is not only a sister, but a source of friendship and academic advice all rolled into one. Thank you to the Puntarellis- for being there, and for being family. And thank you to Mason Cassady, whose generosity of heart supported me in saying yes to this dream and has helped carry me through, even from afar.

May I conclude these remarks by borrowing from an African proverb through which I was reacquainted via Brandon:

"If you want to go fast, go alone.
If you want to go far, go together."

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List of Abbreviations

Acronyms and Definitions	
ArcPro	Esri ArcGIS Pro v 2.5
BR(s)	Biosphere Reserve(s)
CBD	Convention on Biological Diversity
EBV	Essential Biodiversity Variable
EO	Earth Observations
GEEE	Google Earth Engine Editor
GEO BON	Group on Earth Observations Biodiversity Observation Network
IUCN	International Union for the Conservation of Nature
K2C	Kruger to Canyons
KNP	Kruger National Park
LCC	Landcover Change
LD	Land Degradation
LUDs	Land-use Decisions
LULCC	Land-use Landcover Change
MaB	Man and Biosphere
MLC	Maximum Likelihood Classifier
PA(s)	Protected Area(s)
PAME	Protected Area Management Effectiveness
PAN	Protected Area Network
RS	Remote Sensing
RSA	Republic of South Africa
SC	Supervised Classification
SDG(s)	Sustainable Development Goal(s)
SES	Socio-Ecological System(s)
SSA	Sub-Saharan Africa
UNCCD	United Nations Convention to Combat Desertification
UNDP	United Nations Development Programme
UNEP	United Nations Environment Program
UNESCO	United Nations Educational, Scientific, and Cultural Organization
UNFCCC	United Nations Framework Convention on Climate
WNBR	World Network of Biosphere Reserves

Chapter 1: Research Context and Justification

1.1 Introduction

Human influence on the Earth and its systems is profound. Over two-thirds of the planet's land surface is directly utilized by people (IPCC 2019), and this 'human footprint' continues to expand and intensify its pressures on the environment (UNCCD 2017; Venter *et al*. 2016; Ellis *et al.* 2010). This trend is largely driven by global population growth and the corresponding increase in natural resource consumption this entails (Hooke and Martin-Duque 2012; Hughes 2009). As a countermeasure to human exploitation, the international conservation community strives to protect a representative sample of biodiversity in perpetuity (CBD 2010), primarily through the establishment of designated protected areas (PAs) (Watson *et al.* 2014). Despite important progress in developing the global protected area network (PAN) (Gannon *et al*. 2019; UNEP-WCMC and IUCN 2018), biases and gaps in coverage still exist (Venter *et al.* 2014; Joppa and Pfaff 2009), threats to biodiversity have never been greater (CBD 2014), and ongoing losses continue at an unprecedented and accelerating rate (Ceballos *et al.* 2015; Ceballos *et al.* 2017).

Human land-use decisions are a key driver behind patterns of environmental change observed across local, regional, and global scales (Folke 2006; Foley et al. 2005; Verburg *et al.* 2015). Land-use itself is not inherently a problem, however it poses trade-offs as to what landcover and ecosystem services are retained, transformed, or lost (Foley *et al.* 2005). Some land-uses better support conditions for biodiversity than others (Sanderson *et al.* 2002). This is especially true in modern history, where immediate- to near-term resource utilization has often been prioritized over considerations of long-term sustainability (Meadows *et al.* 2005; Foley *et al.* 2005). Widespread overexploitation of natural resources and the degradation and transformation of natural landcover is well documented (CBD 2014; UNEP 2014; UN 2019). The knock-on-effects of this are many. Land-use landcover change (LULCC) is directly implicated in significant declines in biodiversity (McGill *et al.* 2015; Newbold *et al.* 2015;

Powers and Jetz 2019; Gray *et al.* 2016), reduced or lost ecosystem functionality (Oliver *et al.* 2015), ecological regime shifts (Rocha *et al.* 2015; Johnstone *et al.* 2016), altered biogeochemical cycles (Duveiller *et al.* 2020), and changing climatic conditions (IPCC 2019). The ramifications associated with any one of these changes is of major consequence, but taken together, the cumulative impacts are potentially catastrophic (Rockström *et al.* 2009; Scheffer and Carpenter 2003; Leadley *et al.* 2014).

Of the many facets that contribute to this situation, experts agree that limiting the conversion of natural landcover is of great importance. Socio-economic and political contexts inform land-use decisions, thus, to adequately address LULCC requires accounting for the societal challenges that exist in parallel with environmental crises (Pool-Stanvliet *et al.* 2018). Social factors can compound or amplify problems associated with landcover change (LCC). This dynamic is of particular importance with regards to agricultural-based settlements around the world. More than half of the global population are urban dwellers (UN-DESA 2018), but rural agricultural communities cover a greater spatial footprint and still account for nearly 25% of the total human population (Ellis and Ramankutty 2008). They also tend to be characterized by the highest intensity of land utilization practices (Ellis and Ramankutty 2008) as they are more directly reliant on natural resources to supplement or provide their livelihoods (UNDP 2019; Matsika *et al.* 2013). Without proper planning and management, natural resource depletion is likely as LCC occurs (UNDP 2019; Folke *et al.* 2005). When settlements are forced to expand further afield to meet their needs (Coetzer *et al.* 2013; Coetzer-Hanack *et al.* 2016), this generates a self-reinforcing cycle of expansion/resource-depletion, illustrating how social factors mediate land-use decision-making as a driver of land degradation and transformation.

Consequently, to adequately address issues of LULCC, the international conservation community increasingly advocates for a Socio-Ecological Systems (SES) approach. Under this framework, humans are recognized as dynamic actors embedded within the environmental system, rather than separate from it (Colding and Barthel 2019; Folke *et al.* 2016). Applied to conservation, social, economic, and political factors that shape human behavior must be accounted for in the conservation planning process (Pool-Stanlivet *et al.* 2018; UNESCO 2017). Political traction for the SES-based conservation model abounds. Evidence that supports this includes:

1. The evolution in perspective on the role of PAs (Palomo *et al.* 2014; Kennedy *et al.* 2019; Watson *et al.* 2014)
2. The establishment of PA management effectiveness (PAME) as a key mediator of conservation outcomes (Matar and Anthony 2017; Leverington *et al.* 2010; Margules and Pressey 2000)
3. The explicit integration of sustainable use concepts into targets to reduce threats to biodiversity (CBD 2010)
4. As well as the inverse, the integration of conservation into sustainable development dogma (UN 2019), and
5. The growing recognition of the impact that land-use choices have on climatic change (IPCC 2019).

Additionally, a proliferation of policies and research foci at the international (IUCN 2016; IUCN-WCPA 2019) and state levels (Wright 2019; Fitzsimons 2015) reflect a growing emphasis on the role of communities and individual actors in mediating conservation outcomes (Stolton *et al.* 2014). The diversifying array of conservation mechanisms and governance tools aim to integrate human and environmental concerns such that conservation benefits accrue to both (Schaaf and Clamote Rodrigues 2016; Wright *et al.* 2018), further evidencing the growing acceptance of a SES-based approach to conservation. In light of these trends, it is likely that conservation models that move beyond the traditional scope of strict PAs will be increasingly promoted (Laffoley *et al.* 2017).

One such approach that exemplifies the tenets of a SES-conservation philosophy is the United Nations Educational, Scientific and Cultural Organization's (UNESCO)'s 'Biosphere Reserve' (BR) model. BRs apply spatial planning with different levels of permitted land-uses across a designated area where both human populations and important biodiversity features comprise a mosaic landscape (Coetzer-Hanack *et al.* 2016; UNESCO 2017). Proponents of this model claim that it is a "practical implementation mechanism" for achieving conservation goals and sustainable development simultaneously (RSA-DEA 2015). Consequently, this model is attractive to diverse stakeholders, particularly in countries characterized by developing economies (Coetzer *et al.* 2014; Pool-Stanvliet *et al*. 2018). The adoption of the Sustainable Development Goals (SDGs) in 2015 bolstered support for this model (Pool-Stanvliet 2013), which now records more than 700 reserves across 124 countries (UNESCO 2020a).

1.2 Research justification

While there is reason to be optimistic about the joint conservation and sustainable development possibilities proposed by the BR model (Cuong *et al.* 2017; Ertürk 2015; Fayad 2018; Pulido and Cuevas-Cardona 2013; Blackman 2014; Zhang et al. 2014), their purported theoretical conservation benefits cannot be taken as a given (Carballo *et al.* 2019; Ma *et al.* 2009), particularly since information on the management effectiveness of BRs is limited (Matar and Anthony 2017). BRs are highly place-specific (Bridgewater 2002) and, correspondingly, exhibit great variability in their characteristics (RSA-DEA 2015; Matar and Anthony 2017). Globally, and even within a single state, BRs are not uniform in their management capacity, level of funding, degree of stakeholder buy-in, or type of support provided by other institutions (RSA-DEA 2015; Matar and Anthony 2017). Such variability suggests that this conservation model will produce different biodiversity outcomes from one reserve to the next. Due to the irreversible nature of some biodiversity losses, the need to efficiently allocate limited financial and human resources, and the political traction garnered by BRs in recent decades, there is an acute need to empirically validate that BRs do in fact deliver their purported conservation promises. Because there is no single variable or index to quantify conservation effectiveness, management effectiveness is often used as its proxy. For BRs, the differing management mandates of each of the three zones of the BR model suggest that the zones will have differential representation of landcover. The 'core' zone, which is managed with a focus on conservation, is expected to be characterized predominantly by 'intact vegetation' whereas the 'buffer' and 'transition' zones are expected to contain greater levels of 'impacted vegetation' and areas of 'settlement,' where vegetation has been fully transformed (Coetzer *et al.* 2013; Coetzer-Hanack *et al.* 2016). The expected landcover types can be compared against the observed landcover to determine the degree of (non)compliance between the theory of the BR model and real-life practices.

1.3 Research aim

The overarching aim of this study is to quantify landcover dynamics in the Kruger to Canyons (K2C) Biosphere Reserve in South Africa for the time period between 2013 and 2019. The study will address three essential questions associated with landcover change: "how much, where, and what type of landcover change has occurred?" (Alo and Pontius 2008). The specific aim of this research is to address these key questions in the context of the study area from a two pronged approach: both at the landscape level (i.e. examining landcover dynamics across the entirety of K2C), and also with regards to the BR's designated zones (i.e. landcover dynamics within the core, buffer, and transition zones). Three priority landcover classes, identified as: 'intact vegetation,' 'impacted vegetation,' and 'settlement,' will be the focal landcover categories by which this study measures change dynamics, in alignment with previous K2C research (Coetzer *et al.* 2010; 2013; Coetzer-Hanack *et al.* 2016). Landcover comprised of 'intact vegetation' can be considered most suitable for positive biodiversity outcomes (Coetzer *et al.* 2013). In contrast, 'impacted' and 'settlement' landcover classes represent a continuum of reduced biodiveristy value whereby 'settlement,' and its associated infrastructure correspond to landcover types that exhibit a complete loss or transformation of the original landcover's ecological function (Coetzer *et al.* 2013). This study will inform the understanding of the degree to which the entire K2C landscape retains landcover that fosters the conservation of its biodiversity heritage, as well as the degree to which the 'biosphere reserve' designation fulfills its conservation mandate. These findings could inform continued management efforts or future policy development that will support positive biodiversity conservation outcomes for Kruger to Canyons Biosphere Reserve.

1.4 Objectives

To achieve the aim, Earth Observations data will be analyzed using geospatial analysis software (ArcGIS Pro v 2.5 and TerrSet IDRISI Land Change Modeler). The primary objective is to quantify the spatial patterns of landcover change (2013-2019) for both the entire area covered by K2C as well as with regards to the transitions undergone within and between the theoretically demarcated core, buffer, and transition zones of the K2C BR.

To achieve this principal objective, a series of specific components must be addressed in sequential order, as delineated in Table 1. First, it is necessary to classify the landcover that was present in K2C in the start and end years (2013 and 2019) of the study period (Table 1, Objective 1). Following the initial classification, the identified landcover will be aggregated into three priority landcover classes (Table 1, Objective 2) for the following reasons: to simplify the interpretation of change dynamics (Aldwaik *et al.* 2015), align the classification schema with previous K2C research, and to provide a workable framework by which to analyze the implications of landcover change in the context of biodiversity conservation within K2C (Table 1, Objective 2). Next, TerrSet IDRISI Land Change Modeler will be used to compare the mapped outputs of priority classes from 2013 and 2019 to quantify the landcover change dynamics of the priority classes for the entire K2C (Table 1, Objective 3) and with regards to each of the BR's zones (Table 1, Objective 4). Throughout, the results will be analyzed and interpreted in the context of the implications on biodiversity across the study area and in context of K2C's conservation mandate; based on the findings, relevant recommendations will be made for future research or management actions (Table 1, Objective 5).

Table 1. Delineation of the principal research objective and its subcomponents.

Principal Objective: Quantify the spatial patterns of landcover change (from 2013 to 2019) for the entire K2C study area and with regards to the BR zonations (core, buffer, and transition zones).	
1	Classify the landcover in K2C in 2013 and 2019 (via Esri ArcGIS Pro v. 2.5)
2	Aggregate the identified landcover classes into three priority classes: 'Intact Vegetation,' 'Impacted Vegetation,' and 'Settlement' (via Esri ArcGIS Pro v 2.5)
3	Quantify the landcover change dynamics of the priority classes for the entire K2C study area (via IDRISI Land Change Modeler) (Eastman 2016)
4	Quantify the landcover change dynamics of the priority classes class within each zone of the BR (via IDRISI Land Change Modeler) (Eastman 2016)
5	Interpret the findings in context of the implications for biodiversity across the study area and in context of the BR's conservation mandate; provide recommendations for future research or management actions.

1.5 Thesis structure

The structure of this thesis is summarized as follows. Chapter 1 introduces the background context and justification for the current research, including a clearly identified aim, principal research objective, and a list of subcomponents that must be addressed in order to achieve the aim. Chapter 2 presents a literature review on the key areas that inform the present study. Chapter 3 introduces the study region, data acquisition and pre-processing, and the geospatial methods that are employed in this analysis. Chapters 4 and 5 present the results of the analysis and their interpretation, respectively. The thesis concludes with Chapter 6, wherein the key findings and points of discussion are summarized.

Chapter 2: Literature Review

2.1 Status and trends in biodiversity

Evidence points to a worldwide biodiversity crisis, albeit characterized by differing levels of intensity and magnitude across spatial scales (i.e. global, regional, local). Globally, the current biodiversity loss is greater than at any time in history, with the majority of species extinctions recorded in the last 250 years (Ceballos *et al.* 2015). This troubling trend is viewed by many as a harbinger of both a mass extinction event and a new geologic era (i.e. the "Anthropocene"). Accelerating rates of species extinctions, ongoing declines in the population abundances of animals, collapsing ecosystems, and increasingly fragmented landscapes are collectively leading to irreversible ecological change (Novacek and Cleland 2001), which bears critical implications for human health and well-being (IPBES 2019; MEA 2005). An examination of current data indicates that at least a quarter of the world's mammalian species are threatened (i.e. those listed in the IUCN's Red List as Critically Endangered, Endangered, or Vulnerable), 14% of bird species, and nearly 41% of amphibians (IUCN 2020c). These numbers may in fact underestimate reality, as a paucity of data limits scientists' ability to accurately capture the severity of the problem across all taxa. This is especially the case for invertebrates, plants, and fungi, for which less data has been collected; in all likelihood, species of these taxa demonstrate similar trends observed in other species, thereby presenting critical implications for ecological integrity, as these taxa form the support base of all terrestrial food webs. Similar to the trajectory of species declines, data on population abundances for over 4,000 species indicate that in the last fifty years, animal population sizes have steadily declined, and are now recorded at less than two-thirds of their totals in the1970s (WWF 2018). Degraded habitat quality and greater levels of habitat fragmentation are the primary contributors to the aforementioned declines, with overexploitation, pollution, and climatic change also key contributors to biodiversity loss. Reflecting the role that habitat loss plays in species persistence and overall biodiversity health, the Species Habitat Index indicates that suitable habitat intactness for mammalian species has declined by nearly a quarter since the 1970s (WWF 2018), a change that, incidentally, mirrors the proportion of threatened mammals reported today. Additionally, the ongoing degradation and loss of habitat across the world now records an estimated Total Economic Value of $231 billion in damages annually, attributed to the depletion not only of landscapes themselves, but also the resultant loss of ecosystem services these landscapes once provided (Nkonya *et al.* 2015).

The African context for biodiversity loss mirrors that of the global situation (WWF 2018). This is particularly troubling since the continent is home to nearly a quarter of the world's biodiversity and is also the single most important contributor to the persistence of the world's remaining large mammal species (UNEP-WCMC 2016; IPBES 2018b). Furthermore, Africa ranks second among the continents with the greatest level of endemism (Skowno *et al.* 2019), with eastern and southern Africa containing one-fifth of the world's identified biodiversity hotspots (IUCN 2020b). If threats to biodiversity are not checked, models predict not only continued biodiversity declines but greater net losses than predicted for other parts of the world (IPBES 2018b). This is due in large part to the higher severity that climatic change is predicted to play in biodiversity outcomes across Africa, which could result in the loss of over 50% of the continent's bird and mammal species by the end of the century (IPBES 2019). The breadth and irreplaceability of biodiversity that is represented across the African continent therefore presents significant implications for global conservation in the wake of the biodiversity crisis (IPBES 2018b).

Like the role that Africa plays in the global context, the Republic of South Africa (RSA) mirrors this characterization. The RSA is one of the most biodiverse places in the world, identified as one of the 17 'megadiverse' countries, a nomination that is due in large part to its third-place rank worldwide for its high endemic value (Skowno *et al.* 2019).

Unfortunately, biodiversity in the RSA exhibits similar trends as those recorded at the continental and global scales. Drivers and pressures that contribute to biodiversity loss in the RSA are increasing (RSA-DEA 2015), which is reflected in the most recent National Biodiversity Assessment that reports that nearly 50% of the country's ecosystems are at risk of transformation to such a degree that their ecological integrity is unlikely to be preserved if current trends persist (Skowno *et al.* 2019). Assessment of the nation's biodiversity at the species level also reveals a high degree of threat (Skowno *et al.* 2019; IUCN 2020c). In the RSA, nearly 600 species are listed as threatened, including 20-40% of the nation's 136 endemic species of reptiles, amphibians, birds, and mammals (Table 2).

Table 2. Number of threatened species in South Africa.

	All Species	Endemic Species		
Taxonomic Group	**# Threatened**	**Total #**	**# Threatened**	**% Threatened**
Mammals	30	36	12	33
Birds	54	18	7	39
Reptiles	19	15	3	20
Amphibians	16	52	15	29
Aquatic animals	150	15	5	33
Other Invertebrates	174	-	-	-
Plants	154	-	-	-
Fungi and Protists	0	-	-	-
Total	597	136	42	31

Source: IUCN 2020c (with amendments)

The ongoing biodiversity crisis in the RSA is implicated not only in the nation's ecological well-being, but that of its human communities as well, which rely on the nation's biodiversity resources for subsistence, employment, and medicine derivatives, which collectively hold an estimated value of $3 billion USD annually (Skowno *et al*. 2019).

2.2 Land-degradation: A key threat to biodiversity

Humans have always utilized the environment and been active participants in shaping its characteristics and dynamics (Hughes 2009). However, the degree and extent to which people have altered the earth's landcover has reached unprecedented levels (Sanderson *et al.* 2002). The preponderance of land-use decisions (LUDs) in modern history strongly favor short-term gains over longer-term sustainable use principles (Venter *et al.* 2016; Foley *et al.* 2005). The cascade of effects that arise from LUDs often have a lag time of months or even years (IPBES 2018a), further distancing decision-makers from the outcomes of their choices. A repeated pattern of modification of intact natural landcover towards that which is characterized by overt human intervention has become the norm (Fig. 1) (Foley *et al.* 2005; Turner II *et al*. 2007; Baldwin and Fouch 2018) with little regard for the negative ecological externalities that such broad-scale change incurs (biodiversity as a 'public good'- Kolstad 2000).

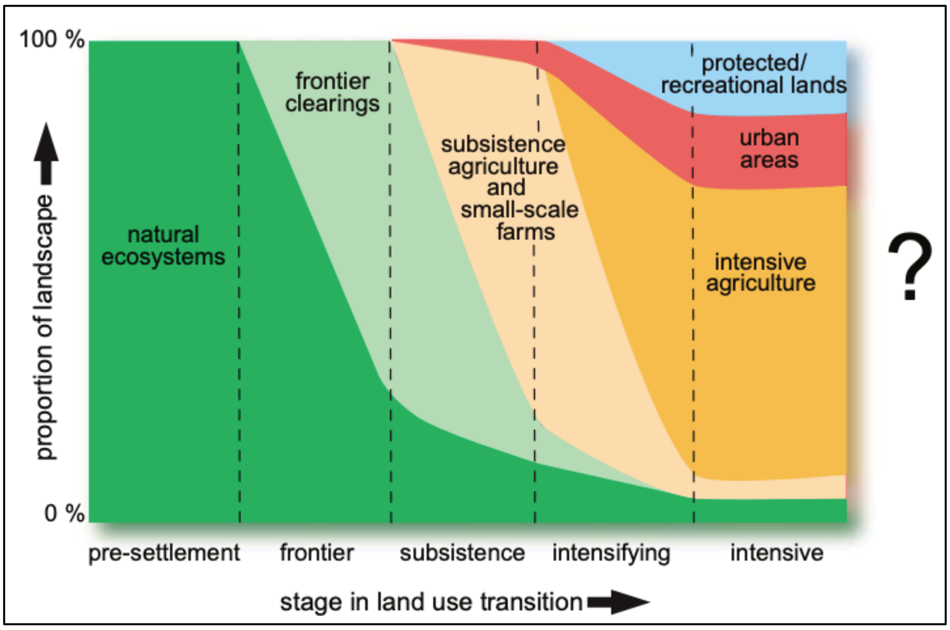


Figure 1. Land-use transitions. Source: Foley 2005.

Landcover change that results in the modification of intact habitats such that landcover is significantly altered, transformed from one landcover type to another, or even outright eliminated is the primary force that drives land degradation (LD) across the globe (Kuenzer *et* *al*. 2015; Niklaus *et al*. 2015). Land degradation in turn is identified as the leading cause of global biodiversity loss (Newbold *et al*. 2015; Jacobson et al. 2019; Sala *et al.* 2000), more so than any other anthropogenic or naturally occurring factor (IPBES 2018a; IPCC 2019). Consequently, understanding the drivers and implications of LUDs that lead to land degradation are necessary to successfully combat the biodiversity crisis.

Land-use decisions are informed by both social (economic, demographic, technological, cultural) and ecological (resources present, areal extent, environmental quality) characteristics of the human-landscape mosaic (Turner II *et al*. 2007; IPBES 2018a). Inherent to decision making, LUDs are associated with tradeoffs with regards to the ecosystem services (Niklaus *et al.* 2015; McShane *et al.* 2011) and net biodiversity outcomes (Sanderson *et al.* 2002) that a resultant landcover supports. Such tradeoffs are difficult to quantify- they are constantly in flux and tend to derive from multiple, simultaneous LUDs. Furthermore, the effects of LUDs compound on one another over time and are interlinked across scales (Foley *et al*. 2005), often creating feedback loops between anthropogenically-driven and naturally occurring degradative processes (Niklaus *et al.* 2015; Lambin *et al*. 2001). Consequently, to quantify the impact of individual determinants of LUDs on biodiversity outcomes is complex.

However, the resultant outcome of all global LUDs is clear: humans have modified more than three-quarters of the planet's land surface (WWF 2018), and highly degraded more than 20% of its vegetated areas (UNDP 2019). The social impact of land degradation indicates that the well-being of anywhere from 1 (UN 2019) to 3 billion (WWF 2018; IPBES 2018a) people are directly harmed. Collectively, the economic losses associated with land degradation-induced biodiversity and ecosystem service loss is equivalent to >10% of the annual global gross product (IPBES 2018a). Environmentally, the impact of LUDs that lead to land degradation is similarly dire. Basic ecological theory posits that maintaining biodiversity is paramount for ecosystems to be resilient and adapt to disturbance (Folke *et al.*

2004). Consequently, it is concerning that estimates suggest that nearly 60% of terrestrial ecosystems have been utilized and degraded to such an extent that a critical functional threshold has been breached (Newbold *et al.* 2015). Modern LUDs present a serious bane for biodiversity, contributing directly to phenomenon associated with LD which negatively impacts ecological and social well-being, ranging from: the loss of ecosystem services (Metzger *et al.* 2006; IPCC 2019), species losses (Fischer and Lindenmayer 2007), development of conditions that favor invasive species spread (Hobbs 2000), shifts in community assemblages (Foster *et al.* 2003), habitat fragmentation (Fischer and Lindenmayer 2007; Fletcher *et al.* 2018), reduction in areal extent and connectivity of intact habitat patches (Baldwin and Fouch 2018), and homogenization at the landscape scale (Hansen *et al.* 2004).

Net global LD is predicted to continue, and to do so at an accelerating rate (IPBES 2018a), unless global restoration efforts successfully changes this trajectory. The retention of areas characterized by intact landcover has been identified as a priority by multiple intergovernmental agencies and institutions (IPBES 2018a; RSA-DEA 2015). The United Nations Framework Convention on Climate Change (UNFCCC) explicitly supports the prevention of further land degradation because of the role that terrestrial biomass plays in regulating greenhouse gas cycles and ultimately on global temperature controls (Niklaus *et al.* 2015). Likewise, the United Nations Convention to Combat Desertification (UNCCD) is organized around the key aim of preventing "human activities and habitation patterns" from furthering the loss of intact landcover (Fensholt *et al.* 2015). To achieve the SDG Agenda by 2030, halting land degradation and restoration efforts are recognized as an essential effort, with especially high relevancy (>80%) in achieving goals numbers: 1-2, 6, 11-13, and 15 (IPBES 2018a).

Understanding the drivers of LD is essential to combat its continuation. While different habitat types are targeted more intensely by different anthropogenic pressures

(Lambin *et al*. 2001), the single greatest driver of LD worldwide is the transformation of intact vegetation to cropland (Hooke and Martin-Duque 2012; IPBES 2018a). This transition is driven by food security needs to support an ever-growing human population, which is predicted to reach 8.5 billion by 2100 (UN-DESA 2019a). Modern agricultural systems largely denude or fundamentally alter the ecological integrity of intact ecosystems (Riseng *et al*. 2011); correspondingly, it is unsurprising that models predict that the conversion of intact vegetation to agriculture is the primary driver behind (terrestrial) ecological regime shifts (Rocha *et al.* 2015). Of the environmental variables that drive LD, climatic change is the primary contributor at the global scale (IPBES 2018a). Higher global surface temperatures promote a LD feedback loop via altered patterns and intensity of precipitation and/or the capacity of landcover to serve as a carbon sink (IPCC 2019). The interplay between social and environmental drivers of LD are noteworthy for their feedback on all facets of the human-landscape system. Globally, populations that are particularly impacted by the interactions of social and environmental drivers of LD include those living in Least Developed Countries (IPBES 2019) or those living in already degraded landscapes and which exhibit a reduced capacity to mitigate the effects of ongoing climatic change (IPCC 2019).

The status of LD across Africa is more severe than that of average global conditions (IPBES 2019). More than 500,000 km^2 across the continent is degraded (IPBES 2019), and within sub-Saharan Africa (SSA) alone, nearly one-quarter of the land area (22.4%) has degraded since 2000 (UN 2019). Looking ahead to the future, social and environmental drivers are predicted to interact and accelerate LD in Africa. Human population growth and climatic change are both expected to be greater in magnitude and intensity in Africa than in other parts of the world in the coming decades (IPBES 2018b; IPCC 2019). In particular, Sub-Saharan Africa (SSA) is expected to be the center of population growth not only in Africa, but globally as well (UN-DESA 2019a). The Republic of South Africa (RSA) itself is not expected to grow as intensely as other SSA nations (UN-DESA 2019b), however, an influx of migrants from Mozambique may contribute to greater population pressures on the landscape than current population growth figures might suggest (Moagi *et al.* 2018; UNHCR 2020). Climatic change is also expected to particularly contribute to the degradation of Africa's dryland ecosystems, which comprise 43% of land area in SSA (FAO 2008) and are home to 75% of the region's lowest-income populations (IPBES 2018a). Drylands have long been thought to be highly susceptible to desertification, but recent analyses suggest that the greater degradation threat to drylands may be that of 'greening', or encroachment (Fensholt *et al.* 2015; Venter *et al*. 2018). In the last three decades, woody plant encroachment has increased by 8% across SSA (Venter *et al*. 2018). Encroachment can cause a change in species diversity, lowered capacity of rangelands to maintain animal populations, and changes in the portfolio of ecosystem services that the landscape provides (Venter *et al*. 2018; IPCC 2019); it is also predicted as a key factor in dryland ecological regime shifts (Rocha *et al.* 2015). However, the acceptance of broad-scale findings on the drivers of LD (whether they support desertification or encroachment) should be cautioned, as the causal mechanisms of LD are likely to be highly place-specific. Regardless of the drivers of LD however, continued LD in Africa is likely unless swift and concerted action is taken at both local, regional, and international levels.

2.3 Conservation practice: The shift towards a Socio-Ecological Systems Approach

The establishment of protected areas (PAs) has long been the premier conservation tool employed to protect biodiversity around the world (Naughton-Treves *et al*. 2005; Watson *et al.* 2014). Today, the global (terrestrial) protected area network (PAN) constitutes 15.2% of Earth's land surface across more than 245,133 designated sites (UNEP-WCMC and IUCN 2020a). Protected areas, when managed effectively, are shown to play a significant role in biodiversity retention compared to areas of non-protected status (Chape *et al.* 2005; Baillie *et al.* 2016). Whereas early conservation was often based on the preservation of beautiful landscapes (Watson *et al.* 2014), modern conservation efforts have become more targeted and strategic since the advent of systematic conservation assessment and planning in the early 2000s (Margules and Pressey 2000) and the Convention on Biological Diversity's (CBD's) adoption of the Aichi Targets in 2015. These initiatives have increasingly pushed the global protected area network (PAN) towards a more balanced representation of the world's biodiversity at all scales, although significant conservation gaps remain (Gannon *et al*. 2019). Part of the inefficiency of PAs in retaining biodiversity is due to varying levels of management capacity, which limits their ability to achieve desired biodiversity outcomes (Leverington *et al.* 2010); this is of particular concern since anthropogenic threats and pressures on the existing PAN are on the rise (Jones *et al.* 2018), suggesting that management effectiveness will be of increasing importance to ensure positive biodiversity outcomes.

While conservation biases and gaps in coverage can be addressed by continuing to apply and improve upon systematic conservation principles, the challenges presented by the human dimension of conservation present a more complex issue. To address the latter, a large bloc of the conservation community advocates for broadening the scope of conservation itself (Palomo *et al*. 2014; Kennedy *et al.* 2019). While strict conservation does play an integral role in meeting global biodiversity targets (Watson *et al.* 2014), the establishment of new PAs tends to eschew the 'fortress conservation' mentality, which has largely been replaced (Wilshusen *et al.* 2002) by a more human-inclusive 'socio-ecological systems' (SES) perspective (Ban *et al.* 2013; Ferreira *et al.* 2018), whereby humans are recognized as dynamic actors embedded within a "multi-use conservation landscape" (Coetzer-Hanack *et al.* 2016; Colding and Barthel 2019). The argument for an SES-conservation philosophy posits that social, economic, and political factors interact and drive human's land-use decisions, thereby creating pressures on the environment; consequently, these social aspects must be taken into account when planning feasible conservation strategies that deliver their intended outcomes (Pool-Stanlivet *et al.* 2018; UNESCO 2017).

Evidence that the SES-based conservation model is gaining political traction abounds. On the international level, the establishment of UNESCO's 'Man and Biosphere' program in the 1960s and its subsequent expansion over the ensuing decades is notable as one of the first initiatives to pair conservation with sustainable resource use/ sustainable land management principles (Bridgewater 2016). More recently, the 2015 adoption of the Sustainable Development Goals integrates human well-being and conservation practices (e.g. SDG 15), and the Intergovernmental Panel on Climate Change (IPCC) similarly recognizes the role that human land-use plays in the retention of natural landcover, and the implications this has for climate change mitigation (IPCC 2019; Martin and Watson 2016). Additionally, the body of conservation policy and management research increasingly reflects an emphasis on the role that communities and individual actors play in mediating conservation outcomes (IUCN 2016; Bingham *et al.* 2017; Wright *et al.* 2018; IUCN-WCPA 2019), thereby reflecting a diversifying array of human-inclusive conservation mechanisms and governance types which aim to co-benefit human and ecological communities (Stolton *et al.* 2014; Rawat 2017; Mitchell *et al.* 2018; DeVos and Cumming 2019). Lastly, the dialogue shaping the agenda (CBDb 2018; Gannon *et al*. 2019) for the CBD's 2020 COP indicates support for human-inclusive conservation and restoration strategies in order to achieve the conservation goals being scoped for 2050 (IISD 2020).

Within Africa, a similar movement towards the adoption of SES-based conservation practice is observed over the last several decades. Much of the African PAN has its origins in regulations that date to the early 1900s that were designed by European colonists to curb the unsustainable exploitation caused by over-hunting big game populations (Ford 2012; Carruthers 1995). Building upon this, African conservation efforts for much of the 20th century largely favored strict environmental protections at the expense of local communities' subsistence rights and traditional cultural practices (Chardonnet 2019). Today, modern conservation approaches across the 7,000+ PAs on the continent (Chardonnet 2019) increasingly embrace the role of engaging local stakeholders in conservation management to achieve both human-equity and biodiversity protection (Anthony 2007; Chardonnet 2019). Within South Africa in particular, this is well-evidenced by the increasing support the nation places on conservation arrangements beyond those established and governed top-down by the state (DeVos *et al.* 2019; Barendse *et al*. 2016). Since the end of Apartheid in 1994, emphasis on redressing inequities perpetrated against local communities has been at the fore of much of the nation's development policies. This shows up in the country's conservation context in South Africa's National Biodiversity Strategy and Action Plan (RSA-DEA 2015a), which approaches conservation via five key principles, the first of which explicitly states the nation will take a: "People-centered approach to biodiversity, recognizing that the well-being of South Africa's people is dependent on the well-being of the environment" (p 17). Similar values are reflected in the nation's most recent (2016) National Protected Areas Expansion Strategy (RSA-DEA 2015a), and its pioneering Biodiversity Stewardship program (Rawat 2017), which actively engages local stakeholders to protect critical biodiversity areas and other lands deemed of ecological character that enhances the nation's PAN. Furthermore, in South Africa, the Biosphere Reserve model is garnering increasing support across sectors (government, NGOs, local) for its potential to jointly achieve conservation outcomes while supporting sustainable economic development in rural communities that have historically been some of the most marginalized in the country (RSA-DEA 2015b).

2.4 Biosphere Reserves: Exemplars of the SES conservation philosophy

Biosphere Reserves (BRs) are exemplars of the SES-approach to conservation. Situated at the nexus of environment-human interaction, BRs present an actionable opportunity for nations and the collective international community to leverage themselves closer towards meeting global commitments on biodiversity conservation, sustainable development, and climate change mitigation (RSA-DEA 2015b). One of the original goals of MAB was to create a global network of BRs that would be ecologically representative of the world's biodiversity, would operate under sustainable use principles, and would serve as an opportunity for place-based research and teaching labs for further scientific research and education (Bridgewater 2016). Today there are 701 BRs spread across 124 counties, with more sites nominated each year (UNESCO 2020a; Pool-Stanvliet and Coetzer 2020). The principles that guide the purpose and practice of BRs have evolved and been refined over the last five decades (Bridgewater 2016; Coetzer *et al*. 2014) but retain a primary focus on the original three tenets: "conservation, development, and logistical support" (UNESCO 2017). Whereas conservation and development often are framed as competing interests, the BR model aims to implement (and experiment) with measures that enhance resilient landscapes that support human livelihood.

BRs are an official designation which are characterized by human communities living within a bounded geographic area in which three land zonations are managed under one of three corresponding resource management schemes. The three types of zones within a biosphere reserve (core, buffer, and transition) correspond with the following land-use/ resource management mandates, respectively: strict biodiversity conservation (i.e. no human utilization), intermediate-intensity land-use (e.g. grazing, fishing, light natural resource extraction), and intensive land-use (e.g. human settlement, roads, other built infrastructure) (Coetzer-Hanack *et al.* 2016). In all cases, land-use decisions within a BR are expected to align with an agenda that promotes long-term sustainability of both the human community and environmental resources at stake. Whereas the theoretical model would suggest that core zones are ringed by buffer zones, which are in turn ringed by transitional-managed areas on the outskirts of the BR, the reality is that BRs tend to reflect the historical legacy of the human-environment dynamics specific to that place and are dependent upon where existing areas of intact vegetation remain or where human communities are already established (Fig. 2).

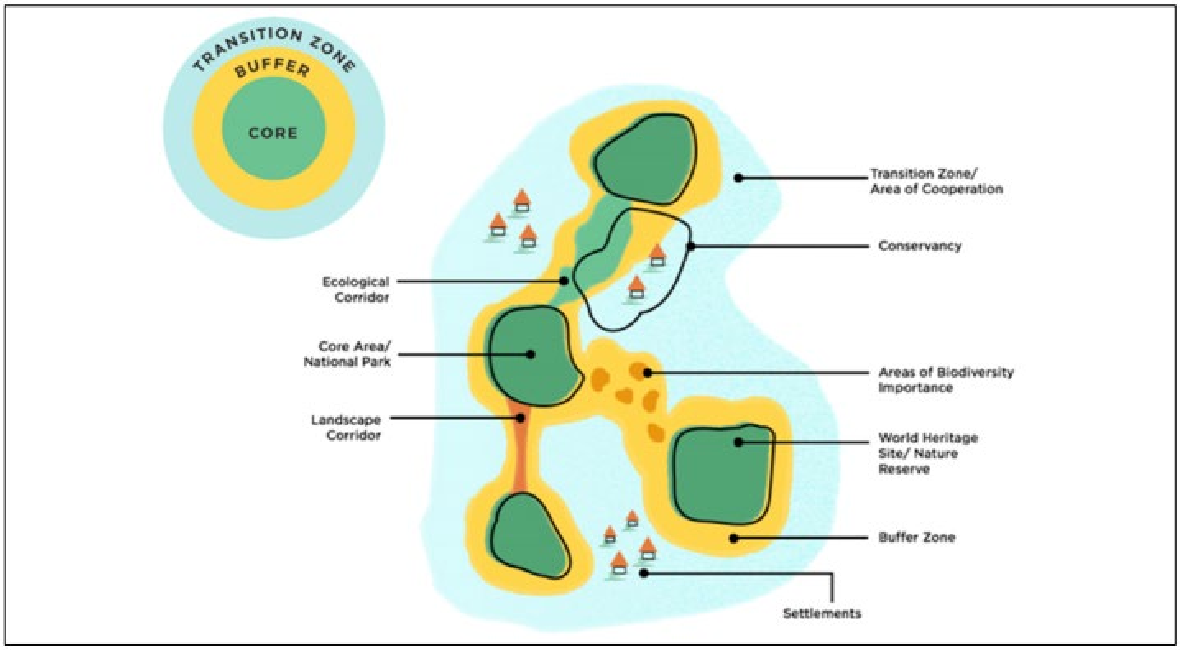


Figure 2. Schematic spatial layout of a typical biosphere reserve. Source: Pool-Stanvliet and Coetzer 2020.

Across the African continent there are 79 BRs across 29 countries (UNESCO 2020a). South Africa in particular has been a leader within the World Network of BRs (WNBR). The country joined the MAB program in 1995 and established its first BR (Kogelberg BR) three years later (RSA-DEA 2015b). Today, there are 8 BRs across the country, each of which is managed independently by non-governmental organizations and/or community volunteers with variable degrees of government support (RSA-DEA 2015b). Since 2010, the nation has seen a push to increase the coordinating and oversight role of the government in BR planning and management, drawing from collaboration across governmental departments as diverse as Environmental Affairs, to Arts and Culture, Public Works, Social Development, and Science and Technology- a reflection of the multifaceted nature of BRs themselves (RSA-DEA 2015b). South Africa views the BR model as a strategic means to achieve many of the nation's long-term policy goals, as more than a dozen programs at the national level demonstrate high "overlap" with the stated objectives of the BR model (RSA-DEA 2015b). To support these efforts, the country has produced national-level guiding documents for its BR network that align with international protocol (RSA-DEA 2015b) and that are also context-specific to South Africa, with the aim to improve the selection and performance of future BRs in the country (Pool-Stanvliet *et al.* 2018).

In practice, achieving the 'dual criteria' of sustainable development and conservation is difficult for BRs, as they face many of the same implementation challenges as other Integrated Conservation and Development Projects (Coetzer *et al*. 2014). BR outcomes can be limited by factors ranging from: the level and consistency of funding available (Bridgewater 2016), the effectiveness of management practices (Matar and Anthony 2017), including the degree to which local stakeholders are integrated into the decision-making and management processes (Baird *et al*. 2018; Schultz *et al.* 2011), the quality and utility of the periodic review/evaluation process (Matar and Anthony 2017; Coetzer *et al.* 2014), and the capacity to communicate objectives clearly (Roldan *et al*. 2019). Notably, these factors themselves are influenced by multiple scales of governance (international down to local) and can vary with time (Ferreira *et al.* 2018). In contrast, incorporating stakeholders in BR operations and governance, as well as ensuring adequate funding for the ongoing management of the BR, have both been identified as characteristics that can aid BRs in achieving their objectives (Cuong *et al.* 2017). Additionally, the high degree of place-specific variability of the physical geography of a given BR, the species and ecosystems that are present, and the historical legacy and current socio-economic conditions in which the human communities operate within the landscape also influence the human-landscape dynamic and inform how well a BR performs (Coetzer *et al*. 2014). Understanding the factors that impact the effectiveness of BR in protecting biodiversity are essential if BRs are to be counted in meeting global biodiversity targets (Butchart *et al.* 2015), and particularly so if nominations for BRs continue to increase around the globe.

2.5 Remote Sensing: Analyzing landcover change for biodiversity conservation

The scientific discipline of Earth Observations (EO) uses Remote Sensing (RS) data (i.e. satellite imagery) to understand past and present conditions and dynamics of the Earth's surface. Time series analysis of RS data can be used to quantity the extent of landcover change on a global, regional, or local scale, as well as trends in the types of landcover 'swaps' (transitions from one landcover type to another) that take place (Aldwaik *et al.* 2015). This means that RS can be used to support the identification and understanding of relevant drivers of landcover transformation (Evans 2017) and their link to biodiversity conservation outcomes (Hansen *et al.* 2004). The importance of EO in managing biodiversity outcomes is evidenced not only by the multi-decadal long history of its application (Kuenzer et al. 2015; Wang *et al.* 2010), but also by the establishment of the "Essential Biodiversity Variable" (EBV) framework by the Group on Earth Observations Biodiversity Observation Network (GEO BON). GEO BON (2020) identifies nearly two dozen indicators that can be monitored via RS, and which can be used by the international community to address Strategic Goal B of the Aichi Framework, which calls for the reduction of direct pressures on biodiversity and sustainable use of resources (O'Connor *et al.* 2015). Consequently, EO analyses can serve a practical role in identifying landcover change and its impact on biodiversity, and are therefore an important toolkit for biodiversity and conservation scientists, policy makers, and managers, at all levels of governance.

Technological advancements and increasingly open accessibility in EO and RS analytics further support their utility and application to biodiversity monitoring and conservation (Kuenzer *et al.* 2015; Young *et al*. 2017). Since the 1970s, seven RS satellites have been launched as part of NASA's Landsat mission, with another satellite expected to be launched in 2020 (Young *et al.* 2017). With each iterative satellite, the frequency and quality of the images captured, combined with the shift towards open access, no-cost datasets and advancements in cloud computing technologies that simplify and expedite image processing, mean that EO and RS offer unprecedented opportunities for assessing landcover change and its biodiversity implications (Zhu 2017; Gorelick *et al.* 2017; Kuenzer *et al.* 2015).

Caveats exist, however, to the utility of RS analytics for monitoring biodiversity. Commonly noted is the limitation presented by the medium- to coarse- resolution of much RS data (wherein pixels represent a land area of $30m^2$ or more), which consequently limits the scale of biodiversity assessment that can be accurately made (Turner *et al.* 2003; Apin 2005; Foody 2015). For example, while RS can be used to identify habitats and higher order scales of biodiversity with relative ease, in many cases, the lack of fine resolution data precludes the accurate quantification of species presence or population abundance (Gillespie *et al.* 2008). This is a problem that is particularly true for migratory species or fauna that have a naturally large habitat range (Leyequien *et al.* 2007), but which also presents problems for the identification of understory plants (Prasad *et al.* 2015; Gillespie *et al.* 2008). Moreover, the use of RS to measure biodiversity at finer scales often relies on inferences based on theoretically derived measures of biodiversity (e.g. alpha- or beta- diversity calculations) which makes such findings fallible to the challenges presented by reliance on simple measures of biodiversity (Rocchini *et al.* 2015). Additionally, medium- and coarse- grain resolution data also contributes to the tendency for RS analyses to over-represent homogeneity in the landscape (Olofsson *et al.* 2013). This is especially the case when the landscape is highly heterogeneous, i.e. where multiple landcover types are present in the area represented by a single pixel, an issue that is commonly known as the “mixed pixel problem” (Foody 2013), and which is only partially addressed by the application of more advanced algorithms, such as fuzzy classification or object-based classification methods (Wang *et al.* 2010).

Additionally, the literature consistently notes that the increasing complexity of computational algorithms within RS analytics software leaves many ecology- and environmental science-trained professionals without the requisite computer science skills that may be needed for analysis (e.g. space-time-cube computing for continuous-data processing, or big data management), especially as computer sciences continue to advance (Young *et al.* 2017; Zhu 2017; Pettorelli *et al.* 2014). Such limitations, however, are insufficient to negate the benefits and power of leveraging EO in understanding the landscape dynamics that influence biodiversity outcomes; moreover, institutions like GEO BON and Google are working to streamline and bridge the gap between advances in RS and environmental practitioners' skillsets (Pettorelli *et al.* 2014). Therefore, at present, discrete temporal time series analyses continue to offer a reasonable lens through which landcover change dynamics can be assessed over a given period, as evidenced by the numerous studies that continue to employ this approach (Kong *et al.* 2019; Young *et al.* 2017; Evans 2017; Pontius *et al.* 2013; Romero-Ruiz *et al.* 2011; Manandhar *et al.* 2010; Alo and Pontius 2008). Consequently, EO and RS remain a central tool to support scientists and practitioners in addressing biodiversity conservation and land-use landcover change.

Chapter 3: Materials and Methods

3.1 Study region

The Kruger to Canyons (K2C) Biosphere Reserve (Fig. 3) was designated in 2001 and extends over nearly 2.6 million hectares in the northeastern region of South Africa, bridging the provinces of Limpopo and Mpumalanga (Coetzer *et al*. 2013; RSA-DEA 2015b).

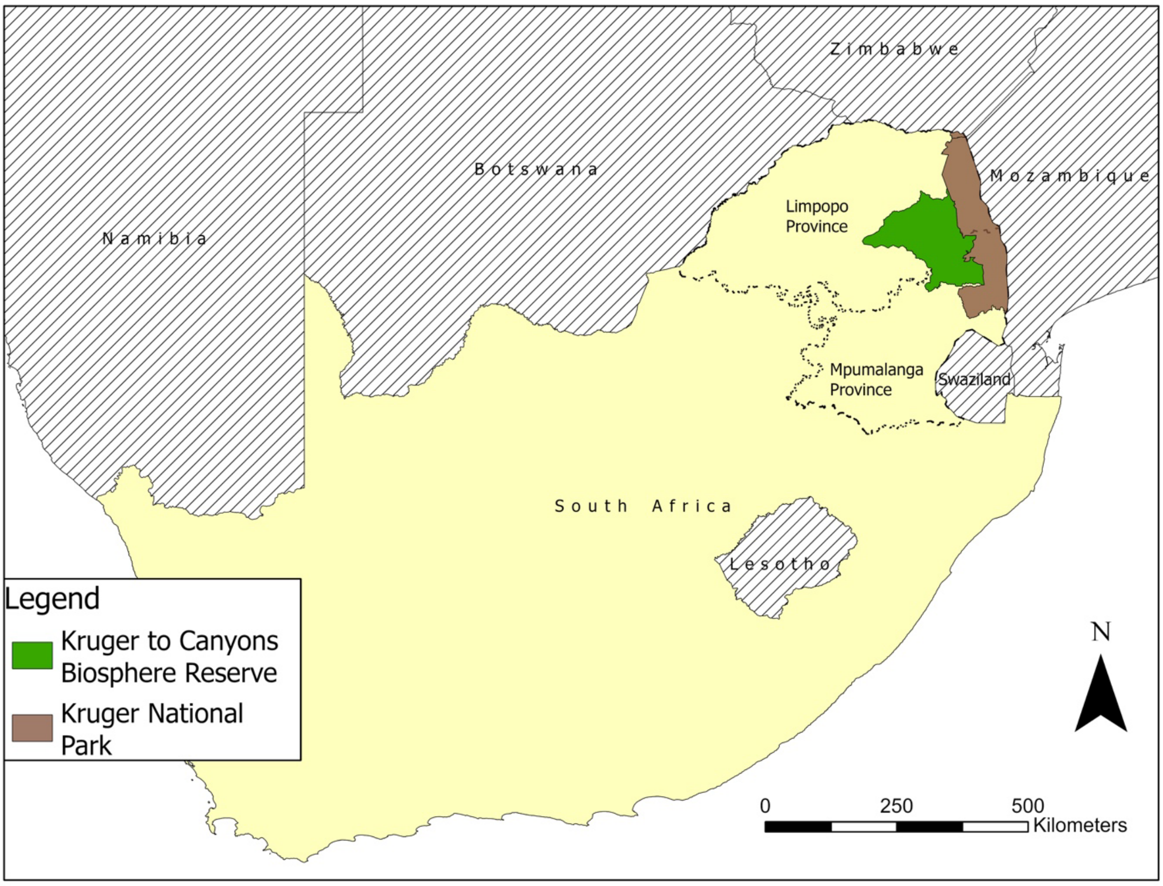


Figure 3. Location of the Kruger to Canyons Biosphere Reserve in north eastern South Africa.

The K2C lies adjacent to Kruger National Park (KNP), the southernmost portion of which is officially considered part of the larger K2C biosphere reserve area. For the purposes of this study and in alignment with previous research (Coetzer *et al.* 2010; 2013; Coetzer-Hanack *et al.* 2016), the area of KNP that coincides with K2C has been excluded. It should be noted that hereafter, reference to the K2C refers only to those areas of the biosphere reserve that do not coincide with the KNP, the area of which is represented by the polygon labeled “Kruger to Canyons Biosphere Reserve” in Fig. 3. The exclusion of KNP from this analysis is primarily because the KNP is officially managed for the strictest level of conservation, excludes human settlements, and receives more robust funding and management efforts than the remaining area under the K2C BR designation (Coetzer *et al.* 2010; 2013). Consequently, monitoring and managing landcover change in the area of interest that lies west of the KNP provides a better conceptualization of landcover change dynamics within the human-landscape mosaic.

With regards to its physical characteristics, the K2C ranges in altitude from 300m above sea level in the east to over 2,000m along its western extent. The region is ecologically notable for the diversity found across its landscape, which includes three biomes (grassland, savanna, and forest), the endemic fynbos ecosystem, and a portion of the Eastern Transvaal Drakensberg Escarpment- an area that is globally recognized for its high biodiversity value (K2C 2020). Human communities are scattered across the biosphere reserve, with population centers at Hoedspruit (3,100 people in 2011) and Phalaborwa (13,000 people in 2011) (Department of Statistics 2020). Notably, the greater Ba-Phalaborwa region within K2C is home to 150,000 people in total, the vast majority (95%) of whom reside within 15km of the city center, indicating an area of high density and high-intensity land utilization within the BR (RSA-DS 2020).

Approximately 54% of the greater K2C region is managed strictly for long-term conservation, if the core area of KNP is included (K2C 2020) (Fig. 4). The remaining area across the K2C study area is mandated for management in accordance with the graduated scale of land-use that is prescribed by the theoretical BR model; this allows for a diversity of activities in the K2C that draw upon the region's natural resources to varying degrees. Whereas approximately 50% of the non-strict conservation area was still vegetated with intact natural landcover communities as of 2012 (Coetzer-Hanack *et al*. 2016), human land-use that may impact vegetation is wide-spread across K2C, including activities ranging from: agriculture (commercial and subsistence), mining (gold, phosphate, copper), tourism, commercial forestry, and rural and urban development projects (K2C 2020). The management plan for the K2C aligns with that of the theoretical BR Model, but it is worth noting that the spatial configuration of areas that are managed as ‘core’ (923,000ha), ‘buffer’ (485,000ha), and ‘transition’ (1.2 million ha) (UNESCO 2020b) zones do not form a concentric ring (Fig. 4), as the region’s human-environment mosaic was established long prior to the passage of the BR designation in 2001 (Coetzer *et al.* 2013).

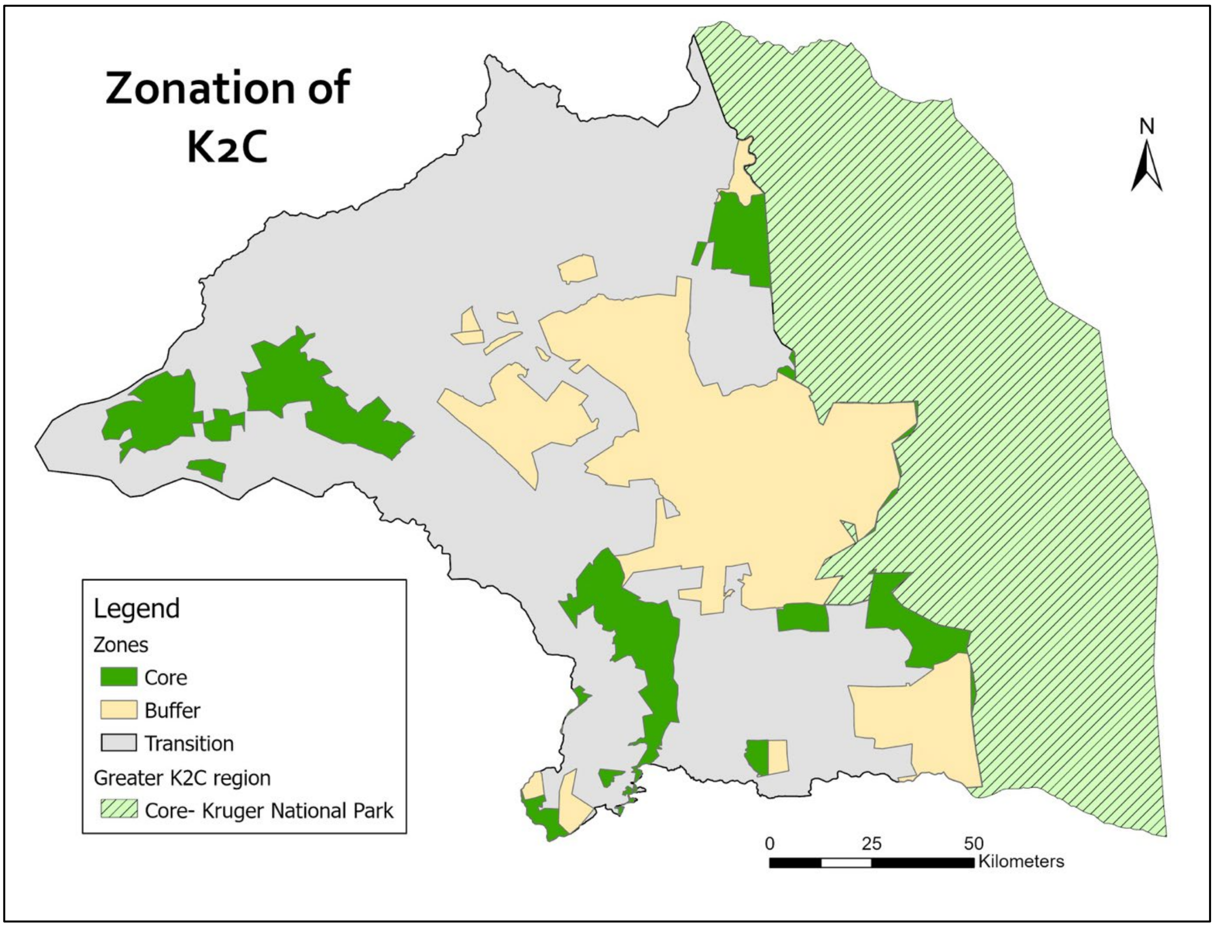


Figure 4. Zonation of Kruger to Canyons Biosphere Reserve.

Previous studies of landcover change in the K2C have revealed trends of increasing settlement expansion and impacted vegetation across the BR coupled with declines in the spatial extent of intact vegetation (Coetzer *et al.* 2013; Coetzer-Hanack *et al*. 2016). Consequently, without the passage of conservation-oriented policies or other interventions, it is predicted that the degradation of natural vegetative landcover may continue into the future (Coetzer-Hanack *et al.* 2016).

3.2 Data sourcing and pre-processing

The study design and analysis aligns with previous landcover change studies conducted for K2C for the time periods from 1993-2006 (Coetzer *et al.* 2013) and 2006-2012 (Coetzer-Hanack *et al.* 2016), with slight modifications due to both advancements in computing techniques and lockdown conditions presented by the Covid-19 global pandemic.

With regards to computing advancements, whereas previous analyses utilized Landsat7 satellite imagery, this study employs images from the collection generated by Landsat8, first launched in February 2013 (NASA 2020). Consequently, the time series analysis for this study is based on the period between 2013 to 2019 (rather than 2012 to 2019), leaving a one-year gap in the overall time series analysis when taking into consideration the aforementioned K2C studies that date to 1993. The change in image source was made for several reasons, chiefly to eliminate the noise in images that results from the Landsat7 scan-line error (Coetzer-Hanack *et al.* 2016), and to ensure future study compatibility, as Landsat7 will be retired in late 2020 when the new Landsat9 launches (USGS 2020). Additionally, a second computing-related deviation in this study that contrasts to previous K2C study designs concerns the boundary of the area of interest that is investigated. Previous studies were unable to capture the full extent of K2C (largely due to the time-consuming nature of manual image rectification and lack of data storage capacity), and thereby excluded a large portion of its northern region (Coetzer-Hanack pers.comm.). The improved data processing and computing power provided by the cloud via the freely-available Google Earth Engine Editor (GEEE) make it possible for this analysis to employ datasets that represent the entire extent of the K2C biosphere reserve.

Geographic data was sourced from the World Database of Protected Areas, the South Africa Database of Protected Areas (SAPAD), the Scottish-based "Map Library," the USGS

Landsat8 collection via the GEEE, and from Dr. Coetzer-Hanack (for complete metadata, see Appendix A). The area of interest (K2C) was delineated by taking shapefiles of the K2C BR and Kruger National Park (KNP) and excising the latter, in congruence with the previous K2C time series to reflect the focal study area outside of KNP. Shapefiles for the BR zonation (core, buffer, and transition) were sourced in part from shapefiles shared by Coetzer-Hanack and SAPAD, and further supplemented by manual creation by the author. Files shared by Coetzer-Hanack did not completely reflect the estate of core and buffer zones because they were originally developed from a 2005 dataset and were therefore outdated for this study (pers. comm.). To improve the zonation dataset, the author identified additional core and buffer zones within the K2C by comparing the SAPAD files that fell within the boundary of K2C to an updated (2019) map of the BR produced by a K2C Stewardship Ecologist and shared via Coetzer-Hanack (pers. comm.). In some instances, SAPAD files did not exist to correspond with zones marked on the map. When possible, the author manually created polygons to represent the missing zones by tracing their outlines from the Esri Street base map (i.e. for Letaba Ranch Nature Reserve north of Phalaborwa, Bewaarkloof Nature Reserve, the southern block of Blyde River Canyon Nature Reserve, and Wolkberg Caves Nature Reserve). Additional cleaning of the zonation shapefile data included filling in the spaces between identified parcels, in accordance with both the Stewardship Ecologists's visualization and on recommendation from Coetzer-Hanack (pers. comm.). It should be noted that the set of buffer and core zones used for this study is not fully reflective of the management areas on the ground in K2C; however, without access to an official dataset and because landcover change is being measured as a relative comparison between the start and end of the study period, the dataset was determined sufficient for these purposes. The shapefile for the transition zone was created to represent all areas external to core or buffer regions within K2C.

The raw satellite imagery was sourced and prepared using the GEEE tool (Gorelick *et al.* 2017). To do so, the shapefiles for the area of interest were imported alongside the image collection sourced from Landsat8 (*N.B.* pixel resolution $30m^2$). The example script for 'Filtering an ImageCollection' that is provided by Google was manually modified to conform to the specific parameters and criteria of this study (Appendix B). Unlike previous K2C landcover change studies, the data for this study does not rely on a primary image filled with ancillary image data (Coetzer-Hanack pers.comm.). Instead, all images the Landsat8 recorded between the selected dates in 2013 and 2019 (8 and 16 images, respectively) were compiled to generate the least cloudy composite across the range of dates specified using the GEEE 'filter' algorithm. Winter months (May-July) are consistently less cloudy than other times of the year (Coetzer *et al.* 2010), and consequently are better-suited for satellite image analysis of South African landscapes. Therefore, the 2013 composite image is comprised of data collected between June 1-30, 2013, and the 2019 composite image is comprised of data collected between June 1- July 15, 2019. The different length of time over which images were filtered is tied to the cloud-filtering algorithm in GEEE which generates a resultant image that is the least cloudy (i.e. the inclusion of dates prior to or beyond June 2013 led to a cloudier composite image, and likewise for the date range selected for the 2019 composite image). Consequently, the images produced for 2013 and 2019 using the GEEE tool are virtually cloud free, thereby facilitating more accurate identification of the landcover contained therein. The resultant composite images were exported for further spatial analysis in Esri's ArcPro 2.5 and TerrSet's IDRISI Image Processing software.

Complications arising from the global lockdown due to the Covid-19 pandemic meant that a reference dataset for validation purposes could not be produced from ground truth observations. Consequently, validation of the classified map outputs relied solely on digital validation methods (Wickham *et al.* 2013; Olofsson *et al.* 2014). While ground truthing would have added value to the quantification of error in this study, the global conditions were prohibitive. Additionally, personal communication (Coetzer-Hanack) revealed that previous landcover change studies of the K2C that were partially validated with ground truth data relied on datapoints collected almost solely within easily accessible areas of K2C's southern extent. Non-random sampling as the basis of reference data is often the case with ground truthing, yet such a design presents its own challenges in quantifying the error associated with the classified vs. verified mapped outputs (Congalton 2001; Foody 2010); in fact, the ability to generate a random sample for digital validation is advantageous in this regard (Foody 2002), however best practice (under ideal non-pandemic conditions) would allow for a study design that incorporates both digital and empirical validation methods (Yu and Gong 2011).

3.3 Methods

3.3.1 Supervised Classification

Esri's ArcGIS Pro v 2.5 software (ArcPro) was used to conduct a pixel-based supervised classification of the 2013 and 2019 satellite imagery. Esri's 'Image Classification Wizard' was the primary tool employed, following the workflow presented in Fig. 5. The first step of supervised classification (SC) required the delimitation of a set of discrete and mutually exclusive landcover classes (Foody 2002), *i.e.* a 'classification schema,' by which the observed landcover types were categorized. This study aligned its classification schema (Table 4) with previous K2C research (Coetzer *et al.* 2010; 2013; Coetzer-Hanack *et al.* 2016), with several amendments. The classification schema used for this study was comprised of eight intermediate consolidated landcover classes (Appendix C) and more numerous sub-classes, based on the spectral nuances observed across a single landcover type.

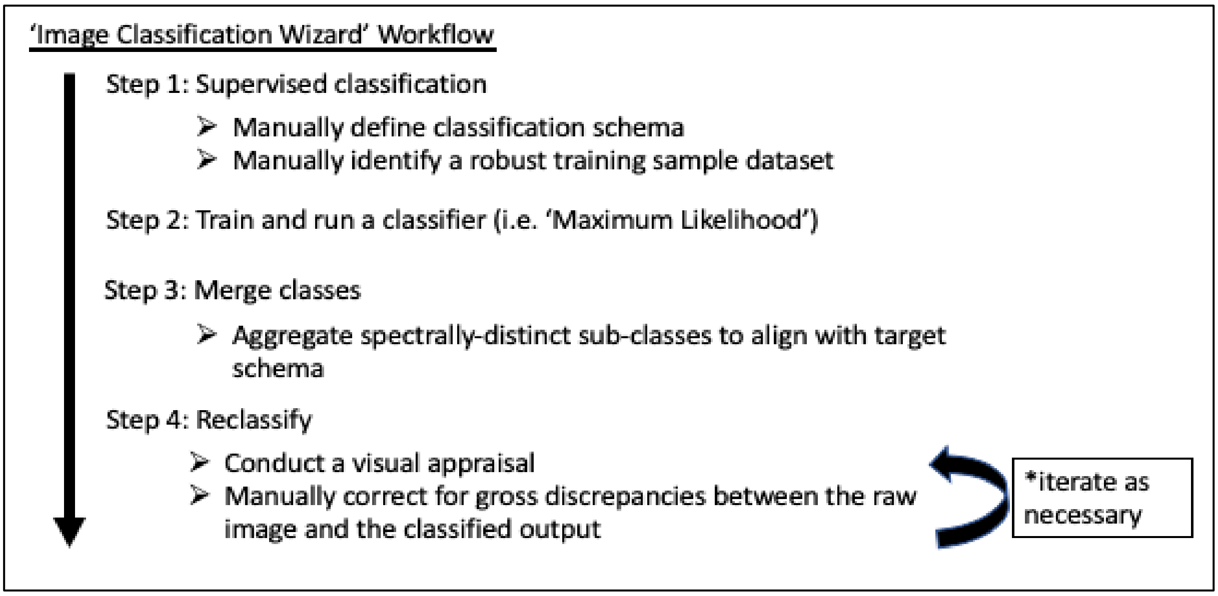


Figure 5. Workflow using 'Image Classification Wizard' in ArcPro v 2.5.

In contrast to the schema employed by previous research, at this stage of analysis, classes for 'Settlement' and 'Mines' were merged as a single intermediate consolidated landcover class ('Settlement') rather than kept separate, due to the similarity of their spectral signatures and shared classification ('Settlement') under the final aggregated landcover classification schema (Table 3). Similarly, two previously separate classes ('Burn' and 'Clearfell'), were merged to a single intermediate class ('Burn and Clearfell'), as the two share similar visual spectral characteristics and were ultimately excluded in the final aggregation of landcover classes (Table 3). Lastly, the schema employed in this study deviated from previous research's schema in that the 'Cloud Cover' intermediate consolidated class was eliminated, due to the negligible presence of clouds in the 2013 and 2019 imagery. The simplification of the schema from that of previous research on landcover change in the K2C did not affect the

Table 3. Final aggregated landcover classification schema.

Code	Final aggregated landcover class	Intermediate landcover class	Landcover sub-classes
1	Intact vegetation	Intact Natural Vegetation	Intact Woodland/ Intact Thicket and Bush/ Grassland
		Forest*	*located within the bounds of the BR's core zones
2	Impacted vegetation	Impacted Vegetation	Impacted Woodland/ Impacted Thicket and Bushland
3	Settlement	Settlement	Settlement/ Mines and Quarries
		Agriculture	Formal and subsistence crops/ Fallow fields
4	Excluded	Exposed Ground	
		Water	
		Burn and Clearfell	
		Forest**	** located outside of the bounds of the BR's core zones

final aggregation of landcover classes (Coetzer-Hanack pers. comm.); furthermore, the simplification was strategic to account for the researcher's lack of place-based knowledge. By aggregating classes of similar spectral signature and that share a final aggregated landcover classification, the researcher was able to more confidently develop the reference dataset (Section 3.3.2).

Following the determination of the classification schema, the 'Training Samples Manager' tool in ArcPro was used within the 'Image Classification Wizard' to develop a robust set of training samples that correspond with each of the classes. Training samples were developed independently for the 2013 and 2019 images, in accordance with previous research methodology (Coetzer *et al.* 2013; Coetzer-Hanack *et al*. 2016) to limit the potential propagation of error associated with building the training sample datasets. Because the training sample set for this time series analysis (2013-2019) was developed by the same individual (the author), any error in the identification of training samples should be consistent between the mapped outputs for 2013 and 2019. Thus, even without the capacity to explicitly quantify the error associated with this stage of the classification process, the common methodology between the two image classifications follows an adequate approach that will allow for the results to be interpreted, at a minimum level of certainty, as indicative of relative change across the landscape over the defined time period (Coetzer-Hanack pers. comm.).

Supervised classification can be conducted based on training samples of which the unit of measurement is an individual pixel or a polygon; the latter is better suited for heterogeneous landscapes (Rogan and Chen 2004) and is what was utilized in the development of the training samples for this study given the highly variable nature of the K2C landscape. Each landcover class in the training sample requires an absolute minimum of 30 samples; best practice encourages ≥50 samples per landcover class (Congalton 2001). For this study, a minimum of 80 samples were manually identified for each intermediate landcover class. To identify areas of the satellite images that share the same spectral signature, the images were visualized using different combinations of the 12 spectral bands of which they are comprised. Multispectral data is useful in image classification because different band combinations allow the interpreter to better see characteristics and distinctions between landcovers in the remotely sensed image (Lu and Weng 2007). For example, toggling between the red/green/blue channel visualizations that depict a '543' band combination provided an important counter visualization (infrared vegetation) to that of the'764' (false color urban) visualization to help determine the boundary between different landcover types that cannot be seen when looking at the image in 'natural color' alone.

Reference to the 2012 K2C map produced by Coetzer-Hanack *et al.* (2016) was made as a general guide for the 2013 classification, since the general positioning of landcover types was unlikely to have dramatically shifted between 2012 and 2013. Additionally, expert feedback was sought from R. Lerm and A. Swemmer of the South African Environmental Observation Network and K2C researcher K. Coetzer-Hanack (pers. comm.) to ensure the accurate interpretation of spectral signatures. Despite these efforts to produce accurate training sample datasets, it should be noted that the spectral appearance of bush encroached areas could not be differentiated against areas of intact thicket and bush; thus, there is an unknown portion of 'intact vegetation' that is actually impacted bushland, an issue that plagued previous K2C landcover change research as well (Coetzer *et al.* 2010; 2013; Coetzer-Hanack *et al.* 2016).

Once the training sample datasets were fully developed, the 'Maximum Likelihood Classifier' (MLC) was run in ArcPro. The MLC was selected as the classifier of choice to align with previous K2C studies (Coetzer *et al.* 2010; 2013; Coetzer-Hanack *et al.* 2016). The running of the classifier relies on software to analyze the spectral signature of the polygons of the training dataset and apply machine learning to identify pixels across the entire image that share those same spectral characteristics. The identified pixels are assigned the numerical code associated with the identified intermediate landcover (Appendix C) to produce a classified map output (see 'Chapter 4: Results'). Subsequently, the sub-classes were merged to accord with the eight intermediate consolidated landcover classes of the schema. Iterative reclassification of the classified map outputs was conducted to correct visually detectable discrepancies between the raw satellite imagery and the classified outputs. For example, the spectral signature of roads was variably identified by the algorithm in some areas as 'settlement' and in others as 'exposed ground,' thus manual effort was made to go in and correct roads marked as 'exposed ground' to reflect infrastructure associated with human 'settlement.' Upwards of 40- and 60-sets of reclassified maps were iteratively generated for the 2013 and 2019 images respectively, with great attention to detail made to improve the visual correspondence of the mapped outputs against the raw imagery prior to an official accuracy assessment. Following the completion of these visual-based accuracy improvements, an official quantitative accuracy assessment was then conducted.

3.3.2 Quantitative Accuracy Assessment

It is necessary to assess and quantify the uncertainty associated with the classified mapped outputs since maps do not fully reflect real world conditions yet are used to inform policy and management decisions (Foody 2002). For time series analyses such as this study, it is particularly important to assess accuracy to ensure that any detected change is a reflection of actual landcover transformation and not a result of error in the classification process (Foody 2002; Lu and Weng 2007; Foody 2015). Since comparison against a ground-truth reference dataset was not an option for this analysis, two different digital validation methods were attempted. For both, a random sample of 500 points was generated; while the selection of pixels as the unit for assessment is an imperfect option due to the possibility that more than one landcover type is located within the area captured by a single pixel (Foody 2013), it is a widely-accepted practice in developing a digital reference dataset (Wickham *et al.* 2013). Additionally, as previously noted, a benefit to the use of ArcPro's random sample generator rather than using ground truth data is that the latter is rarely a truly random sample because of limitations associated with sampling remote or otherwise difficult-to-access locales within a study area (Foody 2002). Thus, the following two digital methods for accuracy assessment were deemed appropriate given both the lack of access to ground truth information presented by current conditions and the rationale behind digital validation methodologies.

For both accuracy assessment methods, after a reference dataset was built, a confusion matrix and kappa statistic were computed, per standard practice (Foody 2002; Lu and Weng 2007; Foody 2010). As with any scientific study, the degree of error that is acceptable in the mapped output will depend on the user's needs. There is no set cut-off point by which the accuracy of map outputs is judged, but standard practice over the last two decades suggests that maps should achieve an accuracy of ≥85% and that no class category exhibit an accuracy below 70% (Foody 2002). The kappa (K) statistic provides another means to evaluate the agreement of the classified mapped output with reality. The value of K can range from +1 to -1, with 1 representing a perfect match between ground conditions and the mapped representation (Coetzer *et al.* 2013). The Kappa coefficient informs the user as to whether the output is significantly different than a map generated from the random assignation of landcover classes across the mapped area (Congalton 2001; Foody 2002).

3.3.2a Method One: Accuracy Assessment via Google Earth

The first effort at validation aimed to align with best practice guidelines which indicate that a digital reference dataset should be constructed from a higher quality resolution image than that of the satellite imagery from which the classified output is rendered (Foody 2002; Yu and Gong 2011; Olofsson *et al.* 2014). Lacking aerial photographs by which to use as a reference resource, for this accuracy method Google Earth imagery was utilized. Google Earth imagery is theoretically suitable for this purpose because of its higher resolution (resolution ≤15m^2) than the Landsat8 imagery (resolution 30m^2 per pixel). However, this method was hampered because the process of identifying landcover using the Google Earth imagery proved to involve a high-degree of subjectivity on the part of the researcher. This provided little confidence to the researcher in this method's capacity to accurately cross-check the classified output derived from the Landsat8 imagery. Consequently, a second accuracy assessment method was conducted. For the sake of recording the effort expended on the Google Earth accuracy assessment attempt, a brief description of its methodology follows.

For this method, the landcover classification was aggregated into eight intermediate classes (Appendix C); notably, all types of non-forest and non-agriculture vegetation (i.e. woodland, thicket and bushland, ang grassland) were aggregated based on their 'intact' or 'impacted' status. This was done in order to support the researcher's ability to identify vegetation, as the capacity to identify 'intact' vs. 'impacted' was greater than the capacity to confidently identify narrower vegetation classes. A random sample of 500 points was generated from each of the classified images in ArcPro using the "Create Random Points" tool. These reference datasets were then converted to kml file format for import into Google Earth, where each point was zoomed to by clicking on its metadata signature. A copy of the attribute table for the reference points was exported to Excel where the reference classification data was recorded as it was interpreted. The column within the datast that contained the classification associated with each point as mapped by the Landsat8 data was hidden so as to reduce bias in the interpretation of the Google Earth imagery, per methodology described by Wickham *et al.* (2013). Additionally, the researcher recorded the degree of confidence with which each reference point was identified, using the Wickham *et al.* (2013) rating system, whereby: 1= not confident in the identification of the landcover at the reference point, 2= somewhat confident, and 3=confident.

To classify the landcover at the reference points using Google Earth, the time scale was toggled to the appropriate reference year. The time-consuming nature and lack of confidence in the output of this method resulted in the development of a reference dataset (using this method) for only the year 2013. For the reference dataset for 2013, the date range of the reference imagery in Google Earth ranged from April to December 2013, with some instances where clouds obscured the visibility of the ground cover; in these cases, the time horizon in Google Earth was advanced towards the next cloud-free image capture in 2014 (rather than reversing in time to an earlier image capture from 2012) to limit the possibility of including landcover transformation that may have occurred in advance of the defined study period (2013- 2019). Despite the higher resolution of Google Earth imagery, the researcher found it highly subjective to identify, for example, woodland that was 'intact' vs. 'impacted,' in part because of lack of familiarity with place-based conditions, but largely because there was no method to decipher how closely shrubs/trees needed to be located to one another to be considered 'intact' vs. 'impacted.' In K2C, the south eastern region has much more sparse vegetation than in the north eastern extent, potentially because of elephant activity (Lerm pers. comm.) or difference in vegetation type (Swemmer pers. comm.), making it challenging to confidently assess if a refence data point constitutes 'intact' or 'impacted' vegetation.

After all reference datapoints were classified, the data was converted from Excel format into that readable by the ArcPro software, and the "Compute Confusion Matrix" tool was deployed to generate the overall map accuracy and kappa statistics. While it is often accepted that a reference dataset is 'correct' and that any discrepancy between it and the mapped classified output is due to error in the latter (Congalton 2001; Foody 2010; Lu and Weng 2007), this foray into validation using Google Earth imagery highlights the potential pit-falls of accepting this as a blanketly-true statement. This is especially the case since there is no method to quantify the error associated with the classification of the reference dataset. Therefore, based on the evolving dialogue within the remote sensing community around the significance of inaccurate reference data (Foody 2010; Olofsson *et al.* 2014), and because the researcher's confidence in identification for the majority of the reference points using Google Earth imagery were scored as a '1' on the Wickham *et al.* (2013) scale, this raised the question of how reliable this method was for estimating the error in the classified map outputs. Consequently, the researcher determined that an alternative referencing method should be pursued.

3.3.2b Method Two: Accuracy Assessment via Landsat8 Imagery

Because the accuracy assessment with Google Earth imagery was too subjective for this context, an alternative assessment method was conducted that used the same Landsat8 imagery from which the classified maps were produced. When a reference dataset can only be developed from the original remotely sensed image, then the creation of the reference dataset should be more accurate than the process used to create the training samples

(Olofsson *et al.* 2014). Following recommended methodology (Olofsson *et al.* 2014), the reference datapoints generated for this assessment (again using the 'Create Random Points' tool in ArcPro; independent reference datasets were developed for 2013 and 2019) did not coincide with any of the data that comprised the training samples from which the classifier trained (i.e. the polygons selected for training were discrete from any pixels selected as reference data points). The generated reference points were classified by interpreting the spectral visualizations of the raw Landsat8 imagery. As described for the Google Earth validation attempt, the classifications assigned to each reference point were hidden to eliminate bias as the researcher identified the landcover at the reference points. As before, the researcher's confidence in the identification of landcover at each reference point was scored on the Wickahm *et al.* (2013) scale of 1 to 3 (Fig. 6). Following the completion of

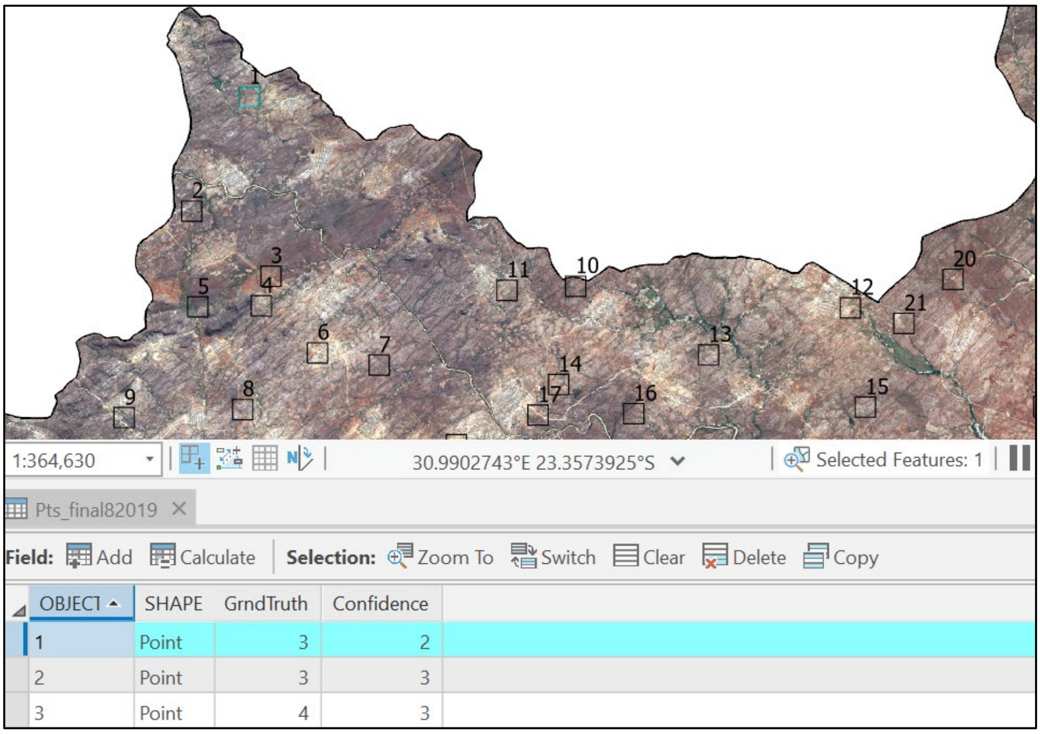


Figure 6. Depiction of building a digital reference dataset in ArcPro.

the classification of the reference dataset, aggregate class accuracy statistics were calculated using the "Compute Confusion Matrix" tool in ArcPro. Based on the outputs of the confusion matrix, landcover classes that had low rates of identification provided insight into where improvement in the training sample set needed to be made. The author iterated the supervised classification process and cross validation via building a reference dataset a total of five times for the 2013 dataset before settling on the results shared in this study. The 2019 dataset iterated the complete process only three times but was completed after the completion of the 2013 outputs, and was therefore informed by the entire process.

After the confusion matrix and Kappa statistics outputs were generated in ArcPro, the confidence limits of the producer's accuracy were manually calculated (Evans 2017) in Excel using the following equation:

$$Confidence\ Limit = Error\ \pm constant * \frac{\sqrt{[(Error * (1 - Error)]}}{n}$$

where the error was calculated by dividing the number of incorrect predictions by the total number of predictions, per class. Additionally, the rates of omission and commission errors were manually calculated in Excel for each class by dividing the sum of incorrect classifications per class by the total number of reference sites per class (moving down each column for omission calculations, and across each row for commission error calculations) (Evans 2017; Humboldt State University 2016).

3.3.3 Spatial Pattern Analysis

To analyze the landcover dynamics across the entirety of K2C and the dynamics with regards to the zones designated within the BR, a series of manipulations were conducted in ArcPro (Fig. 7). First, two independent operations were conducted on the 8-class landcover map (2013) from which the accuracy assessment was conducted. The 8-class map was aggregated into the three priority landcover classes ('Intact Vegetation,' 'Impacted Vegetation,' and 'Settlement') by which the spatial dynamics of this study will be analyzed, and the 'Forest' class was extracted to its own layer and clipped to only visualize forest located in the core zone. Note that 'Forest' landcover located within the core zones of the BR can be considered 'Intact Vegetation,' but 'Forest' located outside of the core zones is excluded for the purposes of this study. The reason for this is that it is not possible in the initial classification process to discern commercial vs. indigenous forest from one another because they share the same spectral signature. Consequently, following the logic of previous K2C research (Coetzer *et al.* 2013; Coetzer-Hanack *et* al. 2016), because forest in the core is known to be indigenous and is managed for conservation, this alone can be considered 'intact.' After the production of the intermediate stage priority class map and the separate

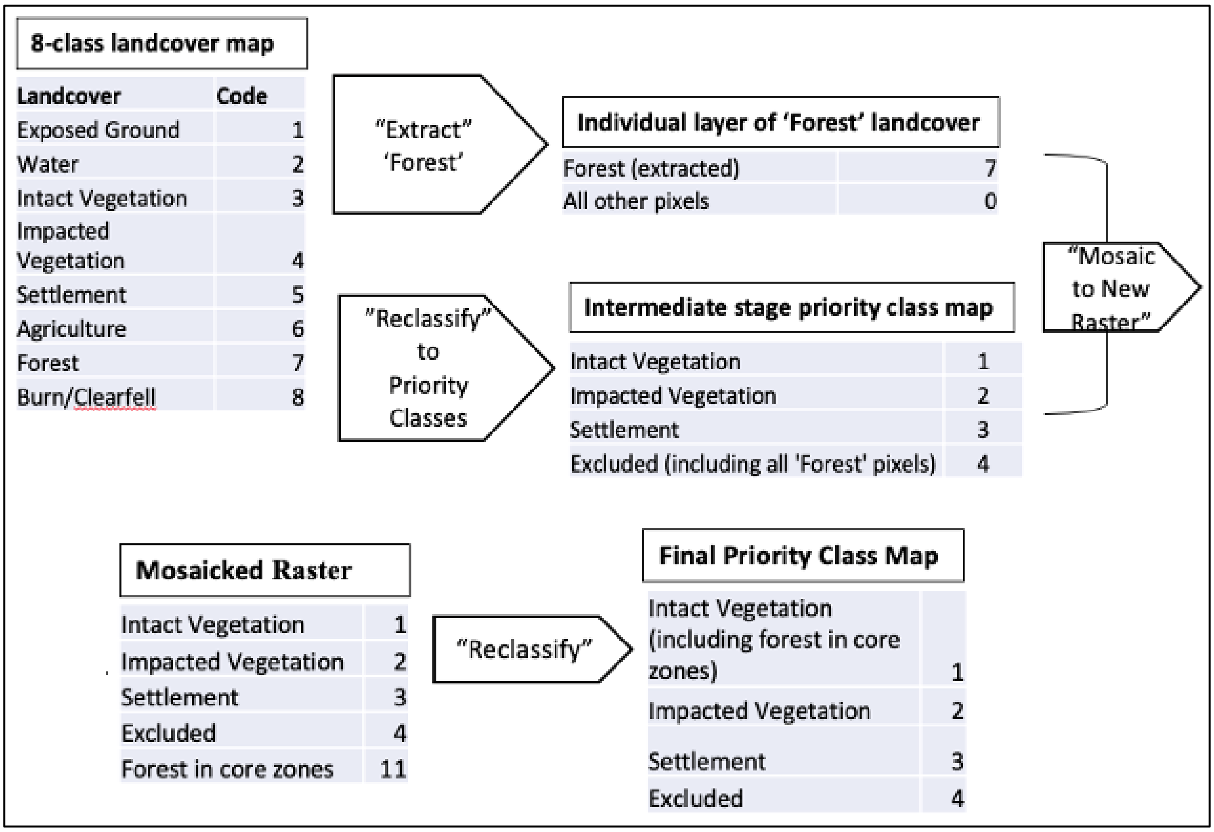


Figure 7. Workflow for production of priority class maps.

core 'Forest' layer, the two were mosaicked together to create a mosaicked raster where all pixels were either assigned a code of 1-4 or 11 (Fig. 7). Because the intermediate stage priority class map coded all forest as '4', when it was mosaicked with the separate 'Forest' layer (which depicted only forest in the core zone and was coded '7'), the pixels resulting in a code of '11' indicate forest located in the core zone. Thus, the final step to produce the final priority class map requires the reclassification of the pixels coded as '11' to '1' to represent 'Intact Vegetation.' This process was repeated independently for the 2019 data.

To generate depictions of priority landcover for each BR zone, the final priority class map was intersected with each of the zones, independently, for both 2013 and 2019. For the final component of analysis, IDRISI TerrSet's Land Change Modeler program was utilized to compute net change statistics and to examine dynamics of landcover gains, losses, and persistence.

Chapter 4: Results

Classification Outputs: Statistics and Visualizations

The quantitative accuracy assessment of the 2013 classification reports an overall classified map accuracy of 89.75% (Table 4). The calculated Kappa value (K) of 0.81 (on a

Table 4. Confusion matrix for the 2013 classified map output.

2013										
Landcover Class	Exposed Ground	Water	Intact Veg.	Impacted Veg.	Settlement	Agriculture	Forest	Burn/ Clearfell	Total Pts Identified	**User's Acc. (%)**
Exposed Ground	9	0	1	0	0	0	0	0	10	90.00%
Water	0	9	1	0	0	0	0	0	10	90.00%
Intact Veg.	0	0	323	10	5	2	3	0	343	94.17%
Impacted Veg.	0	0	14	33	3	1	0	0	51	64.71%
Settlement	3	0	2	0	27	0	1	0	33	81.82%
Agriculture	0	0	0	0	0	17	2	0	19	89.47%
Forest	0	0	2	0	0	0	39	0	41	95.12%
Burn/ Clearfell	0	0	3	0	0	0	0	7	10	70.00%
# Reference Pts	12	9	346	43	35	20	45	7	517	
Producer's Acc. (%)	75.00%	100.00%	93.35%	76.74%	77.14%	85.00%	86.67%	100.00%	**Total Acc.**	**89.75%**

scale where K ranges from 0 to 1) indicates "Almost perfect" agreement between the classified reference dataset and the classified output (Table 5).

Table 5. Interpretation of Cohen's Kappa statistic.

Kappa statistic	**Interpretation: Strength of agreement**
< 0	Poor
0.0–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.0	Almost perfect

Source: Coetzer *et al.* 2010

The complete confusion matrix (Table 4) from the cross tabulation of the 2013 reference points against the 2013 supervised classification (data calculated via ArcPro) indicate both the producer's and user's accuracy for each landcover class. 'User's accuracy' refers to the percent of the time which the viewer of the map can reasonably expect that the classified landcover accurately represents on-the-ground conditions, whereas 'producer's accuracy' refers to the accuracy of the researcher in correctly classifying landcover (Humboldt State University 2016). Both inform the overall accuracy calculation, while the latter is used to report the error (Table 6) associated with the classified map output.

Table 6. Error associated with the Producer's Accuracy of the 2013 classification.

			90% Confidence limits			
Landcover Class	User's Accuracy (%)	Producer's Accuracy (%)	Low	High	Omission Error (%)	Commission Error (%)
Exposed Ground	90.00	75.00	54.50	95.50	25.00	10.00
Water	90.00	100	100	100	0	10.00
Intact Veg.	94.17	93.35	91.16	95.55	6.65	5.83
Impacted Veg.	64.71	76.74	66.18	87.31	23.26	35.29
Settlement	81.82	77.14	65.50	88.78	22.86	9.09
Agriculture	89.47	85.00	71.91	98.09	15.00	10.53
Forest	95.12	86.67	78.36	94.98	13.33	4.88
Burn & Clearfell	70.00	100	100	100	0	30.00

Landcover classes of the 2013 classification exhibit variability in the rate at which they were accurately identified, ranging from 54.50-100% when the 90% confidence limits are considered (Table 6). The 'Exposed Ground' landcover class reports the lowest rate of identification accuracy (75±20.50%), with its lower limit dipping below the 70% threshold suggested by Foody (2002) as the minimum value for interpretation reliability. Both the 'Impacted Vegetation' and 'Settlement' classes also report a comparatively low rate of accuracy in their identification, (76.74±10.57% and 77.14±11.64%). On the other end of the scale, the 'Water' and 'Burn/Clearfell' classes report perfect rates of identification accuracy; the remaining three classes ('Agriculture,' 'Forest,' and 'Intact Vegetation') also indicate relatively high rates of accurate identification that fall within the 80th -90th percentiles (85±13.09%, 86.67±8.31%, and 93.35±2.19%, respectively).

The quantitative accuracy assessment of the 2019 classification reports an overall classified map accuracy of 89.17% (Table 7). The calculated Kappa value (K) for the 2019 classification is, like that of the 2013 classification, also 0.81, indicating an "Almost perfect"

Table 7. Confusion matrix for the 2019 classified map output.

2019										
Landcover Class	Exposed Ground	Water	Intact Veg.	Impacted Veg.	Settlement	Agriculture	Forest	Burn/ Clearfell	Total Pts Identified	**User's Acc. (%)**
Exposed Ground	6	0	5	2	0	0	0	0	13	46.15%
Water	1	8	1	0	0	0	0	0	10	80.00%
Intact Veg.	0	0	294	4	7	1	2	3	311	94.53%
Impacted Veg.	0	0	11	33	1	0	0	0	45	73.33%
Settlement	0	0	3	2	36	0	0	0	41	87.80%
Agriculture	0	0	0	3	0	21	0	0	24	87.50%
Forest	0	0	4	0	0	0	48	0	52	92.31%
Burn/ Clearfell	0	0	3	0	0	0	2	7	12	58.33%
# Reference Pts	7	8	321	44	44	22	52	10	508	
Producer's Acc. (%)	85.71%	100.00%	91.59%	75.00%	81.82%	95.45%	92.31%	70.00%	**Total Acc.**	**89.17%**

agreement between the 2019 reference dataset and the 2019 classified output. The complete confusion matrix for the 2019 dataset (Table 7) indicates that, like the 2013 classification, landcover classes for the 2019 classification also exhibit great variability in the rate at which they were accurately identified. For the 2019 dataset, the lower confidence limit of three classes ('Burn/Clearfell,' 'Exposed Ground,' and 'Impacted Vegetation') drops below the 70th percentile (Table 8). On the other end of the spectrum of identification accuracy, the 'Water' class reports a perfect rate of identification, as was the case in 2013. Three landcover classes ('Forest,' 'Agriculture' and 'Intact Vegetation') report high identification accuracy rates in the 80th to 90th percentiles (92.31$\pm$6.29%, 95.45$\pm$7.28%, and 91.59$\pm$2.54%, respectively). The remaining class, 'Settlement,' also demonstrates a reliable rate of accurate identification (81.82$\pm$9.54%).

A side-by-side visualization of the classified mapped outputs for the 2013 and 2019

Table 8. Error associated with the Producer's Accuracy of the 2019 classification.

			90% Confidence limits			
Landcover Class	User's Accuracy (%)	Producer's Accuracy (%)	Low	High	Omission Error (%)	Commission Error (%)
Exposed Ground	46.15	85.71	64.02	100	14.29	53.85
Water	80.00	100	100	100	0	20.00
Intact Vegetation	94.53	91.59	89.05	94.13	8.41	5.47
Impacted Vegetation	73.33	75.00	64.29	85.71	25.00	26.67
Settlement	87.80	81.82	72.28	91.35	18.18	12.20
Agriculture	87.50	95.45	88.17	100	4.55	12.50
Forest	92.31	92.31	86.02	98.59	8.33	7.69
Burn and Clearfell	58.33	70.00	46.23	93.77	30.00	41.67

classifications is reported in Figure 8. Note that the mapped outputs (Fig. 8) represent the finer-detail landcover classes that distinguish between intact vegetation types (Woodland, Thicket and Bushland, and Grassland) as opposed to the eight-class aggregation by which the accuracy assessment was conducted. The presentation of the overall landcover in this manner (Fig. 8) aligns with the presentation of previous K2C research (Coetzer *et al.* 2010; 2013; Coetzer *et al.* 2016), with the primary purpose of visualizing the images in this way to serve as a reference for understanding the high level of heterogeneity that exists across the K2C landscape. More pertinent to the study of landcover dynamics of this specific research is the side-by-side visualization reported in Fig. 9, which depicts the distribution of the three aggregated priority landcover classes across the K2C landscape in 2013 and 2019. Note that larger-scale visualizations of mapped outputs can be found in Appendix E for ease of viewing, if desired.

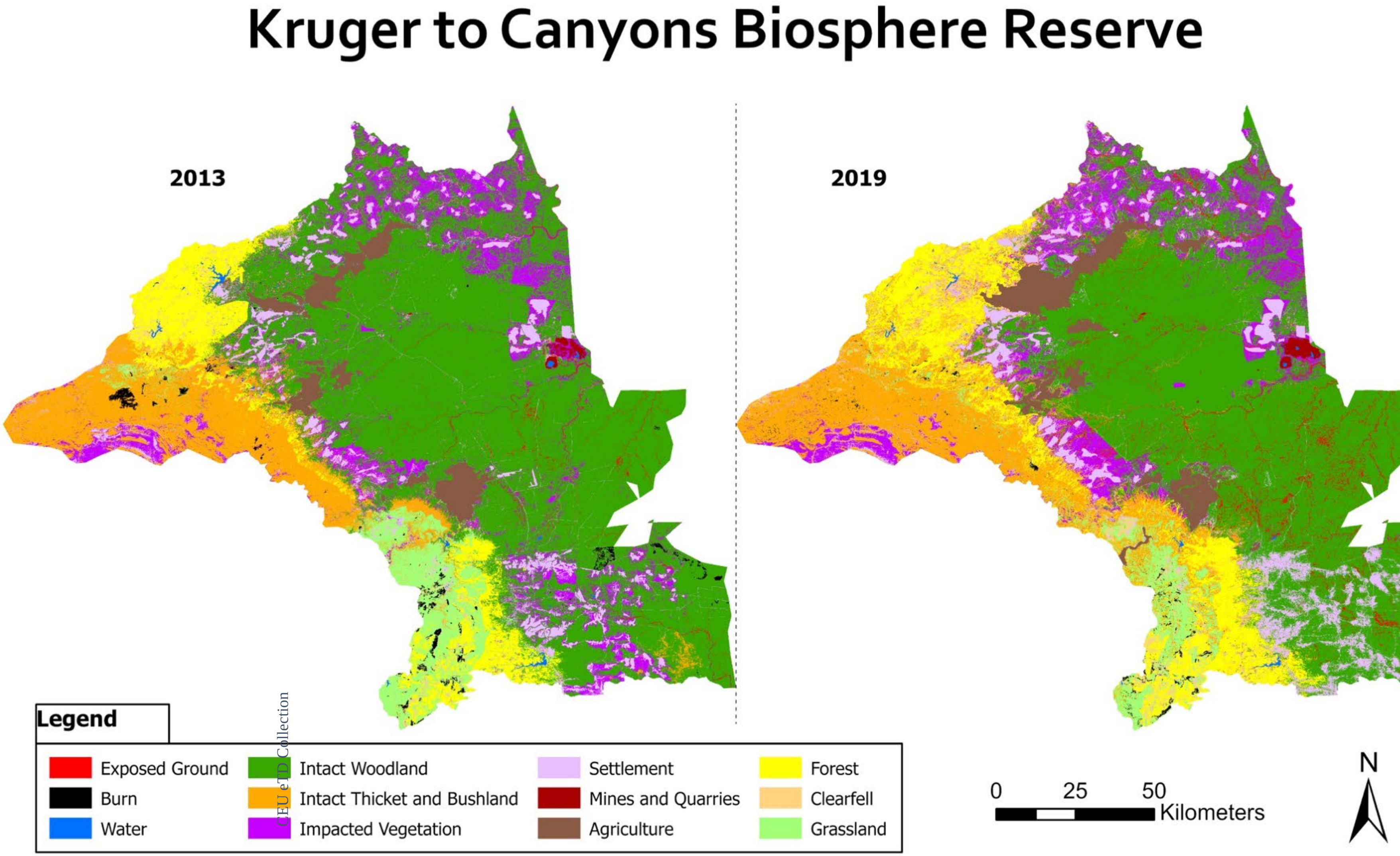


Figure 8. Classification of landcover in K2C, 2013 and 2019.

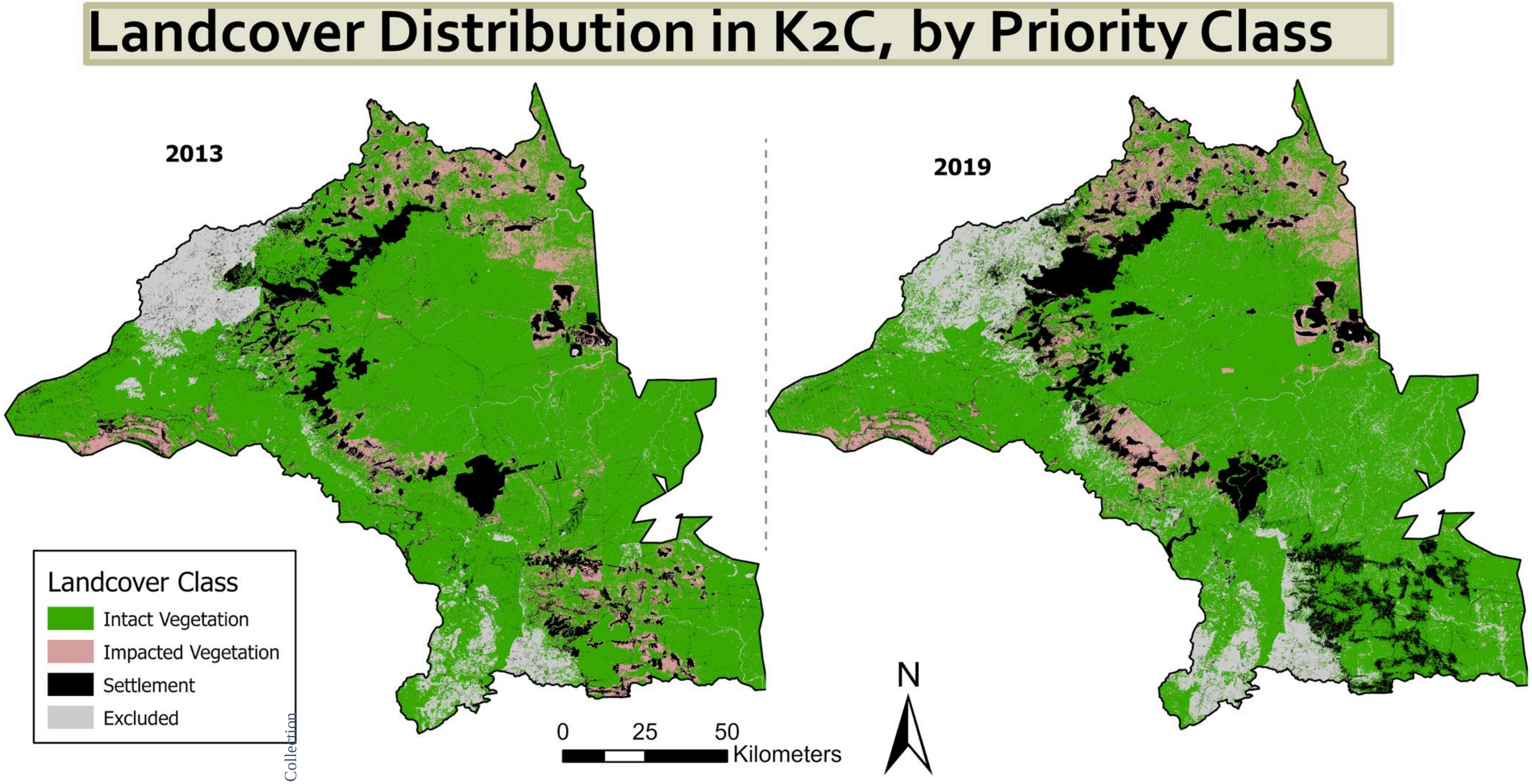


Figure 9. Landcover distribution in K2C, by priority class.

Spatial Landcover Dynamics

Dynamics Across K2C

Each of the three priority landcover classes changed their relative contribution to the entire K2C landscape between 2013 and 2019. Over the course of the study period, 'Intact Vegetation' remained the largest class (Fig. 10). 'Intact Vegetation' represents more than two-thirds of the K2C area in 2013 (70.2%), and just under that threshold in 2019 (64.7%) (Fig. 10; Table 9). Despite its predominance, the 'Intact Vegetation' class recorded the

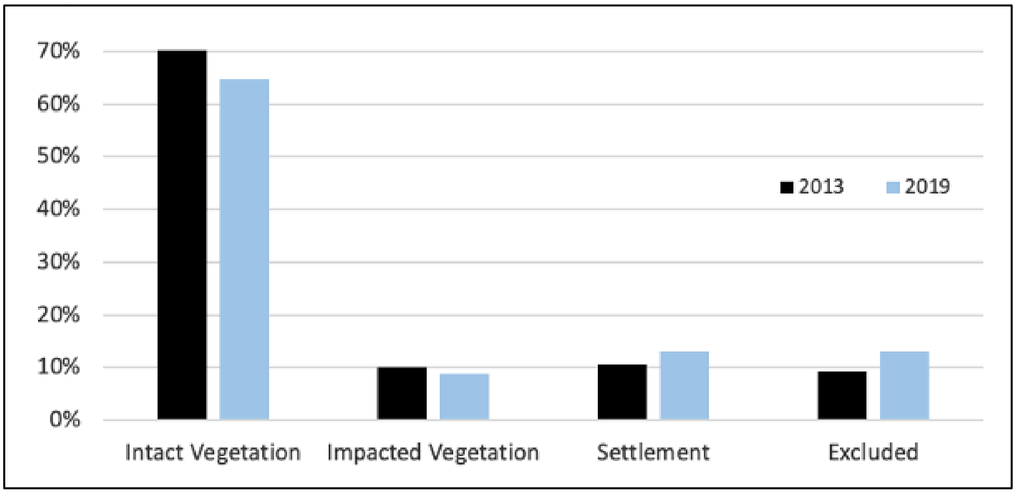


Figure 10. Comparison of landcover composition in K2C, 2013 and 2019.

greatest percent decrease in the landscape (-5.5%) relative to the changes documented among the other landcover types (Table 9). 'Impacted Vegetation' also declined slightly over the

Table 9. Change in relative composition of priority landcover classes across K2C, 2013-2019.

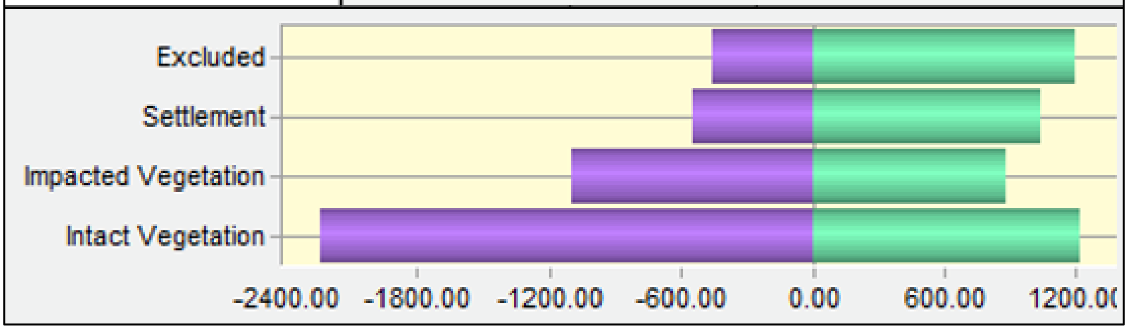
Landcover Class	% Composition of K2C 2013	% Composition of K2C 2019	% Change 2013-2019
Intact Vegetation	70.2	64.7	-5.5
Impacted Vegetation	10.1	8.9	-1.2
Settlement	10.5	13.2	2.7
Excluded	9.2	13.2	4

course of the study period, dropping from 10.1% to only 8.9% of the landscape by 2019. Of the three priority classes, only 'Settlement' demonstrated an increase, gaining 2.7% land area and representing 12.2% of the K2C landscape in 2019. Whereas the 'Excluded' class is not the primary focus of the change dynamics pertaining to the conservation potential of the study region, the quantity of landcover that was classified as such did increase by 4.0%, notably becoming as equally abundant across the landscape as 'Settlement' (13.2% of the landscape, each) (Fig. 10).

Further examination of the landcover dynamics across K2C from the perspective of gains, losses, and net change indicates that the priority landcover classes underwent different quantities, combinations, and locations of landcover change (Fig. 11). Transformation of landcover took place via both losses (transformation to another landcover class) and gains (additions from another landcover type). The 'Intact Vegetation' class exhibited the greatest net reduction overall despite it making the greatest quantity of recorded 'gains' amongst priority landcover types (Table 10). In terms of net change, 'Intact Vegetation' lost

Table 10. Gains, losses, and net change across K2C priority landcover classes (2013-2019).

Landcover Class	2013-2019		
	Gains (km^2)	**Losses (km^2)**	**Net Change (km^2)**
Intact Vegetation	1215.2	2240.1	-1024.9
Impacted Vegetation	876.46	1097.13	-220.67
Settlement	1037.97	541.07	496.9
Excluded	1201.46	452.88	748.58



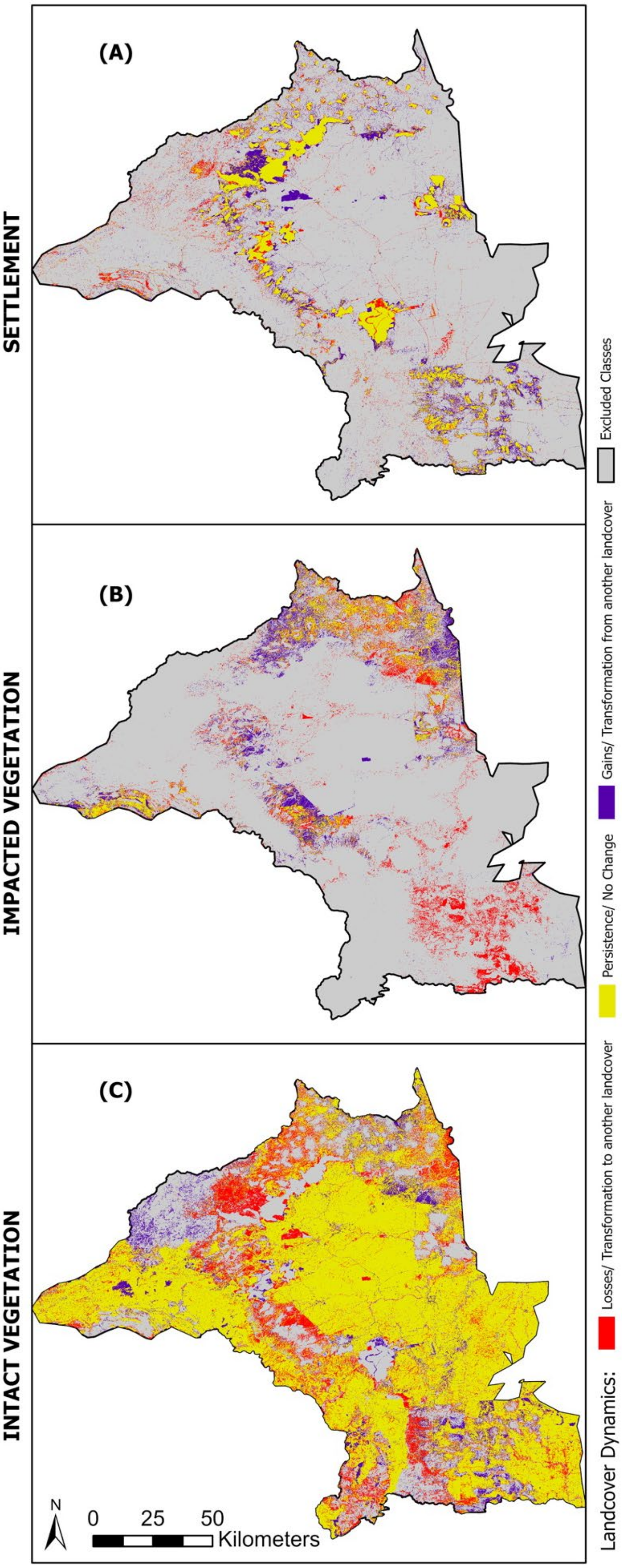


Figure 11. Spatial patterns of Gains (G), Losses (L), and Persistence (P) 2013-2019 across K2C.

approximately double the land area as the ‘Impacted Vegetation’ class (2240 km^2 vs. 1097 km^2), which lost approximately double the area of losses incurred by the ‘Settlement’ class (541km^2) (Table 10). The reduction in net ‘Intact Landcover’ is due primarily to its conversion to the ‘Excluded’ category (Fig. 12a). The ‘Impacted Vegetation’ class was most influenced by conversion to ‘Settlement’ (Fig. 12b). The ‘Settlement’ landcover was most influenced by conversion of both ‘Impacted’ and ‘Intact’ vegetation transforming to ‘Settlement’ (Fig. 12c).

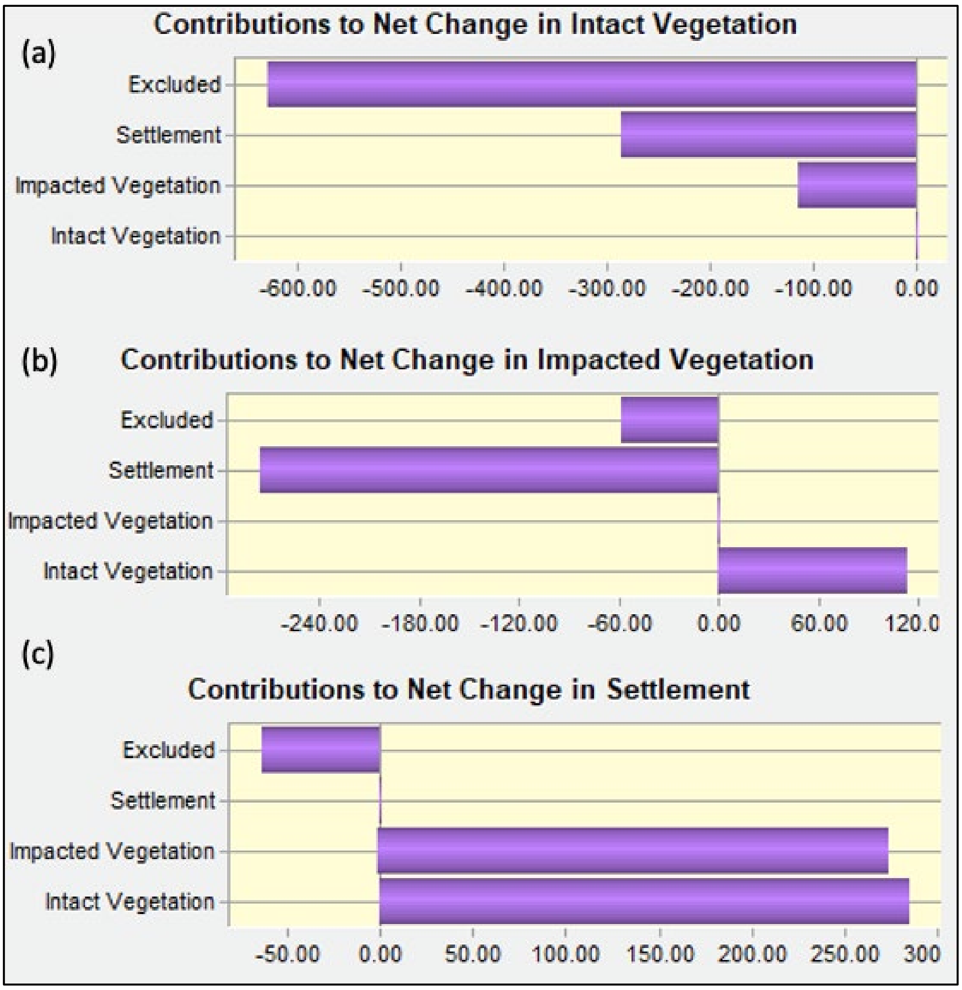


Figure 12. Contribution of losses and gains to net change by priority class across K2C.

With regards to the afore-described net changes (Fig. 9) and changes in gains, losses, and persistence of priority landcover classes across K2C (Fig. 11), several spatially-related points are notable. The ‘Settlement’ class primarily makes gains adjacent to areas where

‘Settlement’ persistence occurs, with more concentrated gains in settlement documented in the northern half of K2C than in its southern extent (Fig. 11a). Losses in ‘Impacted Vegetation’ appear to be concentrated in the southern half of K2C, whereas gains appear concentrated in the north (Fig. 11b). ‘Intact Vegetation’ demonstrates losses concentrated north of Phalaborwa mining operations in the northeast, commercial agriculture/forestry settlements in the northwest, and along the Eastern side of the Escarpment, near to higher concentrations of settlements and areas of persisting human-use (Fig. 11c).

Zonal Landcover Dynamics

The priority landcover classes vary in their relative composition and in the patterns of change and persistence they exhibit, relative to the zonation of K2C. In terms of the relative abundances (Fig. 13) of each priority landcover class, across all three zones ‘Intact Veg.’

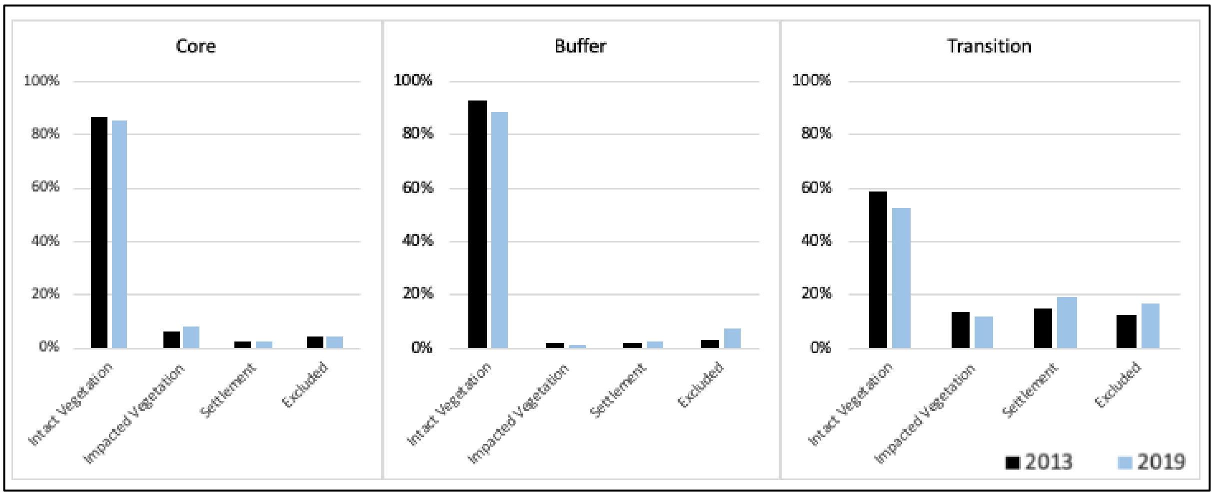


Figure 13. Relative landcover composition within K2C by zone, 2013 and 2019.

declined in its percent contribution to the total landscape. Its greatest losses were recorded in the transition zone (-6.55%), with the least degree of loss (-1.51%) taking place in the core zone (Table 11). Despite losses in the ‘Intact Vegetation’ class, it remained the predominant landcover type across all zones of K2C (Fig. 14). The buffer zone retained its status as the zone with the greatest relative proportional area comprised of ‘Intact Vegetation’ (88.6%); however, the core zone has a comparable level (85.22%) (Table 11). ‘Impacted Vegetation’

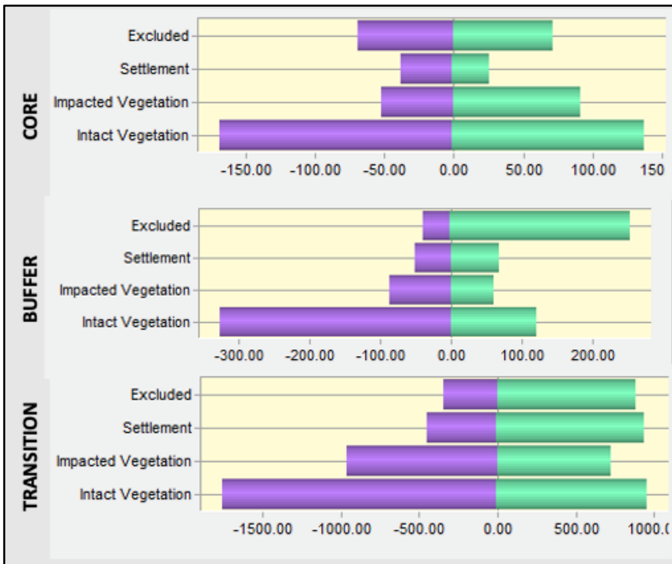
Table 11. Relative composition (%) of priority landcover classes relative to K2C zonation, 2013 and 2019.

Zone	Core			Buffer			Transition		
Landcover Class	**2013**	**2019**	**Change (%)**	**2013**	**2019**	**Change (%)**	**2013**	**2019**	**Change (%)**
Intact Vegetation	86.73	85.22	**-1.51**	92.99	88.60	**-4.38**	58.97	52.43	**-6.55**
Impacted Vegetation	6.27	8.22	**+1.96**	2.09	1.54	**-0.55**	13.71	11.78	**-1.93**
Settlement	2.77	2.22	**-0.56**	1.93	2.30	**+0.37**	15.01	19.06	**+4.05**
Excluded	4.23	4.34	**+0.11**	2.98	7.55	**+4.57**	12.30	16.74	**+4.43**

increased its relative representation in the core by 1.96%, but declined in abundance in both the buffer (-0.55%) and transition zones (-1.93%). In direct contrast to this, the 'Settlement' class increased its relative proportional representation within both the buffer (+0.37%) and transition (+4.05%) zones but declined in the core (-0.56%).

The net change in priority classes within each zone was the result of a unique configuration of gains and losses (Table 12). As described above, 'Intact Vegetation'

Table 12. Gains, losses, and net change of priority landcover classes in K2C, by zone (2013-2019).



Landcover	CORE		
	G (sq km)	L (sq km)	Net change (sq km)
Excluded	71.07	68.78	2.29
Settlement	26.87	38.13	-11.26
Impacted Veg	91.43	51.73	39.7
Intact Veg	137.58	168.3	-30.72

Landcover	BUFFER		
	G (sq km)	L (sq km)	Net change (sq km)
Excluded	253.51	40.21	213.3
Settlement	67.32	50.1	17.22
Impacted Veg	60.06	85.82	-25.76
Intact Veg	120.06	324.83	-204.77

Landcover	TRANSITION		
	G (sq km)	L (sq km)	Net change (sq km)
Excluded	881.87	343.87	538
Settlement	944.81	453.62	491.19
Impacted Veg	724.56	958.96	-234.4
Intact Veg	958.17	1752.94	-794.77

declined in all three zones, with the total area of loss in the transition zone (-794.77km^2) far surpassing that of the core and buffer combined (30.72km^2, 204.77km^2). The primary

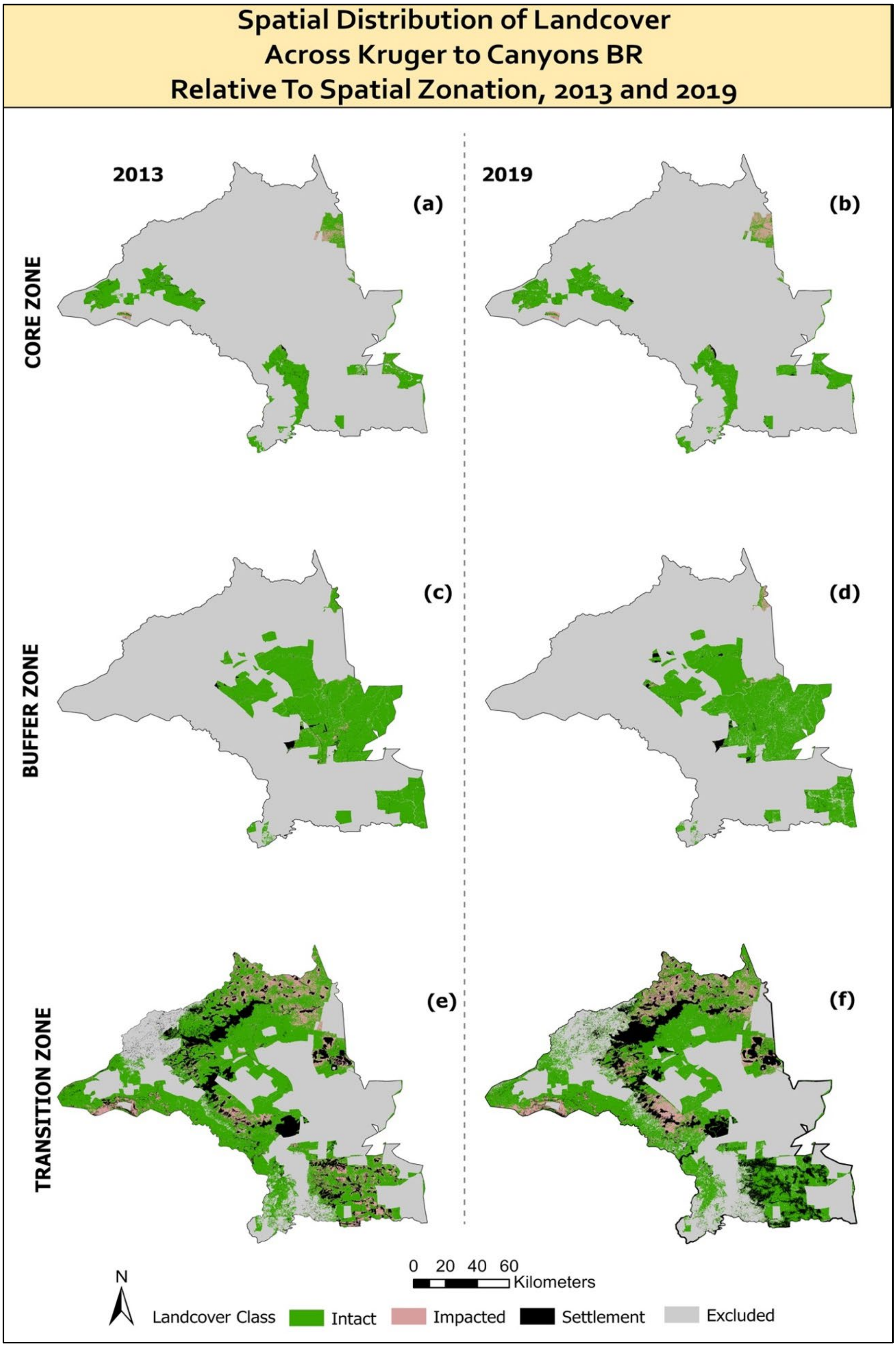


Figure 14. Landcover distribution relative to zonation within K2C, 2013 and 2019.

contributor to the loss of 'Intact Vegetation' in the core zone was its conversion to 'Impacted Vegetation' (Appendix D). 'Declines in 'Settlement' class in the core zone were due primarily to its reclassification in 2019 as either 'Intact Vegetation' or as part of the 'Excluded' class (Appendix D).

In the buffer zone, the primary contributor to the loss of both 'Intact' and 'Impacted Vegetation' was its reclassification as part of the 'Excluded' class in 2019 (Appendix D). Settlement areas in the buffer grew primarily from the conversion of 'Intact Vegetation' (Appendix D).

In the transition zone, the loss of 'Intact Vegetation' was due primarily to its conversion to 'Settlement,' as well as its reclassification as 'Excluded' (Appendix D). 'Impacted Vegetation' declined due primarily to its conversion to 'Settlement' (Appendix D). 'Settlement' grew because of gains derived from the conversion of 'Intact' and 'Impacted Vegetation' (Appendix D).

Chapter 5: Discussion

Classification Outputs and Accuracy

The supervised classification process produced great variability in the rates at which individual landcover classes were accurately identified (range 54.50-100% for 2013, and 46.23-100% for 2019) (Table 6; Table 8). As previously mentioned, classes with accuracy identification rates that fall below 70% do not meet the cutoff proposed by Foody (2002) as the minimum rate for acceptable reliability. For specific landcover classes with rates below this threshold, this raises the issue of their utility for analysis. Evans (2017) indicates that in such instances, spatial changes (i.e. the visualizations that depict the location of change) cannot be reliably assessed. However, even in instances where accuracy rates lie below 70%, the landcover information can still be used to assess the temporal change that occurs in terms of the relative gains and losses over the course of the study period (Evans 2017). Because the image products (2013 and 2019) contain the same type of researcher bias and error in their generation, even if not reliable enough for the location-based identification of certain landcover classes, they can still serve as a tool for the relative quantitative comparison between the start and end of the study period (Coetzer-Hanack pers. comm.). This idea is reinforced by the high overall accuracy rates (89.75% for 2013, 89.17% for 2019) and Kappa values (0.81 for both 2013 and 2019) that the mapped outputs produced, which indicate that there is consistently strong agreement between the classified outputs and the reference datasets against which they were cross-checked.

Whereas the rate of accuracy in identification is an objective, quantitative measurement, it can be worth examining the types of errors of omission and commission behind these values to understand the nuance behind those landcover classes with values lower than 70%. In the case of the 2013 dataset, 'Exposed Ground' (accuracy rate= 75±20.5%) was incorrectly identified as 'Settlement' (in three instances) and 'Intact

Vegetation' (in one instance) (Table 4). Settlement areas are highly heterogeneous, comprised not only of built infrastructure, but also associated vegetation and bare ground that lies within the footprint of high-intensity human-use. Consequently, the classifier tended to produce a mapped output with a 'salt-and-pepper' characteristic in the areas of settlement whereby pixels coded for 'Settlement,' 'Intact Vegetation,' and 'Exposed Ground' were closely interspersed. While concerted effort was made during the process of manual accuracy improvement to rectify the full area encompassed by the settlement footprints to reflect the 'Settlement' class, it was not possible to correct for every area of settlement; it is likely that pixels classified as 'Exposed Ground' remained interspersed within settlement areas and poses a plausible reason as to why there was confusion amongst these classes.

'Impacted Vegetation' was the second landcover class of the 2013 dataset that resulted in a wide-ranging rate of accurate identification wherein the lower limit dipped below 70% ($76.74 \pm 10.56\%$). 'Impacted Vegetation' was incorrectly identified as 'Intact Vegetation' (24 instances), 'Settlement' (three instances), and 'Agriculture' (one instance). Based on this information, the confusion of 'Impacted' with 'Intact Vegetation' presented the greatest challenge to the researcher. In the development of the training samples, 'Impacted Vegetation' was considered as that which was human-impacted. Training samples were taken adjacent to centers of intense human-use and from areas which demonstrated a definite spectral signature different from 'Intact Vegetation' further afield. Therefore, in the process of classifying the reference dataset, any vegetation pixels located far away from settlements were coded 'Intact Vegetation,' and are likely the source of confusion between the classifier and the reference data, as some pixels far away from human centers depicted the same spectral signature as those 'Impacted Vegetation' pixels close to settlements. Effort was made to remove scattered pixels of 'Impacted Vegetation' that were located far from settlement areas, but some were missed and could contribute to the confusion of ‘Impacted’ and ‘Intact Vegetation.’

‘Settlement’ is the final class of the 2013 data that had a wide-ranging rate of accurate identification (77.14 $\pm$11.64%). ‘Settlement’ was incorrectly identified as ‘Intact Vegetation’ (seven instances), ‘Impacted Vegetation’ (three instances) and Forest (one instance). As described above, it is likely that the high degree of heterogeneity of the settlement footprint is a contributing factor in its confusion with these other classes.

The landcover classes of the 2019 dataset that produced low rates of accurate identification share similar challenges as those discussed for the 2013 dataset. In the case of the 2019 data, ‘Exposed Ground’ and ‘Impacted Vegetation’ were subject to the same types of confusion as in the 2013 dataset. In the 2019 dataset, ‘Burn/ Clearfell’ produced a wide-ranging rate of accurate identification (70.00$\pm$23.77%), exhibiting most confusion with ‘Intact Vegetation’ and ‘Forest’ (Table 7). Whereas very recent areas of clearfell have a distinct signature, areas of clearfell regrowth create confusion with ‘Intact Vegetation.’ To improve the classifier’s outputs in the future, consideration should be taken to create more sub-classes of clearfell to better account for this challenge.

In general, the analysis of the errors associated with the landcover types that exhibit low rates of identification accuracy indicate that future research could improve accuracy (sans the option of ground truthing) by undertaking several practices. First, it would be beneficial to create even more comprehensive training samples, conduct more thorough manual rectification of settlement areas, as well as a more comprehensive removal of ‘salt-and-pepper’ noise amongst the other classes. Additionally, changing the sampling structure for the accuracy assessment should be strongly considered. Rather than a random sample design, a stratified random sample design could be deployed to increase the number of reference sample points for classes that are less prevalent within the landscape, as is the case for the ‘Exposed Ground’ landcover class. Increasing the number of total reference points could also improve the understanding of the accuracy of the mapped outputs, particularly if a stratified sample design is utilized. Finally, to most accurately develop the reference dataset it is suggested that three experts independently identify the landcover at the reference points and label the confidence associated with their identification; any discrepancy in landcover classification between the three sets of data reverts to that associated with the greatest level of agreement and confidence between the independent assessors (Wickham *et al.* 2013). It is disappointing to note that ‘lack of time’ is the primary reason this was not conducted for this study, but such a process should be pursued if further investigation with the generated data is to be conducted and ground truth data is not available. However, because all of the reference data and classified map outputs were determined by the same individual (the author) and were based upon that individual’s interpretation of the spectral signatures of landcover that any inaccuracies in identification should be consistent across all datasets, allowing for reasonable comparison of the refence data and mapped classifications.

Spatial Landcover Dynamics

Dynamics Across K2C

The landscape level patterns of change across K2C indicate that ‘Intact’ and ‘Impacted Vegetation’ declined (‘Intact:’ -5.5%, approximately 2200km^2; ‘Impacted:’ -1.2%, approximately 1097km^2), and that ‘Settlement’ increased (+2.7%, approximately 500km^2) across the landscape (Table 9; Table 10). ‘Intact Vegetation’ remains the most prevalent landcover type as of 2019, which bodes well for sustaining biodiversity and ecological integrity across K2C, yet for the first time the abundance of ‘Intact Vegetation’ dropped below two-thirds (64.7% relative abundance in 2019). Additionally, relative to other priority landcover types, the net change in ‘Intact Vegetation’ was the greatest observed change out of all measured gains or losses. This, along with the three-decades long trend of decline that has characterized 'Intact Vegetation' (Coetzer *et al.* 2010; 2013; Coetzer-Hanack *et al.* 2016) indicates that land degradation and transformation is still underway within the K2C.

As Coetzer *et al.* (2010) note, this is not entirely unexpected; some conversion of 'Intact Vegetation' is an unavoidable consequence of human-utilization of the landscape. Likewise, Coetzer *et al.* (2010) also note that the expansion of 'Settlement' is expected when population growth is ongoing, as is the case in K2C. Thus, the finding that conversion to 'Settlement' was a primary contributor to the net loss of 'Intact Vegetation' between 2013 and 2019 (Fig. 12a), and that the growth of 'Settlement' is primarily a result of gains from 'Intact' and 'Impacted Vegetation' (Fig. 12c) aligns with these understandings. While the calculated confidence limits for the accurate identification of some landcover classes suggest that spatial interpretation of the location of changes is not statistically reliable (Evans 2017), it does visually appear that losses of 'Intact Vegetation' are concentrated in areas of known human settlement (Fig. 11c). This is especially noticeable in agricultural areas near Tzaneen, in the north, and along the communities along the eastern side of the Escarpment. Because this is the first study in the time series analysis of K2C to include this portion of the BR, it is not possible to place this in context of historical trends earlier than 2013. However, if the spatial results are to be interpreted, this could suggest that human-utilization of the landscape has expanded in the north in particular (especially the agricultural sector), and therefore that existing policies or enforcement have not stopped 'Settlement' expansion from taking place.

The slight decline that is observed in 'Impacted Vegetation' (-1.2%, or roughly 220km^2) across K2C was primarily caused by the conversion of this class to 'Settlement' (Fig. 12b). Because 'Impacted Vegetation' is primarily located adjacent to 'Settlement,' it can be logically deduced that much of the conversion is due to the expanding footprint of the 'Settlement' class. Again, while the interpretation of the location of spatial change lacks statistical reliability, it does appear that instances of the conversion of 'Impacted Vegetation' occur around known areas of ‘Settlement’ (Fig. 11b), particularly around the communities located in the south eastern reaches of K2C and near to the Phalaborwa mining operations in the north. However, if ‘Settlement’ encroaches on the concentric ring of ‘Impacted Vegetation’ that tends to surround communities, it would be logical that the next concentric ring of ‘Intact Vegetation’ beyond this area would in turn demonstrate signs of degradation; an expanding human footprint will still require utilization of the adjacent landscape, and degradation of ecological integrity would be predicted.

However, this does not appear to have occurred (Fig. 9). In particular, examination of the communities located in the south eastern portion of K2C in 2013 and 2019 depict only the transformation of ‘Impacted Vegetation’ to ‘Settlement,’ but no simultaneous new development of areas of ‘Impacted Vegetation’ status. One possible hypothesis for this (if the mapped outputs are to be interpreted), is that the strong drought conditions that existed leading up to 2019 influenced the spectral signature of the landscape such that existing ‘Impacted Vegetation’ was influenced by the climatic conditions to such an extent that it came to spectrally resemble the signature of the ‘Settlement’ class. When looking at the raw satellite images of 2013 and 2019, the footprints around settlements in the southeast are more easily identifiable in 2013 compared to 2019. In the former, the core areas of built infrastructure tends to have clearly defined perimeters, whereas the image in 2019 depicts settlements in the southeast with less-definition and more connected branches between areas of settlement. A caveat to this hypothesis is that this type of change is not observed uniformly across K2C. ‘Impacted Vegetation’ was not eliminated near settlements of the central or northern reaches, thus this hypothesis would need to be explored further, potentially through the application of precipitation and temperature data to determine if there is a gradient in drought severity that tracks along the northern/southern lines of the study area and which could potentially account for the differences observed in ‘Impacted Vegetation’ in the north vs. the south in 2019. If drought conditions do play a significant role in the conversion of 'Impacted Vegetation' in essentially losing their ecological integrity to the point that they are spectrally-akin to 'Settlement' class or 'Bare Ground,' this would hold important implications for management decisions for the future. Drought and variable precipitation and temperature patterns are predicted to worsen in southern Africa in the coming decades (IPCC 2019) and consequently, climatic influence on landcover change in K2C may need to be incorporated more centrally into planning decisions moving forward.

Zonal Landcover Dynamics

With regards to the priority class landcover dynamics relative to the zonation within K2C, the least change occurred in the core zone and the most change occurred in the transition zone (Table 11). This finding aligns with the gradated scale of management allowed by the BR designation, wherein if on-the-ground practices align with the theoretical mandates of the BR, it can be predicted that the greatest degree of land transformation will take place in the zone in which management allows for the greatest degree of human utilization (i.e. the transition zone). Thus, it would appear that the designations ascribed by the BR are in alignment with current practices in each zone.

In the core, both 'Intact Vegetation' and 'Settlement' demonstrated decreases between 2013 and 2019 ('Intact Vegetation:' -1.51%, approximately 168.3km^2; 'Settlement:' -0.56%, approximately 38.13km^2) (Table 11; Table 12). Because the core is managed primarily for conservation, it is of concern that 'Intact Vegetation,' which is the primary landcover type associated with the conservation of biodiversity, declined in this zone. However, despite the reported decrease in 'Intact Vegetation,' it remains the most prevalent of the three classes, representing more than ¾ (85.22%) of the core's spatial footprint.

Examination of the contributions to net change calculations (Appendix D) indicates that the conversion of 'Intact Vegetation' to 'Impacted Vegetation' is the only contributing factor to the decline of ‘Intact Vegetation’ in the core. This means that no new ‘Settlement’ activity was recorded in core zones, which is positive, given the core’s mandated focus on conservation. In total, ‘Impacted Vegetation’ gained approximately 51.73km^2 in the core, an increase of 1.96% in its relative contribution to the core’s spatial footprint (Table 12; Table 11). As indicated throughout the results and discussion, while the location of spatial change is not statistically reliable for all landcover classes, if the interpretation of the mapped outputs holds some value, it would appear that the location of the conversion of ‘Intact’ to ‘Impacted Vegetation’ is confined to the Rondalia-Letaba Ranch Nature Reserve in the north (RSA-DEA 2019), adjacent to the border with Kruger National Park (Fig. 14). If ground truthing becomes an option in the future, it would be advisable for on-the-ground conditions to be assessed at this locale, and depending on the findings, develop management actions that promote the retention and restoration of ‘Intact Vegetation.’

The dynamics of the buffer zone recorded losses of both ‘Intact’ and ‘Impacted’ Vegetation between 2013 and 2019. ‘Intact Vegetation’ declined more than the losses recorded for the ‘Impacted Vegetation’ class (-4.38%, approximately: 325 km^2 vs. only -0.55%, approximately 85 km^2) (Table 11; Table 12). However, for both classes, the primary contributing factor in their decrease was their reclassification to the ‘Excluded’ class in 2019 (Appendix D). The ‘Excluded’ class is not the focus of the land dynamics analysis of this study, as it does not fit within the framework under which the relationship between land-use, landcover, and biodiversity are analyzed. However, it is interesting to note that an increase in the ‘Excluded’ class may be tied to the drought conditions present in 2019. As depicted in Fig. 8, the quantity of ‘Exposed Ground’ across the entirety of K2C is greater in 2019 than in 2013. The reason for this is unknown, but it is reasonable to suggest that drought conditions which impact vegetation health could be tied to an increase in the relative abundance of bare ground across the landscape. Because ‘Exposed Ground’ is ultimately aggregated into the

'Excluded' class for the land dynamics analysis, its greater representation in the environment in 2019 (in place of 'Intact' or 'Impacted Vegetation') would align with the findings presented here, whereby both 'Intact' and 'Impacted Vegetation' classes decreased and the 'Excluded' class increased. This insight offers another reason as to why future study of landcover change in K2C would do well to consider climatic influence on both the interpretation of landcover dynamics and future management actions.

Concerning the last of the priority classes in the buffer zone, 'Settlement' made gains of +0.37%, or approximately 50km^2 (Table 11; Table 12). This growth in 'Settlement' is primarily the result of the transformation of 'Intact' and 'Impacted Vegetation' (Appendix D). As before, if the spatial outputs hold some value in interpretation despite the lack of statistical reliability across all landcover classes, it would appear that 'Intact Vegetation' was converted to 'Settlement' in the following reserves: Sannie Private Nature Reserve, Andeon Private Nature Reserve, and in the north of the Selati Game Reserve (Fig. 14). Additionally, it would appear that the recorded 'Settlement' in 2013 that is located in the P.W. Willis Private Nature Reserve has expanded to adjacent areas of previously 'Intact Vegetation' between 2013 and 2019 (Fig. 14). Again, because of the questionable statistical reliability of the spatial findings and the lack of ground-truth data, these noted 'conversions' are listed only tentatively. The buffer zone designation of the BR allows for human settlement and intermediate-intensity of land-use, thus the increase in 'Settlement' class is not inherently a reason for concern. However, it could be valuable to communicate with the managers of these reserves to determine the landcover status and to adjust management strategies accordingly.

The transition zone demonstrated the greatest relative change in landcover of the three zones within K2C. This is not unexpected, both in the sense that the transition zone allows for the widest range of human-uses of the landscape and that it comprises a larger area than either the buffer or core (note that this is true only when the KNP core is not considered, in line with the bounds of the study area described for this research inquiry). Within the transition zone, 'Intact' and 'Impacted Vegetation' recorded declines of -6.55% and -1.93% respectively (Table 11), approximately 1750km^2 and 960km^2 (Table 12). These changes mean that 'Intact Vegetation' now comprises just slightly more than half of the surface area of the transition zone (52%) (Table 11). At the same time as these losses in vegetation occurred, the 'Settlement' class increased by 4.05% (approximately 450km^2) and now comprises nearly one-fifth (19%) of the landscape (Table 11; Table 12). The loss of 'Intact Vegetation' is largely due to its conversion to the 'Excluded' and 'Settlement' classes. As discussed before, it is possible that the 'Excluded' class in this case represents noise in the data related to drought conditions rather than a true change in landcover status; however, this is simply hypothetical and should be explored in future research. 'Impacted Vegetation' on the other hand had very little transformation attributable to the 'Excluded' category, as the bulk of its loss was due to its conversion to 'Settlement' (Appendix D). This mirrors the discussion of the landscape level dynamics, where the conversion of 'Impacted' to 'Settlement' with regards to the communities located in the south eastern extent of K2C was discussed. In this region of K2C, where the 'Settlement' footprint gains did not coincide with the creation of new expanses of 'Impacted Vegetation' (Fig. 9), it seems possible that drought conditions may have influenced the spectral signature interpretation rather than recording an accurate change in landcover, however further research is needed to clarify the observations.

'Settlement' gains in the transition zone came primarily from the conversion from 'Intact' and 'Impacted Vegetation' (Appendix D). Based on the visualizations in Fig. 9, if there is some value in its interpretation, it appears that agriculture has intensified in the areas in the north near Tzaneen and contributed to the increase in area classified as 'Settlement.' However, it should be noted that this northwest region of K2C was one of the most difficult areas to classify on the part of the researcher because of the highly intermixed nature of the forested areas with agriculture and settlements. During the manual accuracy improvement process, much effort was focused on improving the salt-and-pepper results that were generated, but it was not possible to have an “equal” number of interventions on the 2013 and 2019 images, as the outputs were generated from different training sample datasets and therefore had different types of ‘noise’ in the results. Therefore, it seems likely that some of the recorded increases in agriculture in this region are an artifact to some extent of unequal intervention on the part of the researcher during the manual accuracy improvement of the 2013 vs. 2019 images.

Because the transition zone allows for the greatest degree of human utilization of the landscape, an increase in the ‘Settlement’ class in this zone is in some ways ideal, if it limits expansion of ‘Settlement’ in the buffer and core. However, the uncertainty in the interpretation of the south eastern community gains from ‘Impacted Vegetation’ and the classification difficulties in the north suggest that the interpretation of ‘Settlement’ growth in the transition zone requires further study.

Chapter 6: Conclusion

Analysis of the landcover dynamics across and within the K2C Biosphere Reserve between 2013 and 2019 reveals that its human-landscape mosaic continues to interact and undergo change. Overall, 'Intact Vegetation' is the most abundant landcover found across the BR, and it is particularly prevalent within the core and buffer zones. Gains in 'Settlement' and declines in 'Intact' and 'Impacted Vegetation' were recorded more in the buffer and transition zones than in the core. The greatest overall landcover changes across all priority classes were recorded in K2C's transition zone. These findings suggest that the theoretical BR zonations, and their associated gradation of management prescriptions, correspond with on-the-ground conditions. This indicates an alignment of intention and practice regarding K2C's commitments to biodiversity conservation.

However, the historical trend of declining 'Intact Vegetation' across K2C continues to hold true through 2019. 'Intact Vegetation' declined more so than any other priority landcover class, dropping to just below two-thirds composition of the BR's land surface for the first time. Therefore, continued monitoring into the future to ensure positive biodiversity outcomes is necessary. Additionally, it is suggested that action be taken to learn more about, or halt, possible losses of 'Intact Vegetation' in the Rondalia-Letaba Ranch Nature Reserve, a component of K2C's 'core' estate. Related to this concern, whereas the buffer zone does allow for some degree of 'Settlement' and intermediate-intensity human utilization of the landscape, ideally the growth of 'Settlement' should be confined to the transition zone. Consequently, the detected expansion of 'Settlement' between 2013 and 2019 in the buffer zone (including areas of the Sannie Private Nature Reserve, Andeon Private Nature Reserve, the north of the Selati Game Reserve, and the P.W. Willis Private Nature Reserve) also warrants further investigation and potential management action to reduce land conversion and to support conditions that promote biodiversity retention in the buffer zone.

The findings of this study also suggest that future research on landcover dynamics of the K2C Biosphere Reserve could benefit from the incorporation of data on climate-land interactions. Drought conditions present at the time the 2019 data was recorded may have contributed to some of the detected landcover change over the course of the study period, particularly concerning conversions between the 'Impacted Vegetation'/'Intact Vegetation' and 'Settlement' classes. If climate change progresses at the rate and severity that is forecast for southern Africa, it is likely that in ensuing decades that landcover change dynamics will be increasingly influenced by both human-utilization and climatic variables. Consequently, the framework by which this study and previous K2C landcover change analyses have been conducted would benefit in the future from the incorporation of data related to climatic factors' influence on the landscape.

This study's findings highlight the dynamic nature of the human-environment interactions that take place across K2C. While 'Intact vegetation' continues to predominate in the core and buffer zones, the greatest level of landcover transition was found to be confined to the transition zone. This congruency between the BR's theoretical zones and detected landcover dynamics suggests that K2C is successfully meeting its landcover goals to support the retention of its incredible biodiversity heritage.

Appendix A

A 1. Metadata of geospatial information utilized in this study.

Source	Format	Data description	Data Availability
World Database of Protected Areas	Vector	Boundaries of K2C, KNP	https://www.protectedplanet.net/ (UNEP-WCMC and IUCN 2020b; UNEP-WCMC and IUCN 2020c)
South Africa Department of Environmental Affairs	Vector	South Africa designated protected areas; used to develop the core and buffer zone boundaries	https://egis.environment.gov.za/#
The Map Library	Vector	Political boundaries of South Africa, provinces in South Africa, countries of southern Africa	http://www.maplibrary.org/library/stacks/Africa/index.htm
The USGS Landsat8 collection via Google Earth Engine Editor	Raster	Satellite imagery from which classified landcover maps were derived	https://code.earthengine.google.com/
Dr. Kaera Coetzer-Hanack	Vector	Shapefile boundaries of some of the core and buffer zones located within the K2C Biosphere Reserve; used to develop the complete dataset for zonations	Personal communication: kaera.hanack@wits.ac.za

Appendix B

B 1. Google Earth Engine script for Landsat8 composite image generation, 2013.

```
Imports (2 entries)
var K2C_aoi: Table users/Training_RI/K2Caoi_edited
var l8: ImageCollection "USGS Landsat 8 Collection 1 Tier 1 Raw Scenes"
// Define a region of interest  (i.e. the shapefile you imported)
var roi = K2C_aoi;

// Load the Landsat 8 scaled radiance image collection.
var landsat2013 = ee.ImageCollection('LANDSAT/LC08/C01/T1')
    .filterDate('2013-06-01', '2013-06-30')
    .filterBounds(roi);
print(landsat2013);


// Make a cloud-free composite.
var composite = ee.Algorithms.Landsat.simpleComposite({
  collection: landsat2013,
  asFloat: true
});

// Clip composite to aoi... 'clipped_composite' is the image you ultimately want to export
var clipped_composite2013 = composite.clip(roi);

//visualize the clipped composite
Map.addLayer(clipped_composite2013, {bands: ['B4', 'B3', 'B2'], max: 0.5, gamma: 2}, 'Natural color', true);
//Map.addLayer(clipped_composite2013, {bands: ['B5', 'B4', 'B3'], max: 0.5, gamma: 2}, 'Color infrared', true);
Map.centerObject(K2C_aoi, 9);


// Select the image and the band combination.
var compositeSelection = ee.Image('clipped_composite2013')
  .select(['B4', 'B3', 'B2']); //natural colors

// Create a geometry representing an export region.
var geometry = K2C_aoi;

// Export the image, specifying scale and region.
Export.image.toDrive({
  image: clipped_composite2013.float(),
  description: 'K2C_June2013',
  maxPixels: 3784216672400,
  scale: 30,
  region: K2C_aoi,
  maxPixels: 3784216672400,
});
```

B 2. Google Earth Engine script for Landsat8 composite image generation, 2019.

```
Imports (1 entry)
var K2C_aoi: Table users/Training_RI/K2Caoi_edited
// Define a region of interest  (i.e. the shapefile you imported)
var roi = K2C_aoi;

// Load the Landsat 8 scaled radiance image collection.
var landsat2019 = ee.ImageCollection('LANDSAT/LC08/C01/T1')
    .filterDate('2019-06-01', '2019-07-15')
    .filterBounds(roi);
print(landsat2019);


// Make a cloud-free composite.
var composite = ee.Algorithms.Landsat.simpleComposite({
  collection: landsat2019,
  asFloat: true
});

// Clip composite to aoi... 'clipped_composite' is the image you ultimately want to export
var clipped_composite2019 = composite.clip(roi);

//visualize the clipped composite
Map.addLayer(clipped_composite2019, {bands: ['B4', 'B3', 'B2'], max: 0.5, gamma: 2}, 'Natural color', true);
//Map.addLayer(clipped_composite2019, {bands: ['B5', 'B4', 'B3'], max: 0.5, gamma: 2}, 'Color infrared', true);
Map.centerObject(K2C_aoi, 9);


// Select the image and the band combination.
var compositeSelection = ee.Image('clipped_composite2019')
  .select(['B4', 'B3', 'B2']); //natural colors

// Create a geometry representing an export region.
var geometry = K2C_aoi;

// Export the image, specifying scale and region.
Export.image.toDrive({
  image: clipped_composite2019.float(),
  description: 'K2C_June2019',
  maxPixels: 3784216672400,
  scale: 30,
  region: K2C_aoi,
  maxPixels: 3784216672400,
});
```

Appendix C

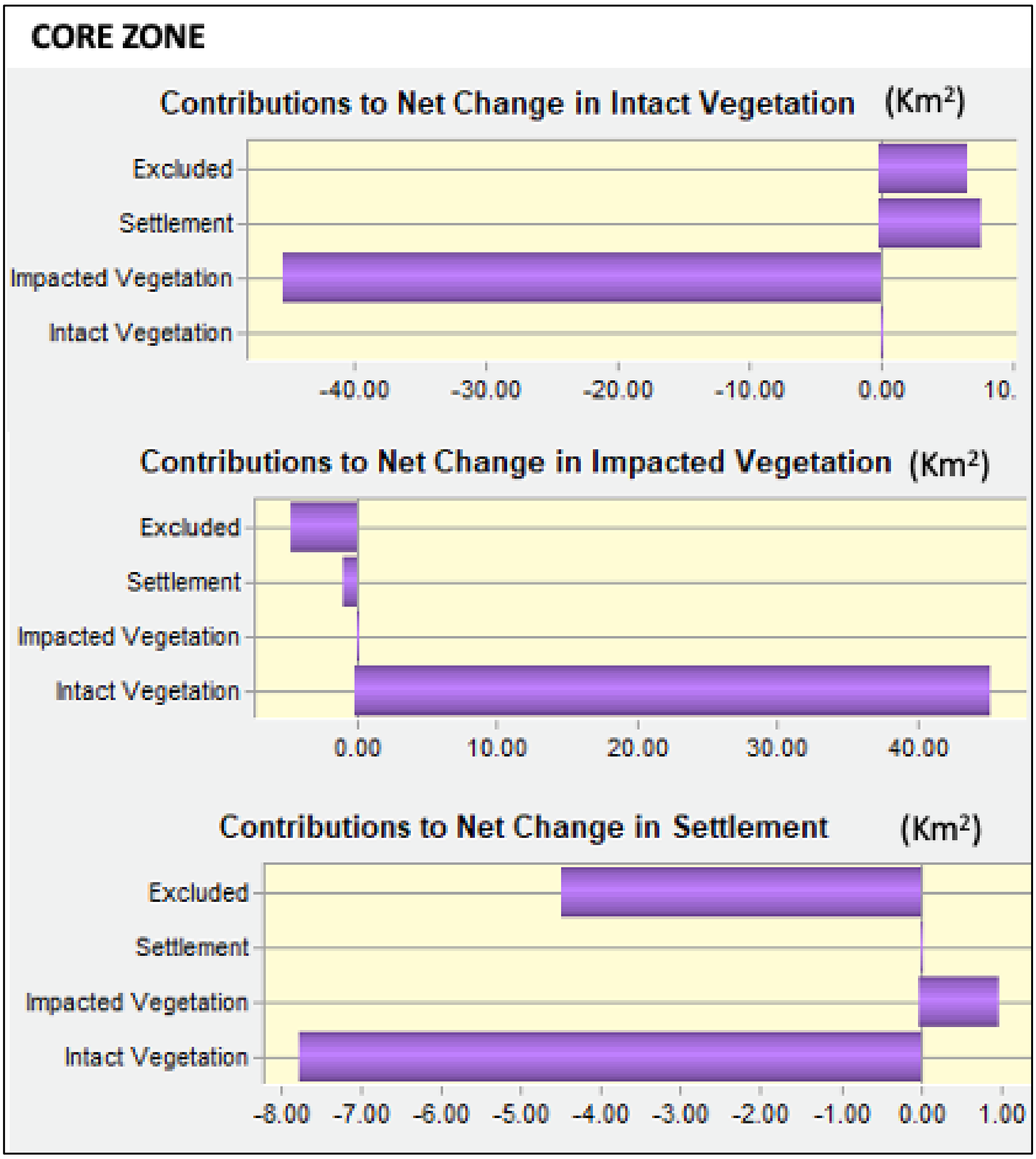
C 1. Intermediate landcover classification schema.

Code	Intermediate consolidated landcover class	Landcover subclass	Description
1	Exposed Ground	Bare Ground & Rock	Areas of exposed sand, soil, rock (excludes opencast mines, quarries, and fallow fields). Includes dry river beds and bare ground along the riparian flanks.
2	Water	Waterbodies & Rivers	Natural and artifical open waters and waterways (excludes dry river beds)
3	Intact Natural Vegetation	Intact Woodland	Intact indigenous plant communities with little anthropogenic modification. Includes areas of more open vegetation resulting from elephant activity
		Intact Thicket & Bush	layer; *includes bush-encroached areas that are ecologically degraded (homogenization of plant community)
		Grassland	Grassland- areas dominated by non-woody plant communities
4	Impacted Vegetation	Impacted Woodland	Human-utilised areas that result in poor ground cover, reduced vegetation and exposed soil
		Impacted Thicket & Bushland	lands), where land is intensively utilised for livestock grazing and natural resource harvesting
			impacts
5	Settlement	Settlement	Permanent or near-permanent settlements; includes the footprint covered by associated garden-plots and farm-holdings
			Transport and infrastructure
		Mines & Quarries	Surface mining and associated operational infrastructure
6	Agriculture	Formal & Subsistence crops	Clearly delineated crop plots and large formally delineated subsistence fields
		Fallow fields	Fallow lands and areas being prepared for crops
7	Forest	Forest (Indigenous & commercial)	Indigenous forest and systematically planted commercial plantations
8	Burn and Clearfell	Burn	Recently burnt areas
		Clearfell	Post-harvest areas within forest plantations

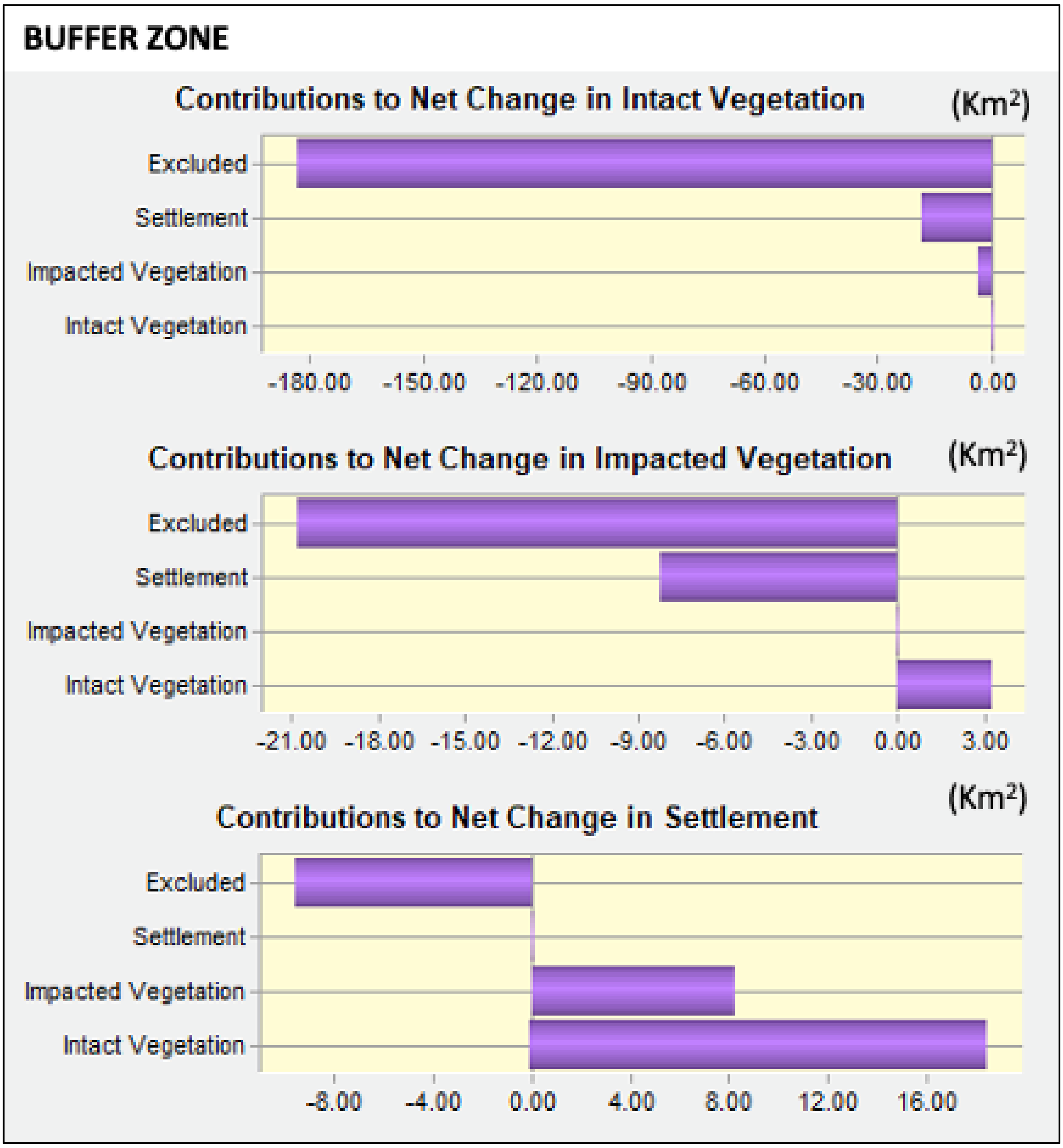
Source: Coetzer *et al*. 2010 (with amendments)

Appendix D

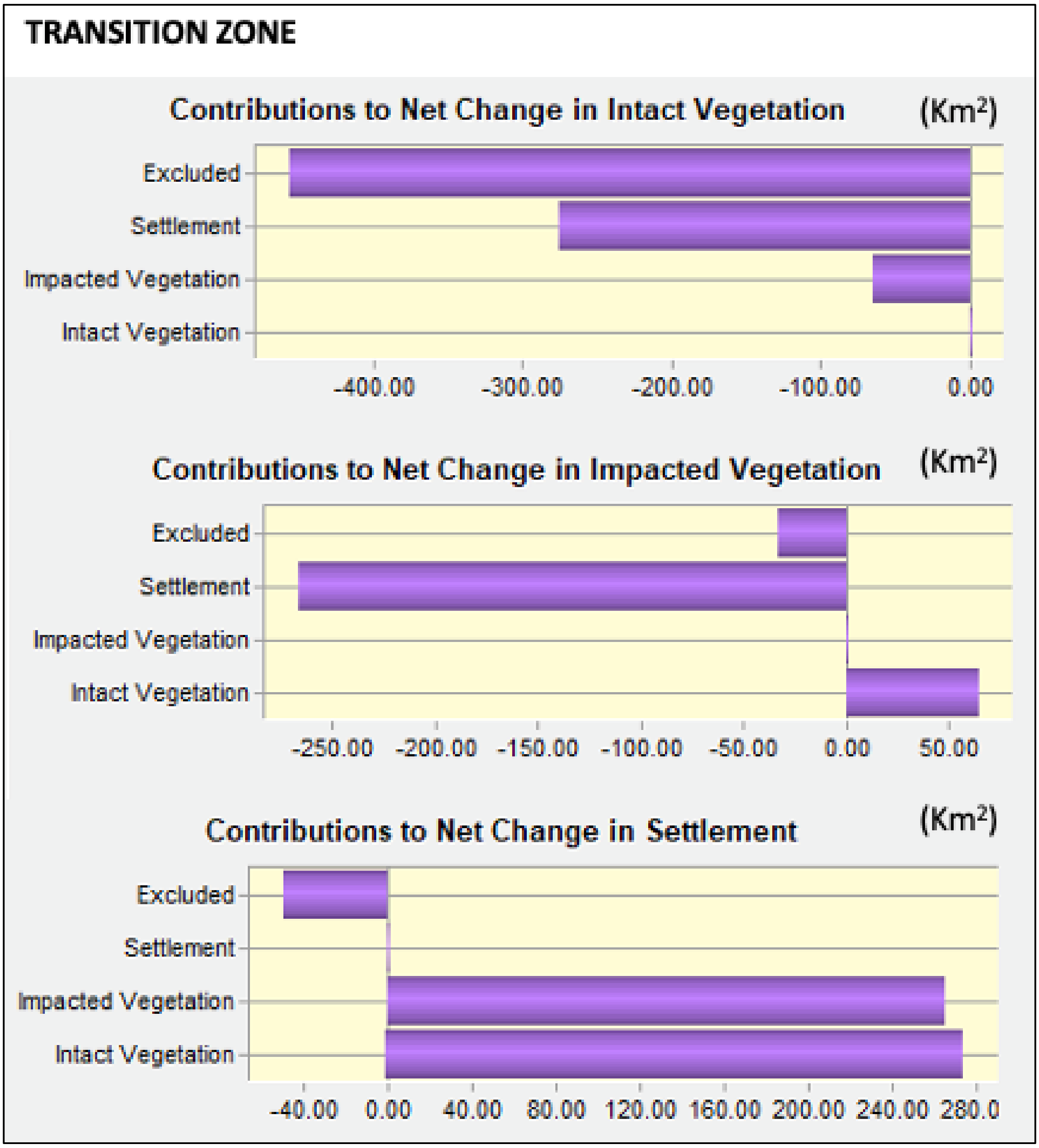
D 1. Contributions to Net Change by Zone: Core Zone.



D 2. Contributions to Net Change by Zone: Buffer Zone.

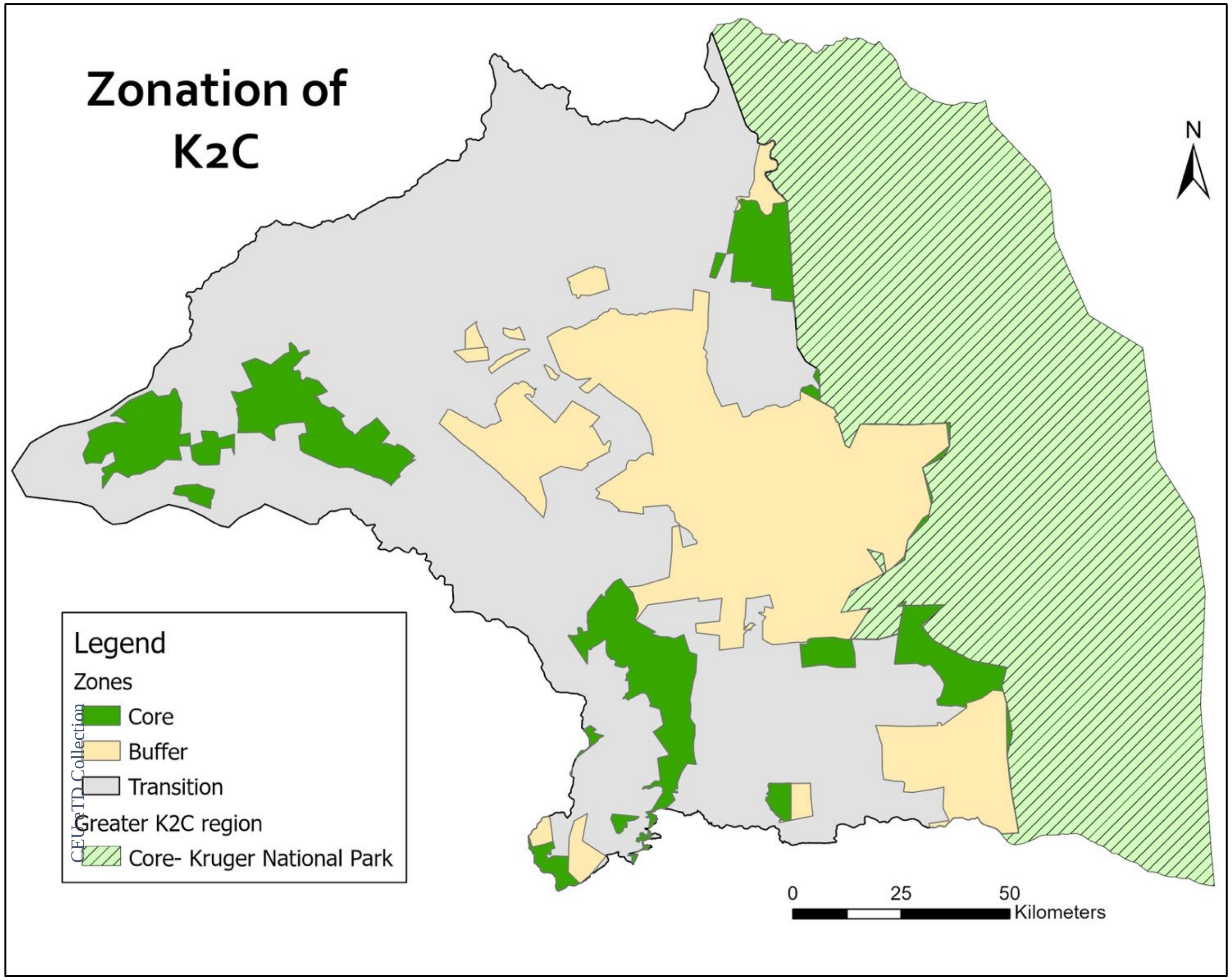


D 3. Contributions to Net Change by Zone: Transition Zone.

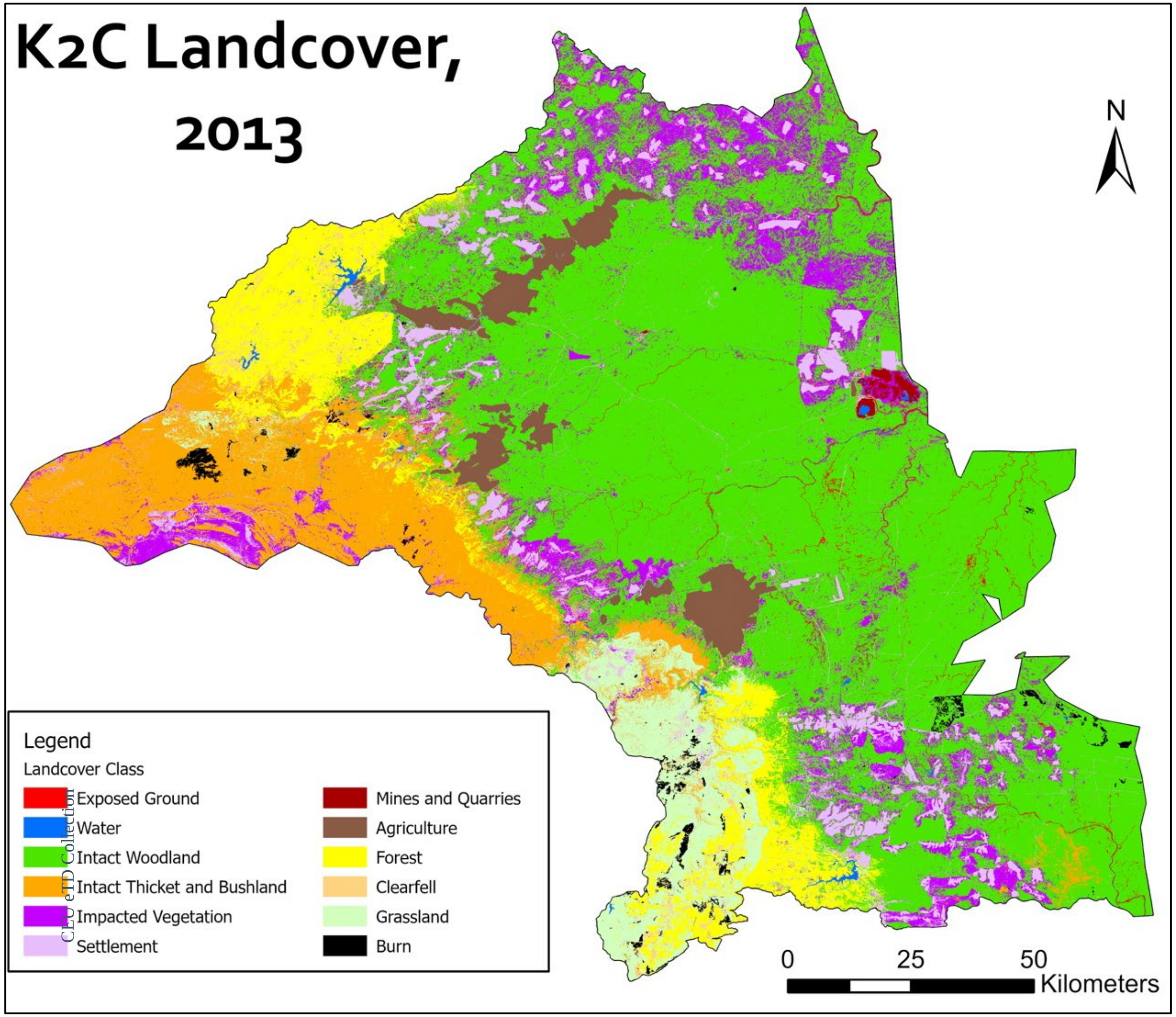


Appendix E

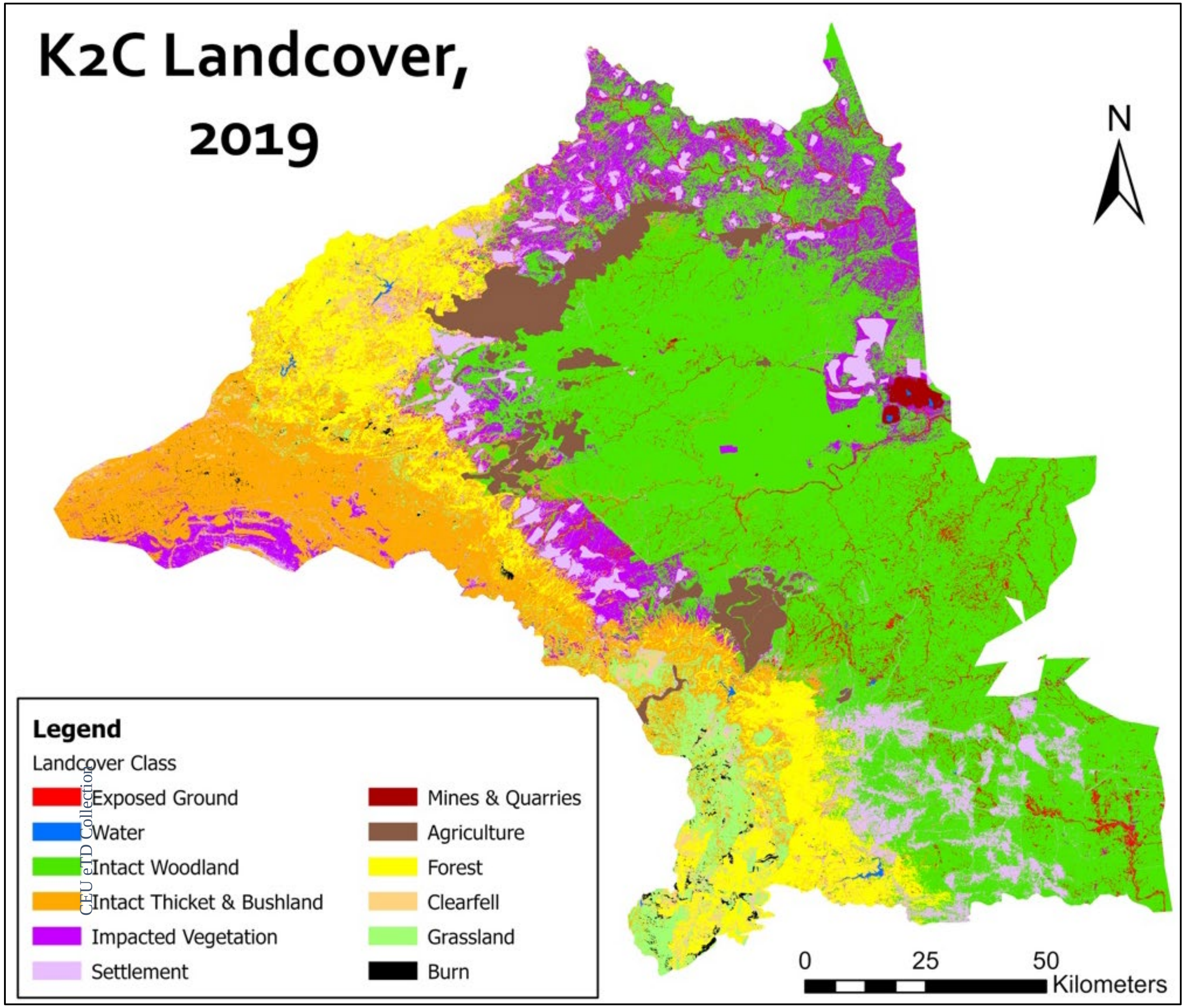
E 1. Zonation of K2C.



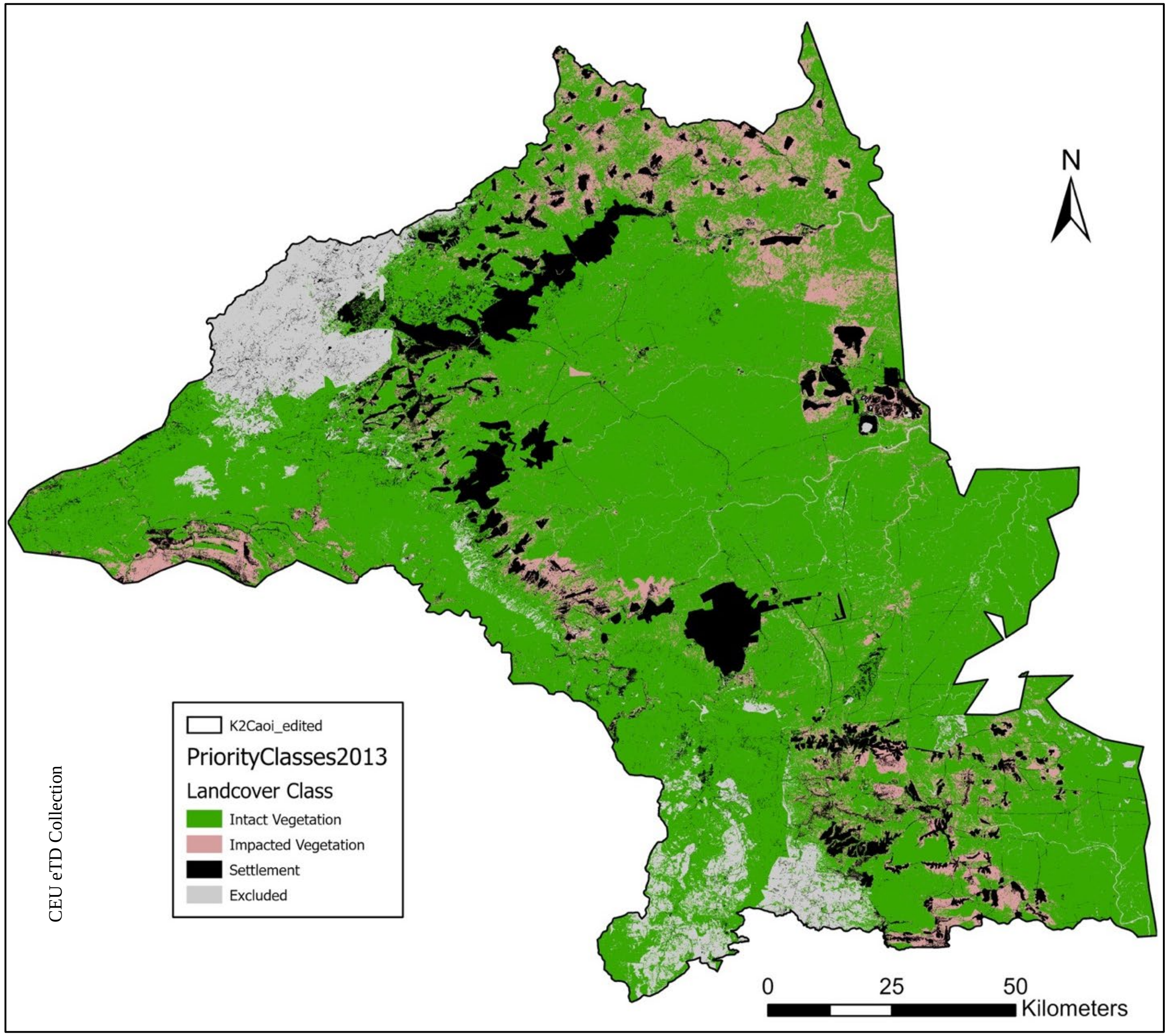
E 2. Classification of landcover in K2C, 2013.



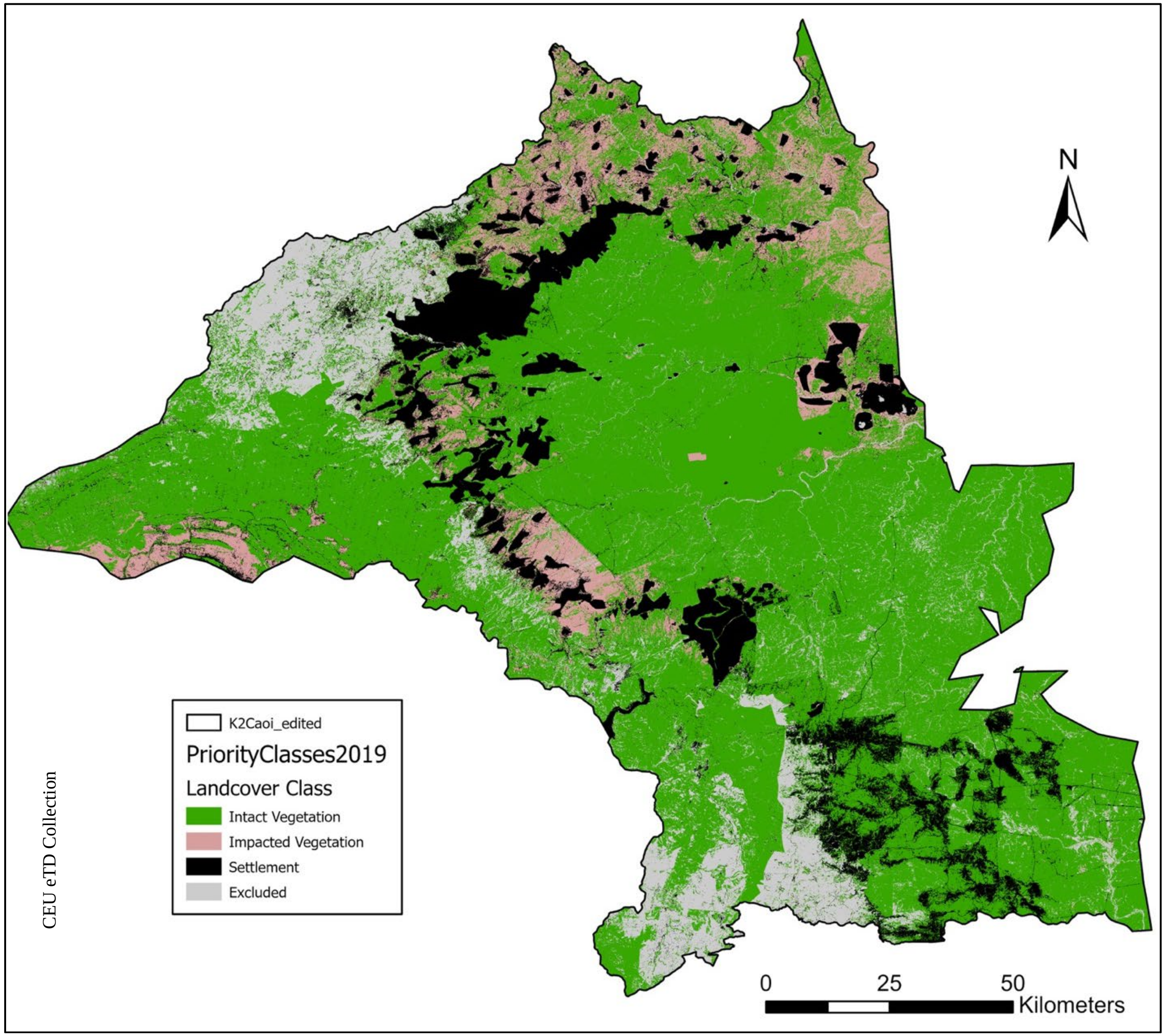
E 3. Classification of landcover in K2C, 2019.



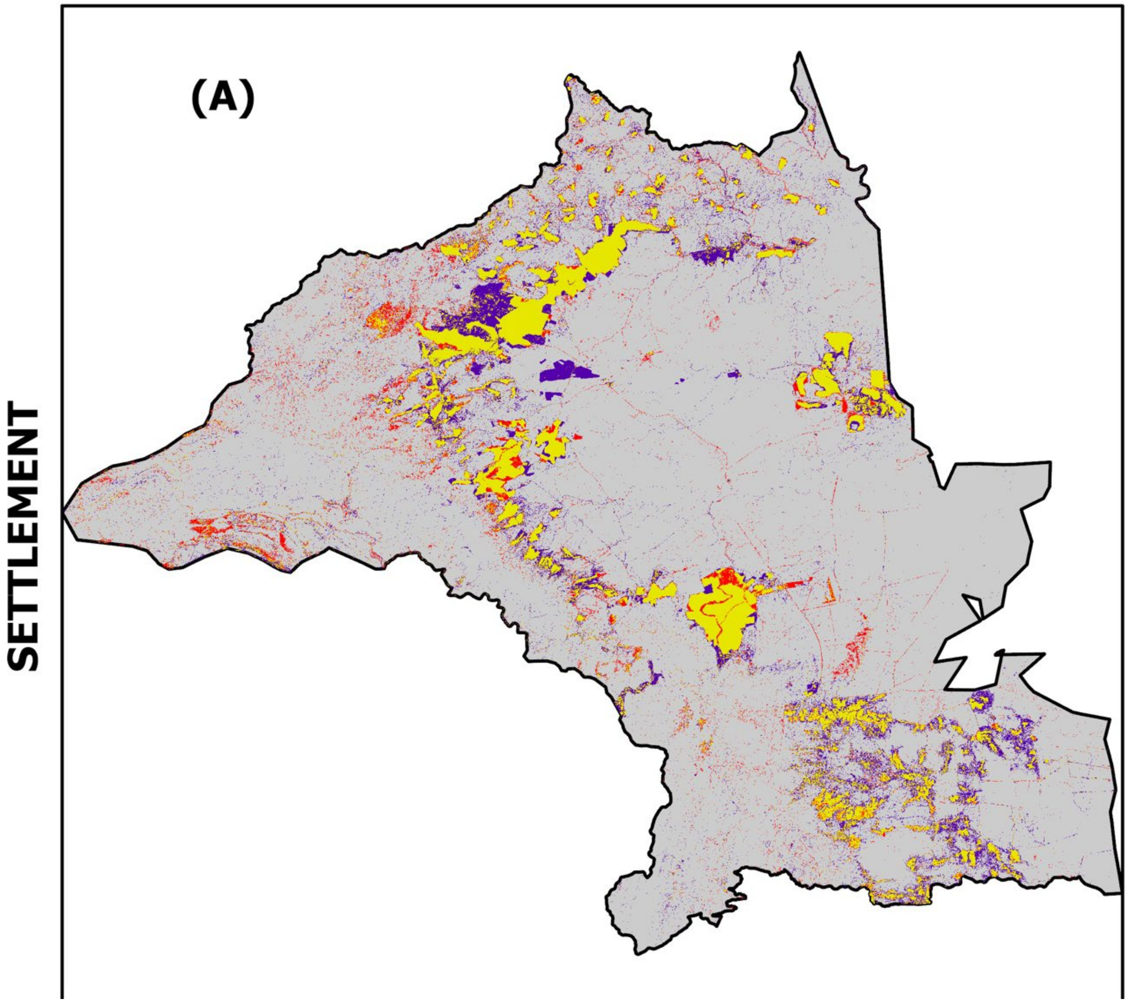
E 4. Distribution of priority landcover classes across K2C, 2013.



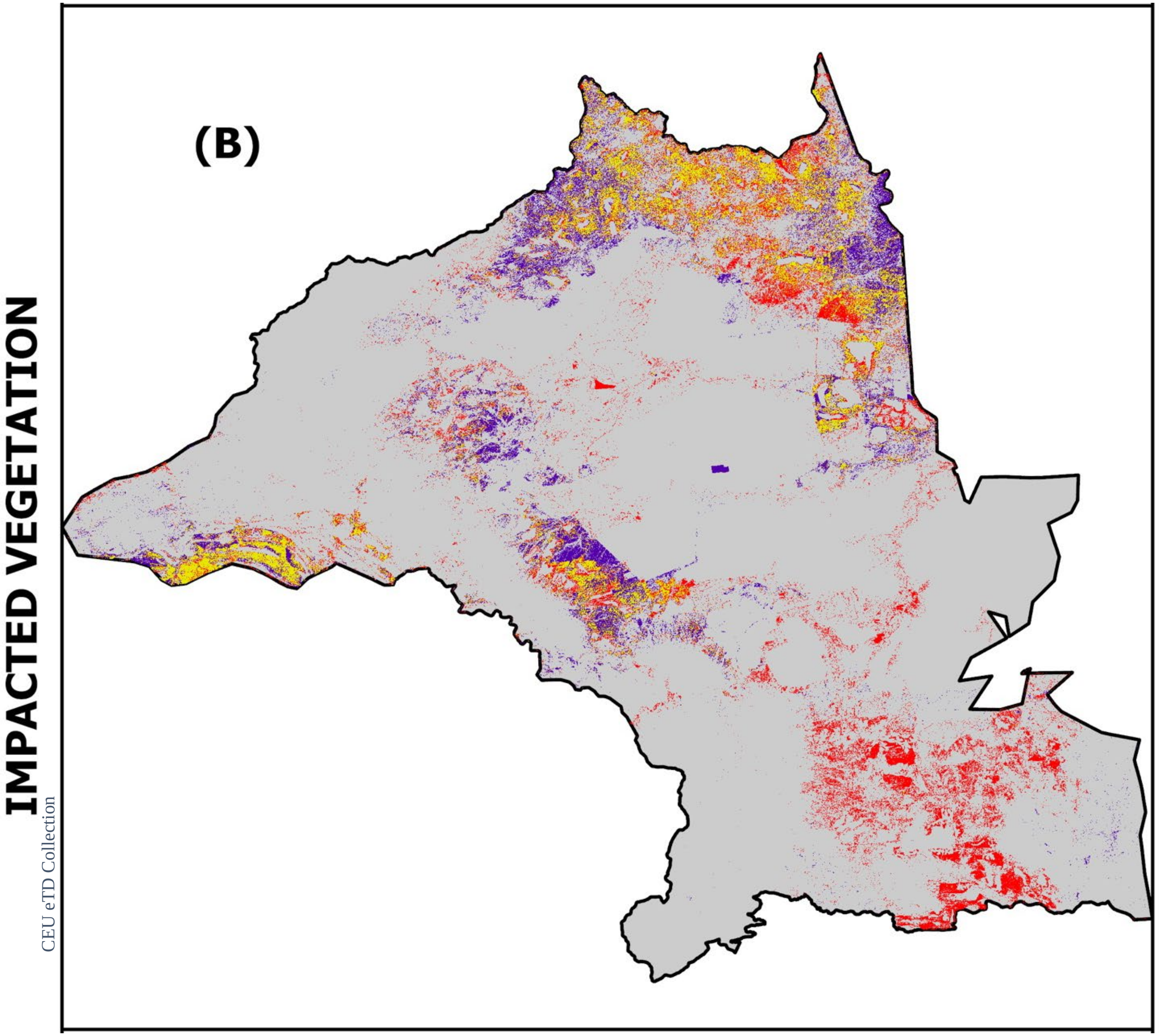
E 5. Distribution of priority landcover classes across K2C, 2019.



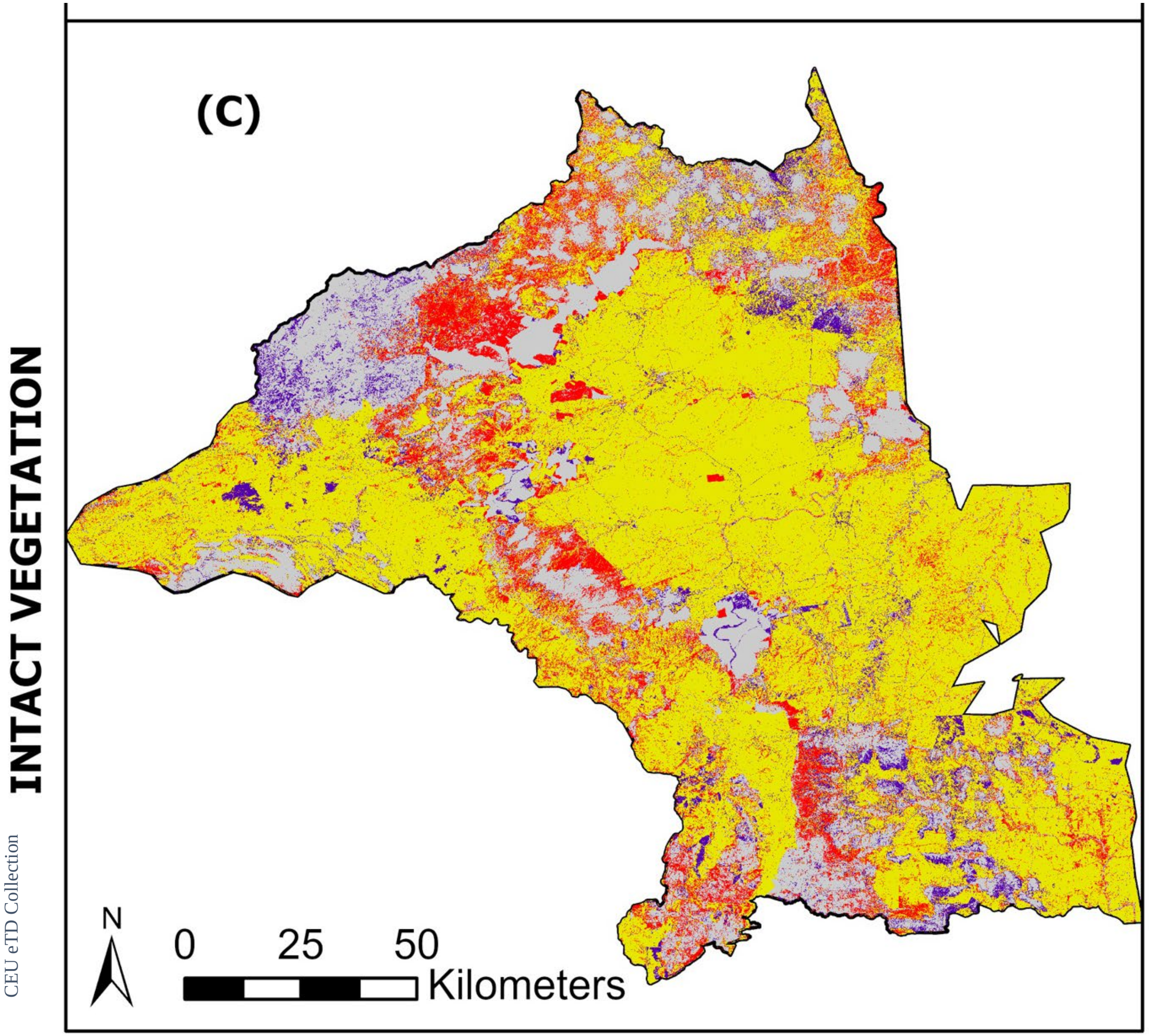
E 6. Gains, loss, and persistence of 'Settlement,' 2013-2019.



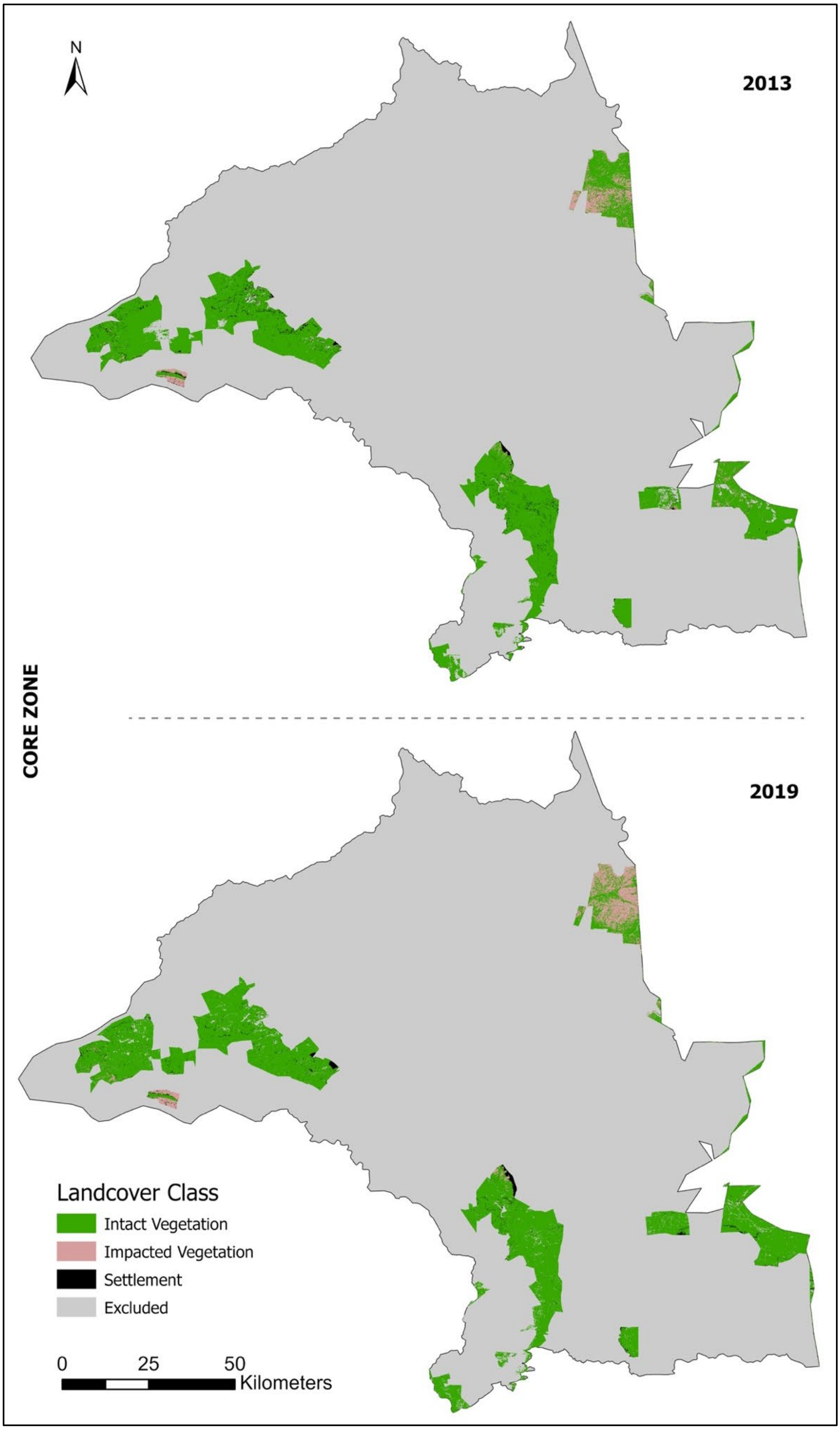
E 7. Gains, losses, and persistence of 'Impacted Vegetation,' 2013-2019.



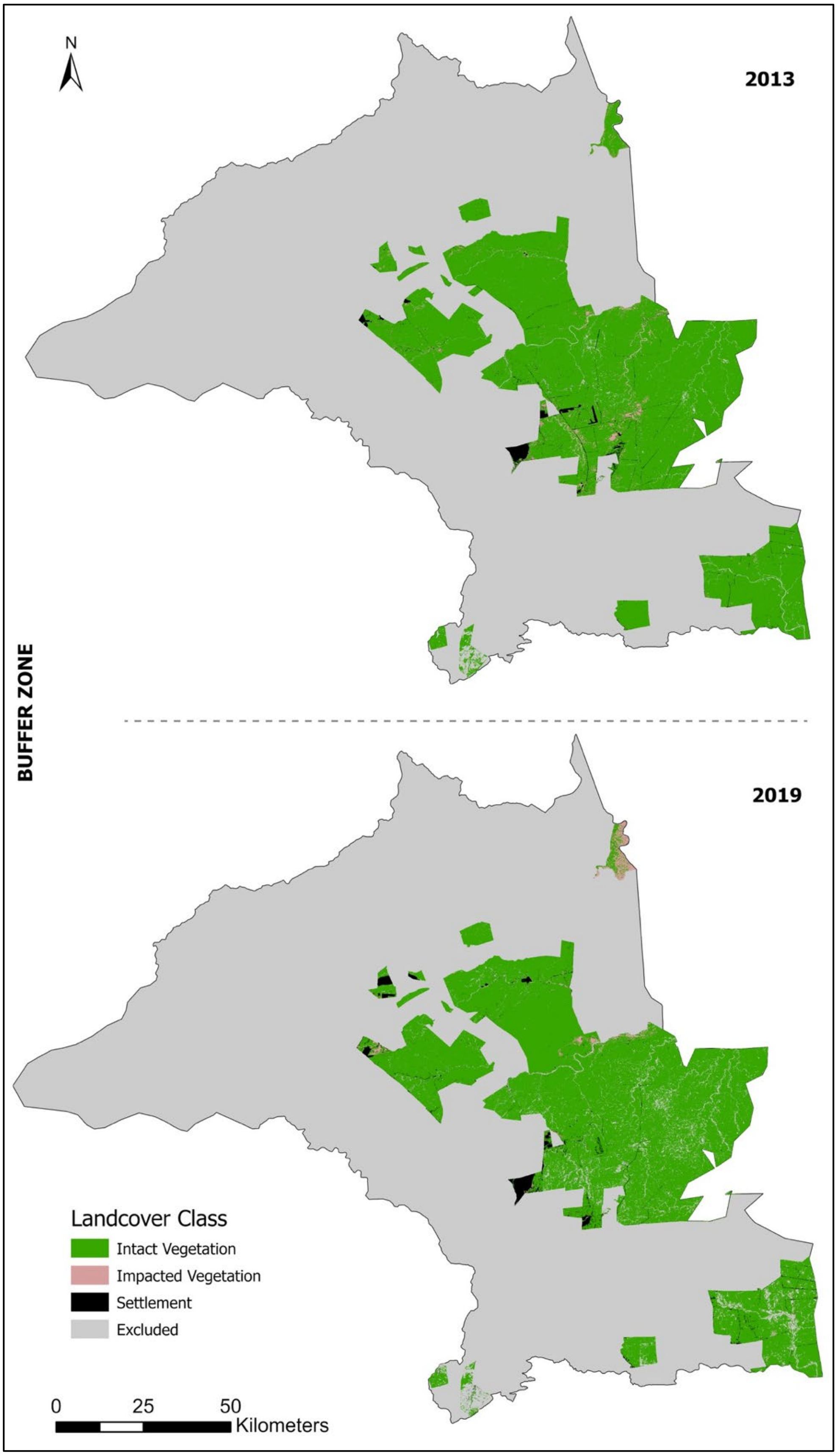
E 8. Gains, losses, and persistence of 'Intact Vegetation,' 2013-2019.



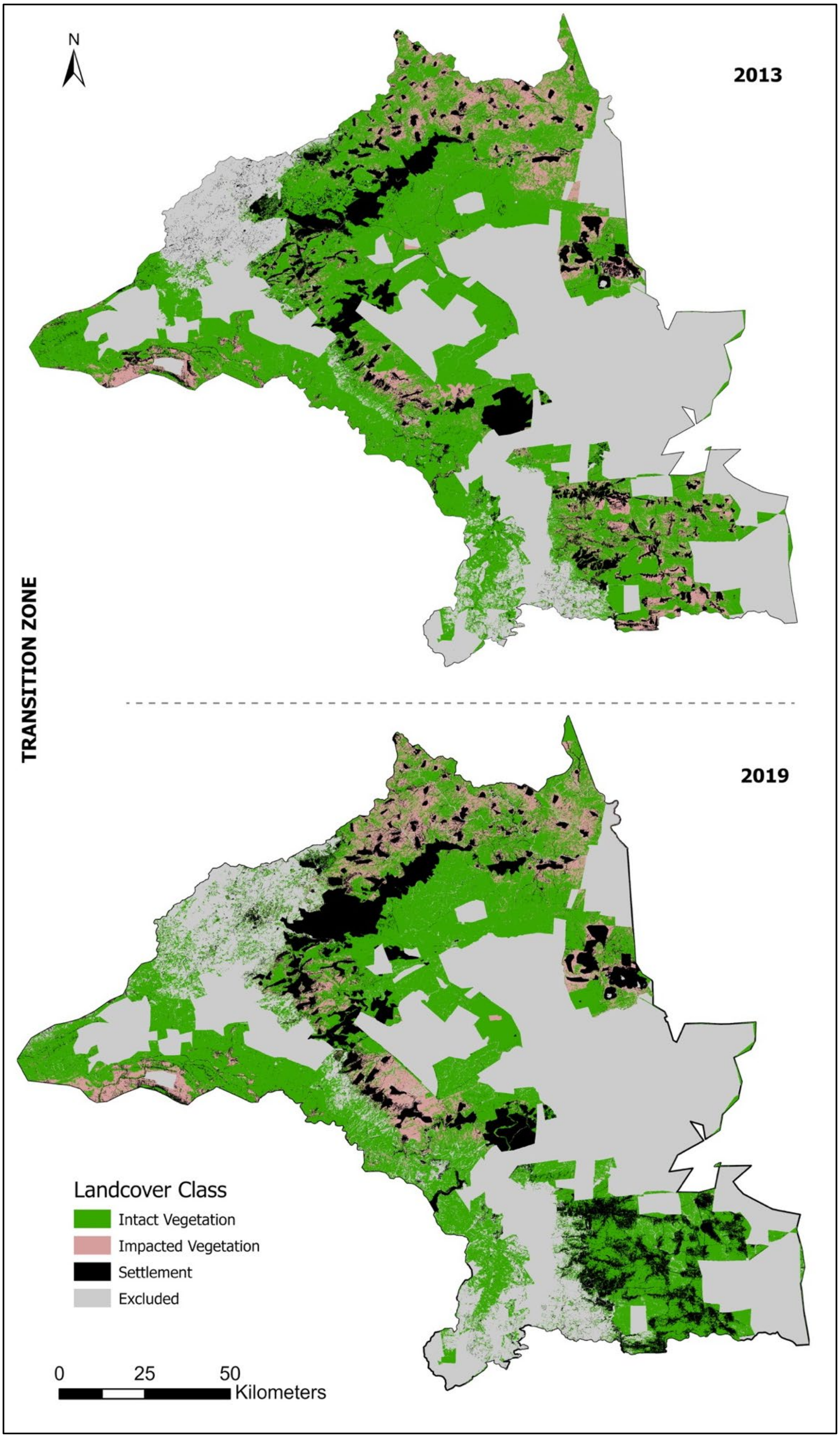
E 9. Comparison of landcover in the core zone, 2013 and 2019



E 10. Comparison of landcover in the buffer zone, 2013 and 2019.



E 11. Comparison of landcover in the transition zone, 2013 and 2019.



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