Leveraging Drone Technology to Optimise Rangeland Monitoring - A Case Study from Namibia's Dryland Savannah

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Dedication

This dissertation is dedicated to my son, Melvis Tunombili, who, towards the end of this journey, cheered me on with his little kicks. May this work inspire you to follow your dreams with courage and passion, always knowing that Mama will forever be your biggest cheerleader.

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Declaration of Author Contributions

This thesis entitled "Leveraging Drone Technology to Optimise Rangeland Monitoring - A Case Study from Namibia's Dryland Savannahs" is based on fieldwork I carried out in Namibia during my PhD at the University of Tübingen, under the supervision of Prof. Dr. Katja Tielbörger and Prof. Dr. Nichola Knox. The three chapters present independent scientific manuscripts, each with co-authors, with the first two published and the third one in preparation to be submitted for publication. The author contributions for each chapter are as follows:

Chapter I: Unmanned Aerial Systems accurately map rangeland condition indicators in a dryland savannah

Vistorina Amputu, Nichola Knox, Andreas Braun, Sara Heshmati, Rebecca Retzlaff, Achim Röder, Katja Tielbörger.

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Conceptualization: VA, NK and KT; methodology: VA and NK; data collection: VA; imagery processing and analysis: VA, with substantial input from AB, SH, RR and AR who validated the developed workflow; data analysis: VA; VA wrote the manuscript with feedback from all co-authors.

Chapter II: Spatio-temporal transferability of drone-based models to predict forage supply in drier rangelands

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Conceptualization: VA, KT and NK; methodology: VA and NK; data collection and imagery analysis: VA; data analysis: VA and FM; VA wrote the manuscript with revisions from all co-authors.

Chapter III: Gradual rather than abrupt responses of rangeland conditions to grazing pressure revealed from drone imagery

Vistorina Amputu, Nichola Knox, Anja Linstädter, Katja Tielbörger.

Conceptualization: VA, NK, AL, KT; methodology: VA, AL, NK; data collection, imagery analysis and data analysis: VA; VA wrote the manuscript and all co-authors reviewed it.

Abstract

Unsustainable farming practices, such as overgrazing combined with impacts of climate change, like frequent and intense droughts, have resulted in the degradation of rangelands, which in turn affect ecosystem functioning and biodiversity. Currently, up to 70% of rangelands are degraded, with at least 20% having crossed thresholds into undesirable states that require substantial effort, resources, and time to reverse. This degradation limits their capacity to provide essential ecosystem services, such as forage, which sustains livestock and wildlife. This, in turn, threatens both the ecological health of these systems and the socio-economic well-being of billions of people who depend on them for their livelihoods. To improve and restore these important ecosystems, there is a need to prioritise adaptive management strategies supported by cost-effective, repeatable and scalable monitoring tools.

Unmanned aerial vehicles (UAVs), better known as drones, equipped with spectral sensors, are a promising tool for ecological research by offering high resolution, intermediate scale data. While widely applied in agriculture and forestry, its application in dryland savannah rangelands remains limited. Therefore, my doctoral research tested the effectiveness of drone mapping for optimising rangeland monitoring in three interconnected objectives: (i) Evaluating the accuracy and efficiency in quantifying key rangeland condition indicators, (ii) assessing the generality of drone-derived prediction models across the spatial and temporal variability characteristic of savannah rangelands, and (iii) examining the impacts of varying grazing pressure and potential thresholds using high-resolution, spatially continuous drone data.

In the first chapter, Drone-derived estimates of available forage and the cover of rangeland features (bare ground, herbaceous plants, and woody plants) closely matched field-based measurements with low prediction errors while being significantly faster, and thus more cost-effective. The workflow presented here provides a replicable and scalable approach for expediting rangeland monitoring. Chapter II investigated model transferability in savannah rangelands, where forage resources are inherently patchy and dynamic in space and time. I tested context-specific models (i.e., spatially or temporally specific) and a general model across contrasting land tenure systems and different times of the growing season. Results highlighted that models that incorporated spatial and temporal variability yield more accurate forage estimations, while models developed for specific spatial or temporal contexts

performed poorly when extrapolated, often overestimating herbaceous plant cover, potentially leading to rangeland mismanagement and overgrazing. A key highlight of this study is, therefore, the importance of robust, generalizable models to guide sustainable grazing strategies and prevent unnecessary degradation.

In the final chapter, using drone imagery, I compared rangeland conditions and piosphere patterns between privately owned farms and communal areas and tested for potential tipping points. Contrasting vegetation structures were found, with healthier rangelands dominated by herbaceous plants in freehold farms, where rotational grazing is implemented. In contrast, communal areas, which are continuously grazed, were characterized by extensive bush encroachment, indicative of severe degradation. Expected piosphere patterns of improving rangeland conditions with decreasing grazing pressure, were only observed in healthier rangelands, while no such variation was found in degraded rangelands. Although no sudden shifts, indicative of tipping points were detected along grazing gradients, the results highlight the critical role of sustainable grazing practices in maintaining rangeland functionality and resilience.

Together, this research demonstrates the potential of drone technology to transform rangeland monitoring by providing high resolution, cost effective, and scalable data. The findings highlight how drone mapping can complement existing approaches to guide adaptive rangeland management strategies and advance the ecological understanding of these vital yet vulnerable ecosystems.

Zusammenfassung

Nicht nachhaltige landwirtschaftliche Praktiken, wie Überweidung, sowie die Auswirkungen des Klimawandels, wie häufige und intensive Dürren, haben zu einer Verschlechterung von Weideflächen geführt, was wiederum Ökosystemfunktionen sowie die biologische Vielfalt beeinträchtigt. Derzeit sind bis zu 70 % der Globalen Weideflächen degradiert, wobei mindestens 20 % eine Schwelle zu unerwünschten Zuständen überschritten haben, deren Beseitigung erhebliche Anstrengungen, Ressourcen und Zeit erfordern würde. Diese Verschlechterung schränkt , wichtige Ökosystemleistungen ein, so zum Beispiel die Produktion von Futtermittel für Vieh und Wildtiere. Dadurch wird sowohl die ökologische Gesundheit dieser Systeme bedroht, als auch das sozioökonomische Wohlergehen von Milliarden von Menschen, die für ihren Lebensunterhalt von ihnen abhängen. Um diese wichtigen Ökosysteme zu erhalten und wiederherzustellen, die durch kosteneffiziente, zuverlässige und skalierbare Überwachungsinstrumente unterstützt werden, Vorrang haben.

Unbemannte Luftfahrzeuge (UAVs), besser bekannt als Drohnen, die mit Spektralsensoren ausgestattet sind, sind vielversprechende Werkzeuge für die ökologische Forschung, da sie hochauflösende Daten in mittlerem Räumlich Maßstab liefern. Während sie in der Land- und Forstwirtschaft weit verbreitet sind, ist ihr Einsatz in trockenen Savannengebieten zur Zeit noch begrenzt. Daher habe ich im Rahmen meiner Doktorarbeit die Wirksamkeit von Drohnenbildern zur Optimierung der Weidelandüberwachung im Hinblick auf drei miteinander verbundene Ziele getestet: (i) Bewertung der Genauigkeit und Effizienz bei der Quantifizierung von Schlüsselindikatoren für den Zustand von Weideland, (ii) Bewertung der Anwendbarkeit von aus Drohnen abgeleiteten Vorhersagemodellen für die räumliche und zeitliche Variabilität, die für Savannenweideland charakteristisch ist, und (iii) Untersuchung der Auswirkungen von unterschiedlichem Weidedruck und potenziellen Schwellenwerten unter Verwendung hochauflösender, räumlich kontinuierlicher Drohnendaten.

Das Ergebnis des ersten Kapitels war, dass die von Drohnen abgeleiteten Schätzungen der verfügbaren Futtermenge und der Bedeckung von Weidelandmerkmalen (nackter Boden, krautige und holzige Pflanzen) gut mit den feldbasierten Messungen übereinstimmten. Bei geringen Vorhersagefehlern waren die drohnenbasierten Schätzungen deutlich schneller und damit kostengünstiger. Der hier vorgestellte Arbeitsablauf bietet damit einen replizierbaren und skalierbaren Ansatz zur Beschleunigung der Überwachung von Weideland. Im zweiten Kapitel habe ich die Übertragbarkeit von Modellen auf

Savannengebiete untersucht, in denen die Futterressourcen von Natur aus lückenhaft und in Raum und Zeit variabel sind. Ich testete kontextspezifische Modelle (räumlich oder zeitlich spezifisch) sowie ein allgemeines Modell in unterschiedlichen Landbesitzsystemen und zu verschiedenen Zeiten der Vegetationsperiode. Die Ergebnisse zeigten, dass Modelle, die die räumliche und zeitliche Variabilität einbeziehen, genauere Futterschätzungen lieferten, während Modelle, die für spezifische räumliche oder zeitliche Kontexte entwickelt wurden, bei der Extrapolation schlechter abschnitten und die Bedeckung mit krautigen Pflanzen oft überbewerteten. Dies könnte potentiell zu Missmanagement und Überweidung von Weideland führen . Ein wichtiges Fazit dieser Studie ist daher die Bedeutung robuster, verallgemeinerbarer Modelle, um nachhaltige Weidestrategien zu entwickeln und unnötige Verschlechterungen zu verhindern.

Im letzten Kapitel verglich ich mit Hilfe von Drohnenbildern den Zustand der Weideflächen und die Piosphärische Muster zwischen Private Farmen und Kommunalen Gebieten Mein Ziel war zu bestimmen, ob es mögliche Kipppunkte in diesen Systemen gibt. Ich konnte gegensätzliche Vegetationsstrukturen festellen, wobei gesündere Weideflächen mit krautigen Pflanzen in landwirtschaftlichen Betrieben in Private Farmen dominieren, wo eine Rotationsbeweidung durchgeführt wird. Im Gegensatz dazu waren die kommunalen Flächen, die kontinuierlich beweidet werden, durch eine starke Verbuschung gekennzeichnet, was auf eine starke Degradierung hindeutet. Die erwarteten piosphärischen Muster einer Verbesserung der Weidebedingungen mit abnehmendem Weidedruck konnten nur in gesünderen Weidegebieten beobachtet werden, während in degradierten Weidegebieten keine derartigen Veränderungen festgestellt werden konnten. Obwohl ich keine plötzlichen Veränderungen, die auf Kipppunkte hindeuten, entlang der Beweidungsgradienten fand, heben meine Ergebnisse die entscheidende Rolle nachhaltiger Beweidungspraktiken hervor, die die Erhaltung der Funktionalität und Widerstandsfähigkeit von Weideland ermöglichen.

Insgesamt zeigt meine Forschung das Potenzial der Drohnentechnologie für die Überwachung von Weideland mit der Hilfe von hochauflösenden, kostengünstigen und skalierbaren Daten . Meine Ergebnisse zeigen, wie die Kartierung mit Drohnen bestehende Ansätze ergänzen kann, um adaptive Strategien für das Management von Weideland zu entwickeln und das ökologische Verständnis dieser lebenswichtigen, aber empfindlichen Ökosysteme zu verbessern.

General Introduction

Rangeland degradation in a changing world

Dryland systems, defined by an aridity index below 0.65, encompass vast landscapes where water scarcity limits primary productivity (Maestre *et al.*, 2022; Zomer, Xu and Trabucco, 2022). Most rangelands, which cover about half of the Earth's land surface, namely, deserts, grasslands, shrublands, woodlands, and savannahs are found in these dryland regions (ILRI *et al.*, 2021) (Figure 1). Rangeland vegetation dominated by grasses, forbs, and woody plants serves as forage for both domestic and wild herbivores and provides critical ecosystem services, such as biodiversity conservation, carbon sequestration, and hydrological regulation (Lund, 2007; ILRI *et al.*, 2021). Moreover, millions of people rely directly on rangelands for their livelihoods (Millennium Ecosystem Assessment, 2005; UNCCD, 2014). However, unsustainable human practices and climate change have caused significant degradation, affecting at least 70% of rangelands globally and about 20% of these have transitioned into irreversible unproductive states (Lund, 2007; Peters *et al.*, 2013). This process is seen in the form of diminished ecosystem services, reduced forage productivity, and biodiversity loss all of which have profound consequences for livelihoods and economies (Dodd, 1994; Heita *et al.*, 2024).

Two major outcomes of rangeland degradation are desertification, marked by a significant decline in vegetation cover, leading to barren landscapes (Peters *et al.*, 2013; UNCCD, 2014), and woody encroachment, characterized by an increase in woody plant abundance (De Klerk, 2004; D'Odorico, Okin and Bestelmeyer, 2012) (Figure 1). Both phenomena often indicate surpassed ecological thresholds, severely compromising the functioning of rangelands (Reynolds *et al.*, 2007; Maestre *et al.*, 2022; Biancari *et al.*, 2024). A noticeable consequence is a decline in the capacity of these ecosystems to provide adequate forage, which is already sparsely distributed (Figure 1), threatening pastoral livelihoods and hampering economic growth (Reid et al., 2014). This impact is particularly evident in developing regions such as sub-Saharan Africa, where rangeland grazing is a cornerstone of agricultural practices (Middleton, 2018; Reynolds et al., 2007).

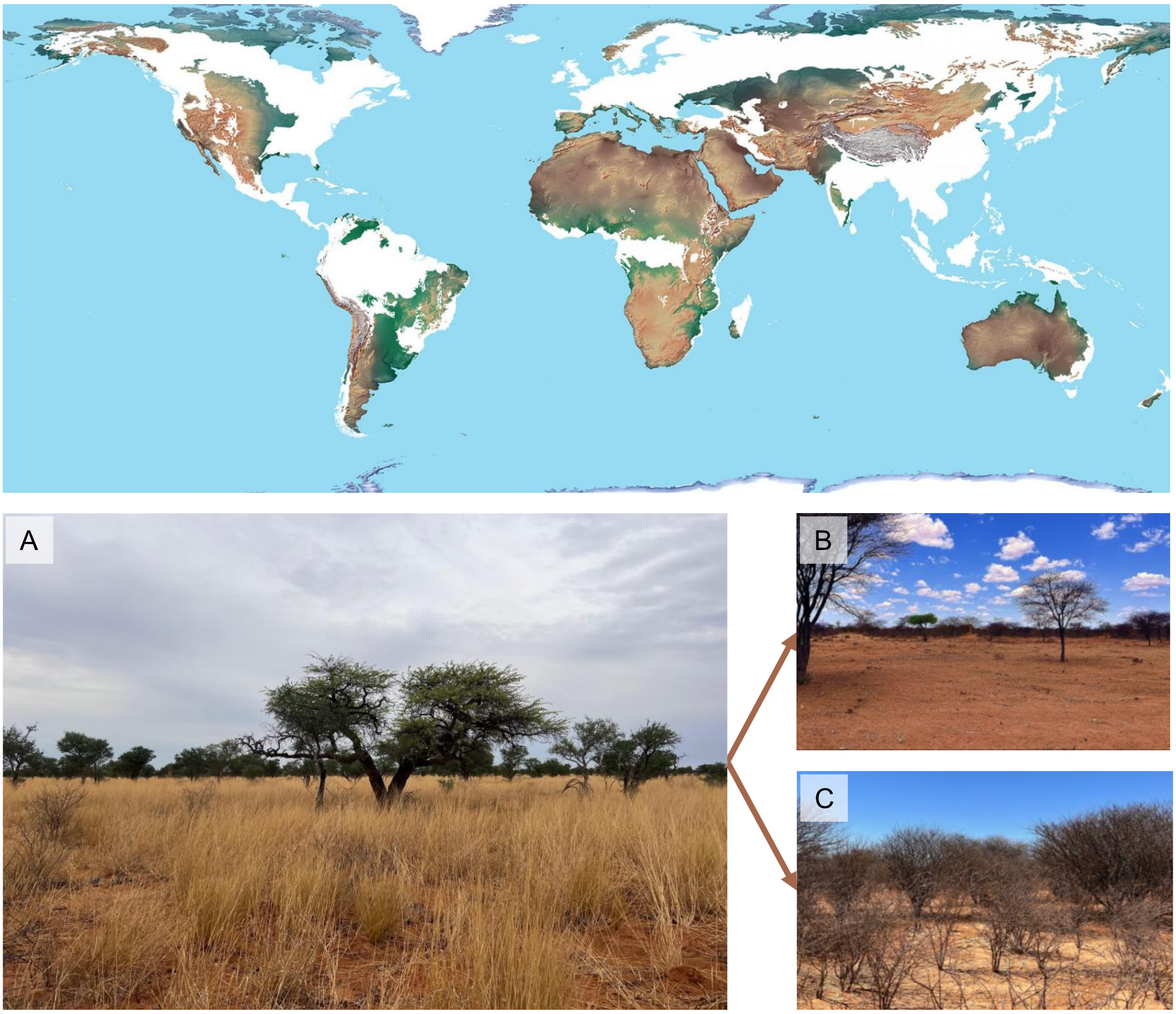

Figure 1. Global distribution of rangelands and examples from Namibia of (A) a healthier savannah rangeland and degraded rangelands with significantly reduced forage that suffer from (B) desertification or (C) bush encroachment. Map source: (ILRI *et al.*, 2021).

Namibian rangelands as a case study

Namibia, the driest country in sub-Saharan Africa, is a representative of many drylands that rely heavily on rangeland grazing and one that will suffer severely from the projected impacts of climate change (Reid *et al.*, 2008). Rangeland degradation affects at least 70% of its population and incurs substantial economic losses in the agricultural sector each year (Ministry of Agriculture Water and Forestry, 2012). Key drivers of degradation include unsustainable grazing practices, increasing climatic aridity, as well as socio-historical factors such as colonial legacies of land distribution (Menestrey Schwieger and Mbidzo, 2020). Consequences include significant losses of perennial grasses, increased abundance of unpalatable plant species, and bush encroachment across Namibian rangelands (Strohbach, 2001; De Klerk, 2004; Zimmermann, 2009; Brinkmann *et al.*, 2023; Kahumba and Tefera, 2023; Heita *et al.*, 2024) (Figure 1B & C). In addition, soil degradation and consequent reduction in vegetation cover in some parts of the country have significantly reduced livestock production, contributing to higher food insecurities and poverty, especially in already marginalized communities (Brown *et al.*, 1999; Reid *et al.*, 2008; Coetzee *et al.*, 2014). The carrying capacity for livestock is expected to continue to decline, particularly in the drier southern parts of the country, which may make livestock farming unfeasible in the near future (Reid *et al.*, 2008). With worsening climatic conditions and intensifying land use to meet the growing demand for animal products, the challenges facing Namibian rangelands will likely increase, straining both social and ecological systems on local and global scales. Addressing these challenges requires effective monitoring of degradation and its impacts to inform the sustainable management of these vital ecosystems so that they continue to function and withstand the impacts of global change.

Understanding the drivers of rangeland degradation is key to sustainable rangeland management. Unsustainable grazing, particularly exacerbated by the sedentarization of pastoralists, is often considered one of the main culprits (Menestrey Schwieger and Mbidzo, 2020). Sedentarization led to the establishment of fences and artificial water points, confining animal movements and concentrating grazing activities around these resource focal areas, increasing degradation through trampling, excretion, and soil compaction (Smet, 2004; Todd, 2006; Derry and Dougill, 2009).

Radiating from these resource focal points are distinct ecological zones, known as piospheres (Lange, 1969; Linstädter *et al.*, 2016). A typical piosphere pattern, also referred to as a grazing gradient, consists of three main areas: a) a sacrifice zone near the water point, where vegetation is nearly absent; b) a heavily grazed transition zone, and c) an outer region that is minimally affected by grazing activities (Manthey and Peper, 2010). Using the classical space-for-time approach (i.e., inferring spatial variability for temporal dynamics), these grazing gradients have been widely used to understand rangeland responses to grazing pressure and identify tipping points, especially given the long-term scarcity of ecological data (Bastin *et al.*, 1993; Pickup and Chewings, 1994; Sasaki *et al.*, 2008; Hoshino *et al.*, 2009; Manthey and Peper, 2010; Peper *et al.*, 2011; Sandhage-Hofmann *et al.*, 2015).

In the context of ongoing climate change, dryland systems are highly vulnerable to the risk of regime shifts, which remain challenging to predict in real-world systems (Scheffer, 2010; Berdugo *et al.*, 2020; Dakos *et al.*, 2024). These shifts are defined as ecological thresholds or tipping points beyond which ecosystems undergo irreversible changes (Scheffer *et al.*, 2001; Bestelmeyer *et al.*, 2013). These transitions are often abrupt and driven by positive feedback mechanisms, where environmental changes and human pressures amplify one another (Scheffer *et al.*, 2009). Once crossed, the recovery of these ecosystems becomes very difficult and only possible with considerable restoration efforts. As these transitions become more frequent and their impacts more pronounced, it is necessary to understand how they occur at scales relevant to on the ground management (Berdugo *et al.*, 2022). For example, understanding these processes *in situ* (i.e., at scales at which management decisions are made) enables land users to implement proactive strategies that prevent irreversible degradation and restore rangeland productivity and its associated ecosystem services.

Common monitoring approaches of rangeland status

Rangeland monitoring strategies are broadly divided into two main groups: on-ground approaches, involving actual fieldwork for direct measurements of ecological indicators, and remote sensing techniques, which are non-intrusive (Al-Bukhari, Hallett and Brewer, 2018). Field based surveys remain the dominant method for assessing rangeland resources in specific locations and times, as they provide detailed information about the ecosystem structure, function, and composition (Herrick *et al.*, 2017; Retallack *et al.*, 2023). Despite their value, these surveys are labour-intensive, time-consuming, and require field experts. Furthermore, they provide limited spatial coverage, making it challenging to adequately capture the spatial and temporal heterogeneity of rangelands (Booth and Tueller, 2003; Reinke and Jones, 2006; Cagney, Cox and Booth, 2011).

Field methods also involve destructive sampling, specifically the clip and weigh technique used for forage biomass. While this method is effective in determining carrying capacity, it is not ideal for long-term monitoring. Another challenge is observer bias, as inconsistencies in data collection may lead to inaccurate estimations (Booth and Tueller, 2003). Making management decisions based on unrepresentative information and an incomplete picture of rangeland status can reduce livestock productivity if forage resources are underestimated. Alternatively, in cases where forage resources are overestimated, it can result in overgrazing (Al-Bukhari, Hallett and Brewer, 2018). These challenges, therefore, highlight the need for non-destructive, repeatable, and scalable alternatives to assess the status of rangelands over larger spatio-temporal scales.

Remotely monitoring rangelands at broader scales

Remote sensing techniques like satellite-based systems, which are widely applied in rangelands, have been instrumental in tracking large-scale ecological changes (Booth and Tueller, 2003; Ganzin *et al.*, 2005; Dhinwa, Dasgupta and Ajai, 2016; Pettorelli *et al.*, 2018). These techniques provide objective, repeatable, and large-scale data on vegetation- and soil-related biophysical indicators, providing an overview of rangeland conditions to guide management practices (Tueller, 1989; Booth and Tueller, 2003; Röder and Hill, 2009; Reeves *et al.*, 2016). Greenness or vegetation indices (VIs) are among the most widely used tools for quantifying vegetation abundance and health. By mathematically combining spectral bands, the amount and condition of vegetation can be estimated, which can subsequently be linked to available forage resources (Tueller, 1989; Booth and Tueller, 2003; Wegmann, Leutner and Dech, 2016) or to detect degradation (Palmer and Fortescue, 2004; Washington-Allen *et al.*, 2004; Röder and Hill, 2009). Most VIs related to vegetation are calculated using the red and near-infrared (NIR) spectral bands, as these wavelengths on the electromagnetic spectrum relate to the photosynthetic activity of vegetation (Wegmann, Leutner and Dech, 2016). The biophysical aspect of this is attributed to the fact that photosynthetic absorption of visible light (i.e., blue, green, and red) is much higher in healthy vegetation, resulting in very low reflectance in the red region and very high reflectance in the NIR region (Figure 2).

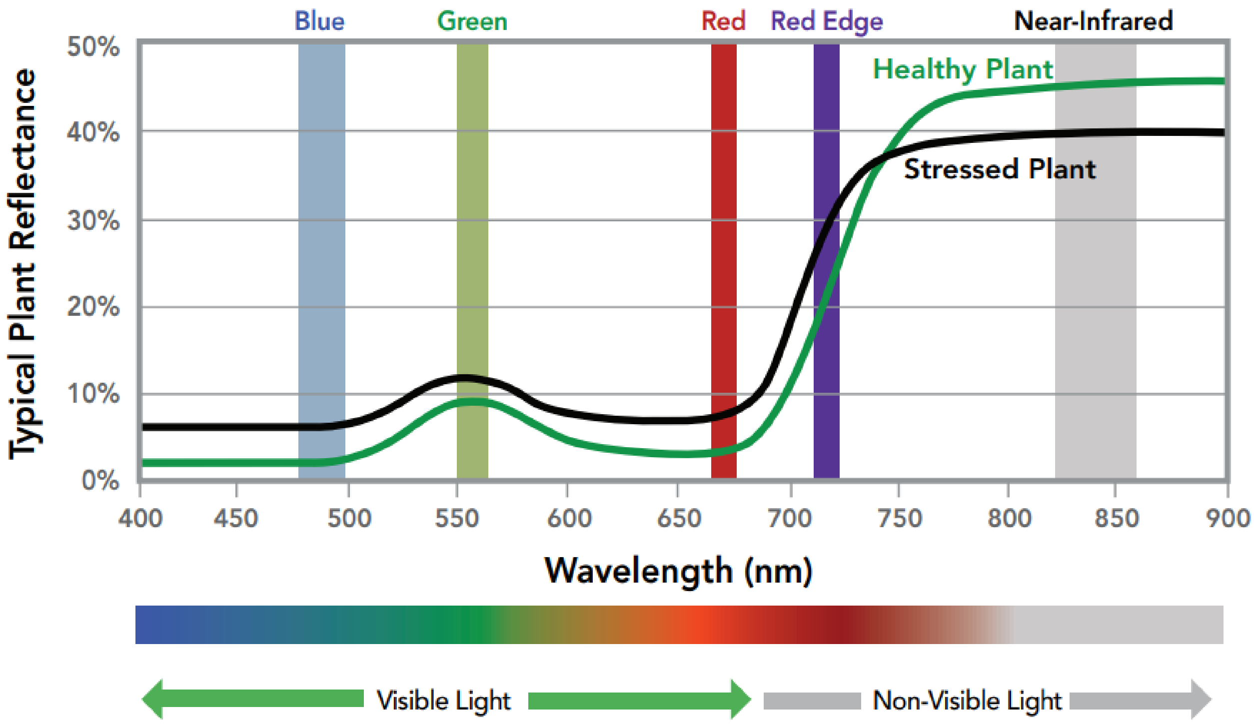

Figure 2. Typical light reflectance of healthy vegetation compared to vegetation in less healthy conditions. Healthy plants reflect more near-infrared light and less blue, green, and red light. The reflectance was measured by a multispectral sensor that was used in this study. Illustration source: MicaSense

One of the oldest, yet most widely used greenness index, is the normalized difference vegetation index (NDVI) (Xue and Su, 2017). Many others have since been developed, like the optimized soil adjusted vegetation index (OSAVI), which is adapted to account for the influence of soil background in sparsely vegetated ecosystems typical of rangelands (Rondeaux, Steven and Baret, 1996; Mansour, Mutanga and Everson, 2012; Wu, 2014; Xue and Su, 2017). Vegetation indices are also often used as predictors for land cover classification, from which indicators such as bare ground, photosynthetic vegetation, and non-photosynthetic vegetation can be estimated to determine rangeland conditions (Retallack *et al.*, 2023). Such spatially explicit information provides valuable insights for tracking and understanding spatio-temporal rangeland dynamics.

There are various operational satellite-based rangeland monitoring systems, like the rangeland and pasture productivity tool (GEOGLAM Rangeland and Pasture Productivity (RAPP)) that regularly monitors the condition of the world's rangelands, the rangeland monitoring system of Queensland in Australia (Statewide Monitoring and Mapping), and in our case study, the Namibia rangeland early warning system that was launched nearly a decade ago (Rangeland early warning system for Namibians). The rangeland early warning system generates monthly maps to provide land managers and policymakers with an overview of rangeland conditions, helping them make timely interventions, like adjusting stocking densities with sufficient lead time.

Despite their advantages, satellite information that is freely accessible may not be sufficient for adapting management decisions or for tracking subtle changes associated with abrupt shifts (Graetz, 1987). This is largely because they have a low spatial resolution, making it able to distinguish between plant functional types, like grasses and woody plants, which can hinder accurate assessments. This limitation is particularly problematic in woody-grass ecosystems like savannahs, where understanding the balance between these plant types is necessary for quantifying available forage (Graetz, 1987; Reinke and Jones, 2006). For example, in such ecosystems, higher greenness values do not always mean healthier conditions or more forage for livestock, because it can be due to shrub encroachment (Figure 1c), one of the two manifestations of degradation (Wegmann, Leutner and Dech, 2016). Additionally, cloud cover during the rainy season that coincides with primary production also poses challenges, making it difficult to accurately quantify forage. Therefore, to improve rangeland management for long-term productivity and to detect potential ecological thresholds, it is important that objective, easily obtainable and high-resolution data are integrated. Additionally, there is a need to combine on the ground methods with remote sensing technologies that are advanced to provide a more robust understanding of the dynamics in rangelands for sustainable long-term productivity.

Harnessing drone technology to optimize rangeland monitoring

In recent years, unmanned aerial vehicles (UAVs), commonly known as drones have emerged as a powerful tool in ecological research, offering solutions to the challenge of traditional methods of surveying. Equipped with high-resolution miniaturized sensors, drones efficiently collect detailed spatial and spectral data. The declining costs and increasing capabilities of drone technology make it highly suitable for rangeland monitoring. Drones can capture ultra-high-resolution imagery, with resolutions of less than 1 cm to 10 cm, enabling the detection of detailed changes in land cover, vegetation structure, and aboveground biomass. Furthermore, drone imagery allows the differentiation between plant functional types, such as trees, shrubs, and herbaceous plants (Laliberte, 2009; Ghazal, Khalil and Hajjdiab, 2015; Théau *et al.*, 2021; Zhang *et al.*, 2021). The information provided by drones is at an intermediate scale between field and satellite approaches and is suitable for informing local management decisions (Gillan, Karl and van Leeuwen, 2020). A main benefit is that drone mapping provides real-time data at user-defined frequencies (i.e., flexible temporal resolutions), making it an ideal tool that could greatly improve adaptive management of the limited forage resources in rangelands. This flexibility allows for targeted monitoring of specific rangeland sites. For example, the effects of resource focal points, like livestock water points where degradation often begins can be monitored; restoration efforts like debushing to combat woody encroachment can easily be tracked; or near-real-time mapping of forage availability and shortages to improve grazing management plans.

Drone technology has the potential to replace certain strenuous field measurements, such as estimating forage biomass or classifying land cover (Laliberte, 2009; Gallacher, 2019; Gillan *et al.*, 2021; Amputu *et al.*, 2023). Field efforts can then prioritize detailed inventories, like plant species identification or seedling counts, which are still challenging to derive from drone data. Also, the spatially continuous high-resolution data presents an ideal opportunity to study grazing gradients and tipping points *in situ* at scales required for making management decisions.

To maintain the benefit of monitoring at larger spatial scales, data derived from drones can also play a key role in improving satellite-based information. This is especially important in addressing limitations associated with low spatial resolution. Drone imagery can, for example, be used to differentiate vegetation into woody and herbaceous components to complement satellite data rather than only providing a general measure of greenness. This improved level of detail enhances the accuracy of estimates of forage availability, significantly advancing grazing management plans (Harkort et al., under review).

Despite these advantages, the integration of drone technology into existing monitoring frameworks remains underexplored. Therefore, to fully make use of the potential of drones, there is a need to develop simple, reproducible, and robust workflows to ensure that such advanced technologies are easily adopted by rangeland ecologists and land users. In doing so, drone technology can advance ecological research, optimize monitoring efforts, and support sustainable rangeland management practices.

Thesis objectives and outline

This study aimed to test the applicability of drone technology to assess key indicators of rangeland conditions and understand land degradation in dryland systems. Namibia's semi-arid rangelands were used as a case study for this, focusing on three key areas: (1) validating drone-based estimates of herbaceous biomass and the cover of rangeland functional attributes using field data and developing a workflow for mapping rangeland status (chapter 1), (2) evaluating the transferability of drone-based prediction models across different land use systems and phenological periods (chapter 2), and (3) comparing levels of degradation among land tenure systems, assessing the effects of grazing intensity on rangeland status along distance gradients from livestock water points, and testing the potential of detecting tipping dynamics from spatially continuous high-resolution drone data (chapter 3)

These objectives were achieved in three chapters that make up the thesis, which is structured as follows:

In **Chapter I**, I compared traditional labour-intensive field measurements with drone derived observations to understand the benefits and limitations of drones in mapping key indicators of rangeland conditions. Specifically, I tested the agreement between estimates of forage biomass and land cover from drone imagery and those measured in the field. I also present a straightforward and reproducible workflow for estimating forage availability in dynamic and heterogeneous ecosystems like savannah rangelands. This chapter was published in *Ecological Informatics*, Volume 75, 102007 (21 January 2023), https://doi.org/10.1016/j.ecoinf.2023.102007. In **Chapter II**, I evaluated the applicability of drone technology for quantifying forage resources in semi-arid rangelands. Given the spatial and temporal dynamics of rangeland ecosystems, model transferability across differing management practices and rapid phenological changes needed to be considered when developing predictive models. In this chapter, I tested the generality of drone-based prediction models beyond the conditions (i.e., in space and time) in which they were trained to predict available forage. I used data collected (i) from two land use systems, namely freehold farms that are fenced and have multiple camps to facilitate rotational grazing and, in contrast, communal areas that typically follow an open-access grazing system. These data provided the spatial aspect. For (ii) the temporal aspect, the data was collected during two periods of the growing season, specifically during the early season and during the peak season. This chapter highlights the importance of adequately capturing the spatial and temporal variability inherent to rangeland systems in model development, as this leads to generalisable predictions of forage resources. This chapter has been published in *Remote Sensing*, Volume 16, Issue 11, 1842 (22 May 2024), https://doi.org/10.3390/rs16111842.

In **Chapter III**, I acquired spatially continuous drone imagery along grazing gradients established from livestock water points (i.e., a proxy for grazing pressure) to compare rangeland conditions within piospheres between two land tenure systems and to test for potential tipping points. I applied the drone-based prediction models developed in the previous two chapters to extract the following rangeland condition indicators from the drone imagery: herbaceous biomass and cover-based parameters, namely, bare ground, herbaceous plants, woody plants <2 m, and woody plants >2 m. I then analysed the response of these indicators to grazing pressure and performed a breakpoint analysis to identify potential abrupt shifts. The results from this analysis revealed that rangeland conditions respond gradually to grazing impacts and underscored the critical role of sustainable grazing practices in maintaining rangeland ecosystem functioning. This chapter further augmented the utility of drone technology to optimize rangeland monitoring and advance ecological research.

Through these chapters, this thesis showcases how drone technology can improve sustainable rangeland management and ecological research by providing cost effective, high resolution and scalable solutions for monitoring dynamic dryland ecosystems.

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Chapter I

Unmanned Aerial Systems (UAS) accurately map rangeland condition indicators in a dryland savannah

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Unmanned aerial systems accurately map rangeland condition indicators in a dryland savannah

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ABSTRACT

Dry savannahs are highly sensitive to climate change and under intense anthropogenic pressure. Therefore, the methods for assessing their status should be easy and repeatable. Monitoring through satellite data and field measurements are limited in accurately assessing the spatiotemporal dynamics of ecosystems. Fortunately, emerging technologies like Unmanned Aerial Systems (UAS) allow to transcend these limitations. But their calibration with field data for application in rangelands is still relatively new and less common than for example in precision agriculture. In this study we developed a drone-based workflow for mapping the condition of rangelands in dryland savannah. We evaluated how accurately and efficiently the two common indicators (i.e., potential forage biomass and rangeland cover type) of rangeland condition can be estimated from drone imagery across a range of conditions (i.e., highly degraded to healthy rangelands). To develop the drone-based potential forage biomass model we tested the accuracy of four vegetation indices to predict field biomass, with the optimized soil adjusted vegetation index (OSAVI) showing the highest prediction accuracy ($R^2 = 0.89$ and RMSE $= 194.05$). The OSAVI-based model yielded a significant strong relationship ($R^2 = 0.80$, $p < 0.001$) between predicted and field observed potential forage biomass across the rangeland system. For land cover, we applied a decision tree classification based on thresholds determined using data mining, with a mean overall accuracy of 95.8%. The drone-based estimates of bare cover, herbaceous cover and woody cover showed strong agreements (R^2 ranging between 0.86 and 0.97) with the two image-truthing methods (line-point intercept and visual estimations) tested. We show that the drone-based approach is more efficient, unbiased, and repeatable than the field methods. Based on these results, the drone-based workflow presented here offers a reproducible, accurate and efficient approach for near-real time monitoring of rangeland condition at a landscape level. This may assist with climate-adapted management to prevent further land degradation and associated threats to biodiversity and human livelihoods.

1. Introduction

Rangelands occupy close to half of the terrestrial surface (Reeves et al., 2016), providing about 70% of forage for domestic livestock rearing and wild herbivores (Lund, 2007). Most rangelands are classified as drylands, based on the widely used aridity index (i.e., the ratio of precipitation (P) to potential evapotranspiration (PET)), where PET exceeds P by at least 150% because of relatively low rainfall and high temperatures (Millennium Ecosystem Assessment, 2005; Huang et al. 2017). Because of this, primary productivity is largely constrained by limited moisture availability. Unfortunately, due to changing climatic conditions coupled with intensifying land use, 70% of rangelands are degraded or on the verge of becoming unproductive for grazing (Reynolds et al., 2007). This compromises the livelihood of millions of people who depend directly on the forage ecosystem service that is provided by rangeland vegetation (Reeves et al., 2016). Therefore, to improve rangeland management and answer ecological questions about how they are changing requires methods that are easy to apply, are reliable and

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repeatable and provide comparable quantifiable results.

The most widely used approach to monitor rangeland conditions are field observations. These provide detailed rangeland condition information based on compositional, structural, and functional attributes (Lawley et al., 2016). However, these are costly, labour intensive, intrusive, and require experienced field specialists (Al-Bukhari et al., 2018; Gillan et al., 2019). The lack of harmonized ground-based data collection methods and consistency of measured parameters also complicates site comparisons and the upscaling of findings (Díaz-Delgado et al., 2019). Additionally, it is impractical for field sampling to cover an entire area of interest and it cannot be conducted frequently. Since rangelands cover close to half of the terrestrial surface area, field observations cover only a minor fraction of the area of interest and rarely represent the highly heterogeneous nature of such ecological systems (Gillan et al., 2019; Reeves et al., 2016). These limitations of ground-based methods highlight the need to integrate cost-efficient approaches that allow the detection of important land cover changes at higher temporal and larger spatial scales.

Therefore, satellite-based remote sensing has been used for monitoring vast areas like rangelands (Bastin et al., 2012; Collado et al., 2002; Mansour et al., 2012; Reeves et al., 2016). It provides objective, automated and repeatable long-term monitoring data of vegetation condition and land cover for detecting change over time at large scales (Tehrany et al., 2017; Xue and Su, 2017). For example, the greenness of vegetation or the decomposition into broad surface categories are reliable indicators of the condition of the land that can be monitored from satellite imagery at national to global scales, thereby providing long-term data that informs management policies and supports decision-making. This has been demonstrated by some of the existing monitoring systems such as the near-real time rangeland and pasture productivity national tool of Australia (https://map.geo-rapp.org/) or the state-wide rangeland monitoring system of Queensland in Australia (https://www.qld.gov.au/environment/land/management) or the national rangeland early warning and monitoring system in Namibia (http://www.namibiarangelands.com/).

However, rangelands particularly in arid savannahs present unique challenges due to cloud cover during the short growing season, i.e., the season most relevant for assessing rangeland condition, high soil background reflectance, relatively low biomass and a complex mosaic of bare ground, herbaceous, and woody plants (Reeves et al., 2016). Therefore, remote sensing techniques for global applications often result in erroneous estimates of ecosystem parameters in these rangelands at the local scale (Smith et al., 2019). Additionally, the spatial resolution of freely available or affordable data products generally limits the level of detail (Knox et al., 2013; Sankey et al., 2019) which is required for rangeland managers to make informed decisions. For example, in savannahs distinguishing primary production of woody plants and herbaceous plants is necessary to determine available forage for grazers. Currently, only very high-resolution (VHR) satellite imagery with spatial resolutions below one meter can be used to distinguish plant functional types (Aplin et al., 2021) and dominant tree species (Fang et al., 2020). But these are expensive to purchase and still risk being affected by cloudy conditions during the appropriate period of acquisition as the number of cloud-free days are limited. Accounting for these shortcomings is imperative for such monitoring approaches to enable adaptive management of declining ecosystem services in these dynamic and heterogeneous landscapes.

So overall, the most widely used approaches for assessing rangeland productivity do not capture the attributes of rangeland condition at a scale that is relevant for management decisions (Al-Bukhari et al., 2018). A solution to that problem may be unmanned aerial systems (UAS, hereafter, drone technology) which have been shown (Assmann et al., 2019; Gillan et al., 2020; Rango et al., 2006; Sankey et al., 2019) to overcome the limitations above more efficiently and at relatively lower costs. The main benefits (detailed descriptions in (Anderson and Gaston, 2013; Assmann et al., 2019; Rango et al., 2006) that make drone technology suitable for rangeland monitoring are that it provides data with exceptional detail at centimeter to decimeter spatial resolutions (i.e., may be equivalent to pure pixels of ecosystem features) and at user-defined temporal resolutions (Berni et al., 2009; Gallacher, 2019). In addition, miniaturized drone multispectral sensors with narrow spectral bandwidths and high radiometric quality are readily available (Aasen et al., 2018; Anderson and Gaston, 2013; Assmann et al., 2019). This facilitates accurate assessments of vegetation health, primary production, and better relation of structure to function, and thus improved understanding of ecological change (Zhang et al., 2021). The operation of drones is also generally simple, requiring at most two individuals to map between 1 and 100 ha of land, the primary limitation being battery power (Zhang et al., 2021). Therefore, ecological research has rapidly adopted drone technology for mapping ecosystem parameters such as soil degradation (Krenz et al., 2019), forest health (Dash et al., 2017; Knox et al., 2018), plant cover, biomass, and structure (Breckenridge et al., 2011; DiMaggio et al., 2020; Navarro et al., 2020; Rango et al., 2006; Théau et al., 2021). However, calibration of any remotely sensed information with field data is compulsory before they are integrated for long-term monitoring (Gillan et al., 2020).

Interestingly, while this method is especially important for large areas that require a relatively detailed assessment, its application has virtually not been calibrated for arid savannahs and little is still known about their accuracy and detection capabilities for rangeland applications (Sankey et al., 2019). Therefore, it is necessary to test this cost-effective approach to fill the gap where satellite imagery seems too coarse and local observations inadequate for optimal rangeland management (Anderson and Gaston, 2013; Laliberte et al., 2007). For this, the following important considerations are required for its application in such systems. Firstly, because the conditions of these rangelands vary primarily due to different management practices, the calibration of such a method must account for spatial differences, as site-specific models may not be transferable across the landscape (Théau et al., 2021). Secondly, their validation needs to ensure that the developed drone prediction models of the rangeland parameters such as available forage consider the temporal variability (i.e., by selecting the ideal time) of range conditions during the growing season (Théau et al., 2021). And lastly, the reliability of the drone prediction models for land cover based on the two common image-truthing methods (line intercept method and visual estimation) needs to be assessed, as their performance has been shown to vary in rangelands that have sparse vegetation cover (see (Zhou et al., 2010).

In this study we propose a simple but robust workflow for mapping rangeland condition using drone imagery for landscape level monitoring. We assess the accuracy of drone-based rangeland condition indicators for a dryland savannah, namely rangeland cover type (hereafter, rangeland functional attributes (RFAs)) and herbaceous biomass (hereafter, potential forage biomass). For the RFAs cover indicator, we evaluate it using the objective, but time-consuming approach (line point intercept method) and the subjective, but more rapid (visual estimation) method to determine whether these field validation techniques produce equivalent results. We expect that the estimates of the rangeland condition indicators made from high-resolution drone imagery are positively and significantly related to those measured in the field.

2. Materials and methods

2.1. Study area

We conducted our research in a semi-arid savannah located in central Namibia (Fig. 1). The study area is representative of many dryland regions in the world that have a scarcity of natural resources due to unfavorable climatic conditions, infertile soils, compounded by a growing human population that largely depends on the provision of ecosystem services (Millennium Ecosystem Assessment, 2005). The study area receives a mean annual rainfall of 400 mm, largely between

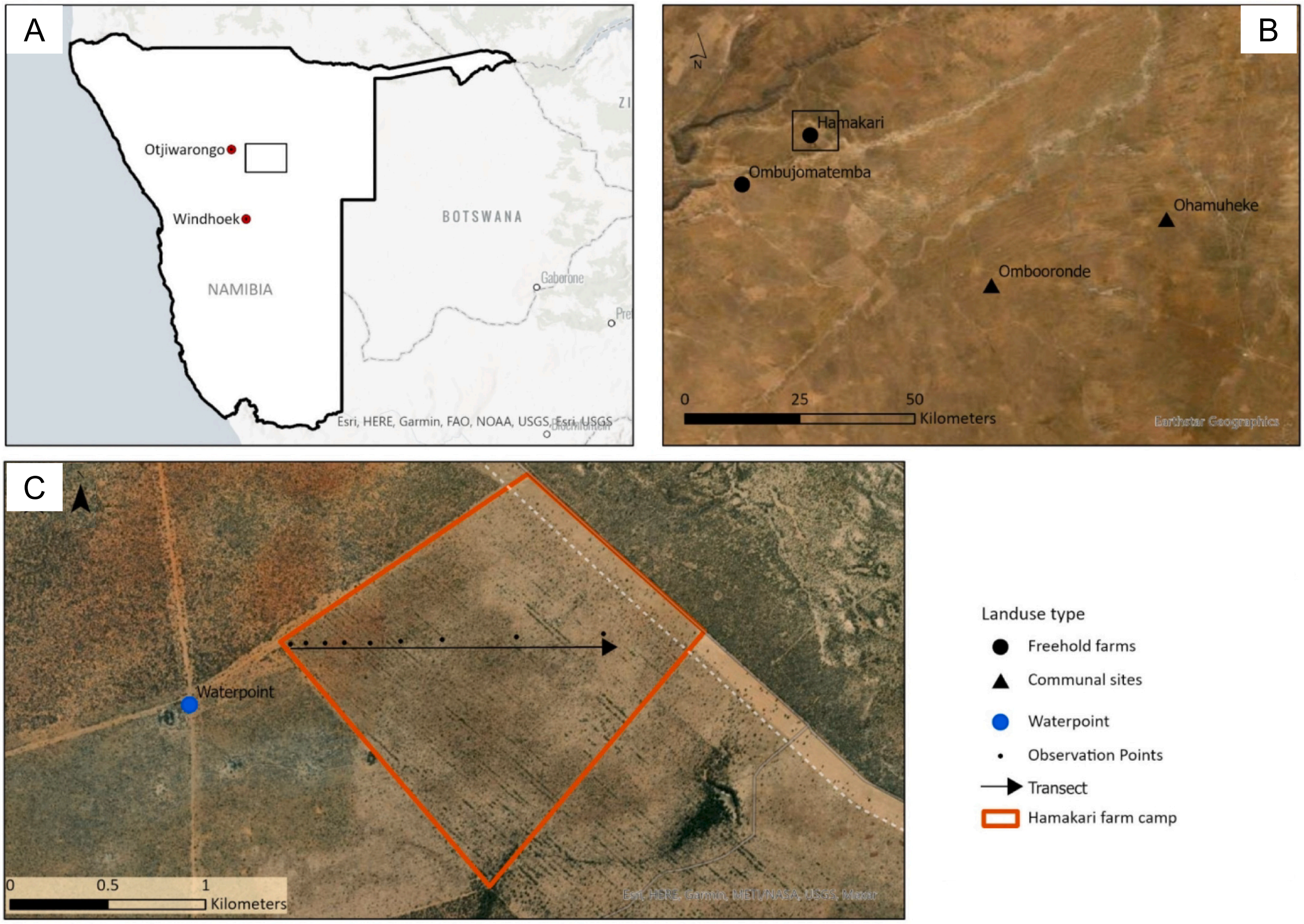

Fig. 1. (a) Location of the study area in central Namibia, (b) with the four sites where data was collected, and (c) the transect example from a freehold farm site with the nine observation plots placed with increasing distances away from a water point.

the months of December and March (Ministry of Environment and Tourism, 2013). The average daily maximum temperature in the hottest months (October to January) ranges between 31 °C and 34 °C, with daily temperatures reaching up to 40 °C, and the average daily minimum temperature for the coldest months (June – August) ranges between 4 °C and 7 °C, with temperatures dropping as low as - 4 °C (Ministry of Environment and Tourism, 2013). Vegetation growth is limited by the lack of moisture in the atmosphere, high temperatures due to intense solar radiation, low rainfall during the short growing period and nutrient-poor soils (ferralic arenosols) (Mendelsohn et al., 2002). The common and relatively palatable perennial grass species are *Eragrostis rigidior* (Pilg.) and *Stipagrostis uniplumis* (Licht.) (Sweet and Burke, 2006). While the common woody species include *Boscia albitrunca* (Burch.), *Grewia flava* (DC.), *Grewia retinervis* (Burret.), *Senegalia mellifera* (Vahl.), and *Terminalia sericea* (Burch.) which sustain browsing game species. The common game species in the region include Gemsbok (*Oryx gazella*), Giraffe (*Giraffa camelopardalis*), Greater Kudu (*Tragelaphus strepsiceros*), and Springbok (*Antidorcas marsupialis*). But the region is predominantly used for livestock production, largely free-range cattle (Ministry of Environment and Tourism, 2013).

There are two main land management systems, namely, privately owned freehold farmlands that are fenced off and dissected into several camps that contain livestock water points (Mendelsohn et al., 2002). In contrast, the communal land where pastoralist communities farm together is generally open with common livestock water points at the center of the settlements (Mendelsohn et al., 2002). Comparatively, most of the area in the latter management system is over-utilized, with escalating land degradation making this ecosystem susceptible to desertification (Menestrey Schwieger and Mbidzo, 2020). We collected our data at four sites, representing the two different land management systems (Fig. 1). At each site we established a line transect with nine 100 m^2 observational plots with increasing distance away from an artificial water point, with the assumption that the rangeland condition improves with increasing distance away from a disturbance source (Pickup and Chewings, 1994), from which cattle disperse into the 'veld'. The observational plots were spaced following a logarithmic order, such that more sampling effort was done at the beginning of the transects where the greatest change in conditions is expected (Linstädter et al., 2014). In the freehold farms, the transects were established in camps with increasing distance away from a water point, while in the communal land the transects were setup with increasing distance away from the edge of the village settlements that surround the common water points (Fig. 1). The four transects were on average 2060 m long, starting on average 1000 m from the disturbance source, to avoid the 'sacrifice zone'. With this setup we were able to capture the entire range of conditions (i.e., highly degraded, moderately disturbed to good rangeland conditions) at local and landscape scales expected in these rangelands.

2.2. Data collection

2.2.1. Drone imagery acquisition

We acquired drone imagery during the onset of the peak growing season between 23 February and 27 March 2021, using a DJI Matrice 200 series V2 drone (http://www.dji.com) on which a RedEdge-MX version RX01 (http://www.micasense.com) vegetation sensor was mounted (Fig. 2). The multispectral camera had five separate sensors that operate simultaneously to capture surface reflectance images in the following five spectral regions: blue (B) 475 nm +/− 20 nm, green (G) 560 nm +/− 20 nm, red (R) 668 nm +/− 10 nm, red edge (RE) 717 nm +/− 10 nm and near-infrared (NIR) 840 nm +/− 40 nm.

Drone images were acquired along the entire extent of the four transects. The flight missions were planned and executed in Pix4DCapture (Pix4D SA, Switzerland) with a side and front overlap of 80%. We conducted all the flights within two hours of local solar noon (12:58–13:05) to minimize the shadowing effect from woody vegetation and to reduce the variations in sun angle (Wang et al., 2021). Each of the flights took approximately 45 min, which included drone setup and the flight. As ambient light conditions during the growing season are highly influenced by the presence of clouds, we ensured radiometric correction with the aid of a Downwelling Light Sensor (DLS) (Fig. 2) in conjunction with the Calibrated Reflectance Panel (CRP), thus enabling us during image pre-processing, to convert radiance in our images into surface reflectance (Wang et al., 2021). The flight altitude was set at 80 m above ground level resulting in a ground resolution of about 5.6 cm/ pixel. This was deemed suitable for quantifying sparsely distributed forage biomass, which is characteristic of drylands (Lu and He, 2018; Maestre et al., 2021).

To ensure that the drone estimates and field observations were from the same area of interest, we placed 60 cm × 60 cm ground markers that are visible in the imagery in the corners of the observational plots during the drone flights.

2.2.2. In-situ data collection

After the image acquisition, we estimated the cover of the three main rangeland functional attributes (RFAs) that characterize arid savannahs and that we could accurately discriminate from the drone multispectral imagery, namely, bare ground, herbaceous plants, and woody plants. We opted to refer to them as RFAs for the roles that they play in rangelands. For example, bare ground cover may be indicative of potential plant colonization or areas at risk of erosion, which makes it a key indicator of rangeland health; herbaceous plants are the main forage source for livestock production and their cover prevents soil erosion; while woody plants sustain browsing game and play a pivotal role in carbon sequestration (Briske et al., 2017). We employed two commonly used cover assessment methods for collecting the image-truthing data. Along each transect, the nine observational plots were sampled. The methods used were the objective, but labour-intensive, line-point intercept (LPI) technique (Herrick et al., 2017), and the more rapid, but relatively subjective visual estimation approach (Zhou et al., 2010). For both methods we used a bird's eye perspective, such that only the upper canopy layer was considered.

We visually estimated the percentage cover of bare ground, herbaceous and woody plants in the observation plots. For the LPI technique, in each plot, four 10 m lines were set up 2 m apart along which readings to record the RFA visible to the drone were done every 20 cm starting at 0.2 m and ending at 10 m (50 points per line; 200 observations in a plot) (Fig. 3). The different RFAs cover was then calculated by dividing the number of observations of a given RFA type by the total number of observations per LPI line, from which the mean RFAs cover were derived for the plots.

To estimate potential forage biomass, on the outside of each 100 m^2 plot, on the NW side, we harvested all the herbaceous plants visible to the drone (i.e., herbaceous plants growing under the canopy of woody plants were not clipped) in a 1 m × 5 m strip (Fig. 3a). The clipped plant material was oven-dried at 65 °C for 48 h and weighed.

2.3. Data processing to develop the drone-based rangeland indicators

The process flow used to develop and evaluate the drone-based rangeland indicators is provided in Fig. 4. To evaluate the efficiency of the application of drone technology in monitoring rangeland condition we timed the entire process.

2.3.1. Pre-processing of drone imagery

The drone images were processed using Pix4DMapper version 4.6.4, a commercial Structure-from-Motion (SfM) software (Pix4D SA,

Fig. 2. The DJI Matrice 200 v2 drone with the RedEdge-MX sensor and the upwards facing Downwelling Light Sensor.

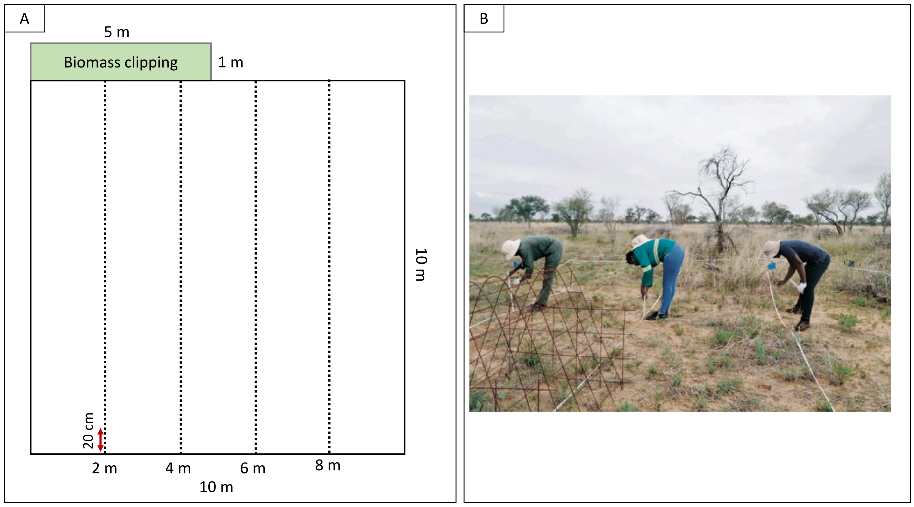

Fig. 3. (a) The set-up of the 10 m × 10 m plot used for the LPI technique and the harvesting of herbaceous biomass in the 1 m × 5 m strip; and b) the RFA observations being done along the lines in the plot.

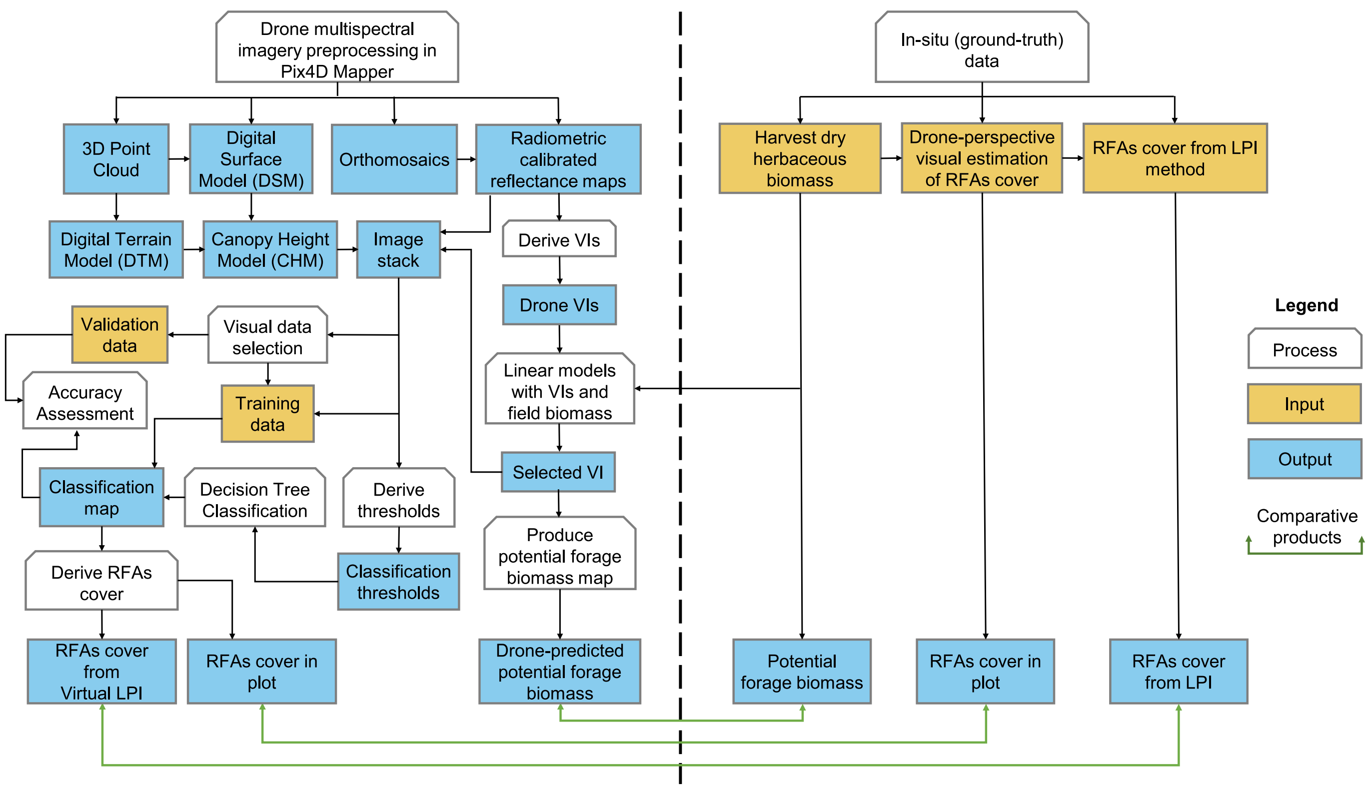

Fig. 4. The general workflow of the drone data products used to characterize the RFAs cover and quantify potential forage biomass (left side). The field observations (right side) were used to assess how accurate the drone estimates are.

Switzerland) using the processing steps described in Mesas-Carrascosa et al. (2015) and Strohbach (2018) to produce mosaicked, calibrated, bottom-of-atmosphere surface reflectance images, digital surface models (DSMs) and digital terrain models (DTMs) for each of the four transects. Because of the importance of tree and shrub height in these systems, from the DSM and DTM layers, we produced a Canopy Height Model (CHM) for each transect (Fig. 9c). These products were then used as input for further analysis as described below to extract the estimates of the potential forage biomass and the RFAs cover.

2.3.2. *Development of the potential forage biomass indicator*

To determine which vegetation index is the most suitable index for estimating potential forage biomass in this dryland system, we first derived multiple indices from the pre-processed imagery (section 2.3.1). We calculated the commonly applied Normalized Difference Vegetation Index (NDVI) and three other vegetation indices adapted for dryland systems, that had been previously tested for predicting plant biomass (Baghi and Oldeland, 2019; Fern et al., 2018; Wu, 2014). These are the Generalized Difference Vegetation Index (GDVI), the Optimized Soil Adjusted Vegetation Index (OSAVI, $y = 0.16$ the optimum constant determined by (Rondeaux et al., 1996), and the Transformed Difference

Vegetation Index (TDVI).

We extracted the mean vegetation index values in the 1 m × 5 m polygons along the four transects (n = 36) from which herbaceous biomass was harvested. We created a woody mask over each transect using the threshold of the CHM to ensure that the mean vegetation index values were not a contributed reflection of the woody plants. Potential forage biomass models were then developed for the four vegetation indices using k-fold cross validation (k = 10) to train, validate and predict dry forage biomass (kg/ ha) from the mean vegetation index values. The potential forage biomass model with the highest prediction accuracy based on the R^2 and RMSE was then selected as the most suitable vegetation index to predict potential forage biomass in this system. The vegetation index that was selected in this analysis was also used as an additional input layer for the RFAs classification described in section 2.3.3.

2.3.3. Development of the rangeland functional attributes indicator

We applied the following six steps to calculate the respective RFAs cover from the drone imagery: (i) created an input image stack consisting of the five spectral bands, the vegetation index and the CHM for each of the transects, (ii) developed a training dataset using visual image interpretation (iii) used data mining to determine important variables and classification thresholds from the input image stacks, based on the training dataset, (iv) sequentially applied the derived thresholds in a decision tree, to classify the RFAs along each transect, (v) validated the classified maps, and finally (vi) extracted the area's covered by the RFAs at plot-level and compared these outputs to the in-situ collected data. These steps are expanded upon below.

The basic image products from Pix4DMapper pre-process (section 2.3.1) and the findings from section 2.3.2 were used to create image stacks for each transect in ENVI version 5.3 (Exelis Visual Information Solutions, Boulder, Colorado, USA). We combined the five spectral bands, the selected vegetation index and the CHM. These four image stacks were then used for developing the RFA classification model.

We manually collected classification training data based on visual interpretation of the high-resolution orthomosaics from the four transects to obtain a representative sample of each of the RFAs in the studied rangeland system. We selected 200 points (i.e., pixels) for every RFA category from each mosaicked image from each transect (i.e., 600 pixels/ transect * 4 transects = 2400 points). The image stack values were extracted at each of these points.

The extracted dataset was fed into the Orange (Python version 3.31.1) data mining toolbox (Demšar et al., 2013), to construct a classification tree as introduced by (Breiman et al., 1984). This dataset was randomly split into a training (70% of points - 1680 points) and validation dataset (30% - 720 points). The validation dataset was used to evaluate the output models and determine the parameters and decision thresholds to be used in the decision tree to classify the RFAs.

We used the defined thresholds from the data mining approach to apply the decision tree classification model in ENVI version 5.3 (Exelis, Boulder, Colorado, USA) to the four transect mosaicked image stacks. To account for the "salt-and-pepper" effect associated with the classification of very high-resolution imagery, a modal smoothing was performed on the classified results to account for individual pixels that are usually incorrectly classified as different from their majority neighbors (Barnas et al., 2019). We used the classification aggregation technique in ENVI version 5.3 (Exelis, Boulder, Colorado, USA) to group regions with a minimum size of 9 to adjacent, larger regions. This was a relatively good compromise to ensure that we did not lose crucial information, such as the preservation of narrow cattle trails that are important features of the rangeland.

To assess the accuracy of the classified maps 600 points (200 points per RFAs) from each transect were selected based on the stratified random sampling approach. The classification class was extracted for these points, and the points were classified into the respective RFAs through a visual evaluation using the orthomosaics (Laliberte et al., 2010). These served as the classification validation dataset to calculate the classified accuracies of each transect (Congalton, 1991). It allowed us to identify the proportion of correctly predicted RFAs against misclassifications between the different classes. Classification accuracy was expressed using the overall producer's and user's classification accuracies, as well as the kappa coefficient (Congalton and Green, 2019).

To compare the classified RFAs cover to the in-situ collected data, we applied the two field protocols to extract the cover values. To evaluate the RFA cover based on the LPI method we established virtual LPI transects in the plots on the classified maps and the RFA type was extracted at 20 cm intervals (Fig. 9a) using QGIS version 3.16.16 (QGIS Development Team, 2018). The percentage of each RFA was determined using the same method used for the in-situ calculations. To evaluate RFA cover, based on the visual estimation method, for each of the field plots within the classified images we obtained the percent cover of each RFA using ENVI version 5.3 (Exelis, Boulder, Colorado, USA).

2.3.4. Evaluation of the drone-based rangeland monitoring workflow

To determine whether this drone-based rangeland monitoring workflow is in fact an effective means to expedite rangeland monitoring compared to solely relying on the field-based method we conducted the following evaluation. The time spent for the different stages to assess the rangeland condition indicators was recorded. The time spent was broken down into 3 stages of the monitoring protocol: i) Data collection, ii) data processing and iii) data extraction. Data collection included the time spent for the field observations at the plot level (i.e., 100 m^2), while the time used for the drone imagery covers the entire transect (i.e., 2060 m long and 80 m wide). Additionally, although we tracked the time spent for the different stages, collecting the data is based on four persons for the LPI method, one person for the visual estimates and two persons for the drone imagery. The data processing for the field method refers to entering the data into Excel, which involved two persons, while for the drone this was the time spent for the preprocessing of the raw imagery in Pix4DMapper (Pix4D SA, Switzerland), mainly computer time (i.e., hands-off). Data extraction refers to preparing the data tables from the field method for the correlations, while for the drone imagery this entailed creating the image stacks, calculating the tested vegetation indices, collecting the training and validation datasets, training the classifier, generating the classification maps, and extracting the RFAs cover data.

2.4. Statistical analysis

To evaluate the drone-based method for quantifying rangeland condition indicators we applied similar statistical approaches used in other validation studies (see (Laliberte et al., 2010; Zhang et al., 2021). The statistical analyses were performed using the stats package in the R Statistical Software version 4.1.2 (R Core Team 2021). First, we determined the coefficients of determination (adjusted R^2) to assess the agreement between (i) the predicted potential forage biomass from the drone vegetation index maps and that estimated in the field, as well as (ii) the RFAs cover estimations from the classified drone imagery and those observed in the field for the LPI technique and visual estimations. For all the parameters using the Metrics package version 0.1.4 in R (Hamner and Frasco, 2018), we also calculated the root-mean-square error (RMSE) to estimate the total error (same units as the parameter) of the drone-based measurements relative to the field observations (Liancourt et al., 2020; Zhang et al., 2021). Additionally, because the data range is relatively large (i.e., representative of the rangeland system) we also present the normalized (relative) RMSE (nRMSE) based on the maximum and minimum values. This represents the error of the drone-based estimates relative to the magnitude of the field observations (Zhang et al., 2021). We also show the deviation from a 1:1 relationship to represent the difference in measurements of the rangeland condition indicators between the drone and field methods (Barnas et al., 2019; Liancourt et al., 2020).

Lastly, to determine if the field measurements and the estimations derived from the drone imagery were significantly similar, we first tested if potential forage biomass and RFA cover followed a normal distribution using a Shapiro-Wilk test (see also Breckenridge et al., 2011; Laliberte et al., 2010; Navarro et al., 2020). Based on this finding we then applied a Wilcoxon Rank test (Wilcoxon, 1946) rejecting the null hypothesis at alpha level of <0.05 to compare the median estimates of potential forage biomass and RFAs cover derived from the drone imagery to those observed in the field.

3. Results

3.1. Evaluation of the drone-based potential forage biomass indicator

The relationship between four vegetation indices (Table 1) calculated from the drone spectral maps and dry potential forage biomass revealed the highest agreement with the OSAVI ($R^2 = 0.89$, RMSE = 192.05). Therefore, to predict potential forage biomass the OSAVI was used (dry forage biomass (kg/ ha) = 2080.45 * mean OSAVI value +8.95). The resulting coefficient of determination from the linear model between potential forage biomass predicted from the mean OSAVI values and that estimated in the field gave a significant positive relationship ($F = 138.7$, $R^2 = 0.80$, $P \leq 0.001$) and a RMSE of 194.14 (Fig. 5). Based on the non-significant Wilcoxon Rank-sum test ($W = 655$, df = 35, p-value = 0.941), the predicted and observed potential forage biomass was also statistically similar.

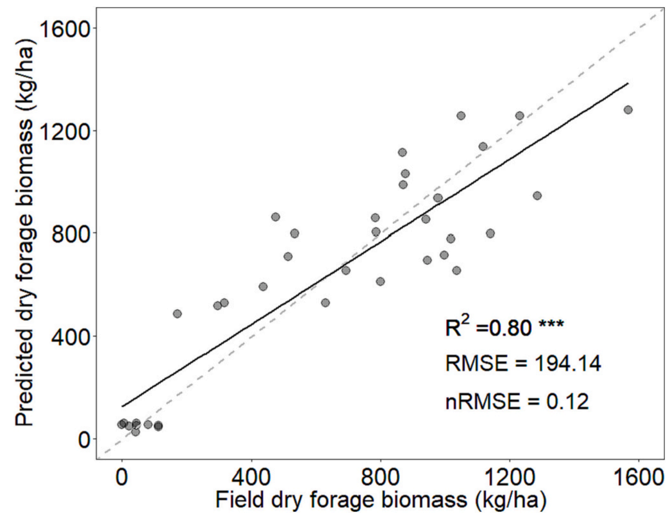

Fig. 5. Scatter plot and linear regression shows the comparison between potential forage biomass observed in the field and that predicted from the drone imagery (n = 36). Continuous black line = linear regression, while the grey dashed line = 1:1 agreement and the asterisks show the significance with a p-value <0.001.

3.2. Evaluation of the drone-based rangeland functional attributes indicator

3.2.1. Classification accuracy of the RFAs

The OSAVI and the CHM were identified as sufficient for classifying the RFAs across the rangeland system, with the threshold of 0.2504 OSAVI value for separating the bare ground from the vegetation and the threshold height of 0.277 m for distinguishing the woody plants from the herbaceous plants (Fig. 6). The supervised classification using a decision tree based on these thresholds produced a high mean overall accuracy of 95.8% and a mean kappa coefficient of 0.94 (Table 2). The producer's and user's accuracies were over 94% and over 90% respectively for all the three RFAs (Table 2). The bare RFA had no misclassifications, while only minor misclassifications were found for the herbaceous and woody RFAs (Table 2). Based on the error matrix, 4.5% and 6.0% of herbaceous cover type were wrongly classified as bare and woody respectively. While 2.3% of the woody cover type was wrongly classified as herbaceous.

3.2.2. Comparison of drone-estimated and field observed RFAs cover

High agreements and very low deviations of the drone-based estimates to the field observations were found for all the RFA cover types regardless of the image-truthing method used (Fig. 7, Table 3). The coefficients of determination between the drone-based and field estimates using the LPI method for bare ground, herbaceous plants, and woody plants show a significant positive linear relationship, with the adjusted R^2 ranging from 0.86 to 0.97 (Fig. 7). This significant positive linear relationship was also found between the drone-estimated and visually estimated RFAs cover, ranging from $R^2 = 0.88–0.93$ (Fig. 7). Overall, the RMSE for the RFA types were relatively low, with this error being largest for the woody cover type (RMSE = 4.86%) when using the LPI and largest for the herbaceous cover (RMSE = 5.60%) when using the visual estimation approach. The nRMSEs were also relatively low across all the parameters, with the largest relative error found for bare ground cover (nRMSE = 0.13) when using the LPI technique and when using visual estimation this error was largest for woody cover (nRMSE = 0.11), both of which had the lowest R^2 of 0.86 and 0.88 respectively.

The Wilcoxon Rank-sum test corroborates the above agreements as it revealed no statistical differences ($p > 0.05$) between the cover medians of all the RFAs obtained from the drone imagery and from the two image-truthing methods (Table 3).

Table 1
Prediction accuracy of linear models between four vegetation indices and dry potential forage biomass (kg/ ha) determined using K-fold cross validation (k = 10).

Vegetation index	Adjusted R^2	RMSE (kg/ ha)
Normalized difference vegetation index (NDVI)	0.64	267.64
Generalized difference vegetation index (GDVI)	0.69	264.96
Optimized soil adjusted vegetation index (OSAVI)	0.89	192.05
Transformed normalized difference vegetation index (TNDVI)	0.81	326.24

3.2.3. Time spent for the drone-based and field estimation RFAs cover

We tracked the total time spent for data collection, data processing and data extraction to obtain the RFAs cover from the drone imagery (128 h in total) and using the two image-truthing methods, the LPI (144 h in total) and visual estimations (50 h in total) (Fig. 8). For collecting the data, the drone method which required two persons and covered about 66 ha was more rapid (12h) than the visual estimation (32h) and the LPI methods (96 h), that both covered only about 0.4 ha. The visual estimations were done by one person, while the time consuming LPI technique required twice as much manpower than the drone method. The processing time was also faster for the drone data which was mainly automated (i.e., hands-off) compared to both the field methods. In contrast, the drone method required more time (104 h) to extract the RFAs cover than the field methods (20 h for the LPI and 2 h for visual estimations). The extraction of the RFAs cover from the drone imagery included identifying a suitable vegetation index, creating the image stacks, collecting training and validation data sets, producing the classification maps, and obtaining the RFAs cover (Fig. 9d).

4. Discussion

Overall, our results from a typical dryland system demonstrate the applicability of drone-based assessment of rangeland condition. We show that our relatively simple and robust drone-based protocol accurately and efficiently maps the two common indicators of rangeland condition. Consistent with our expectations, potential forage biomass

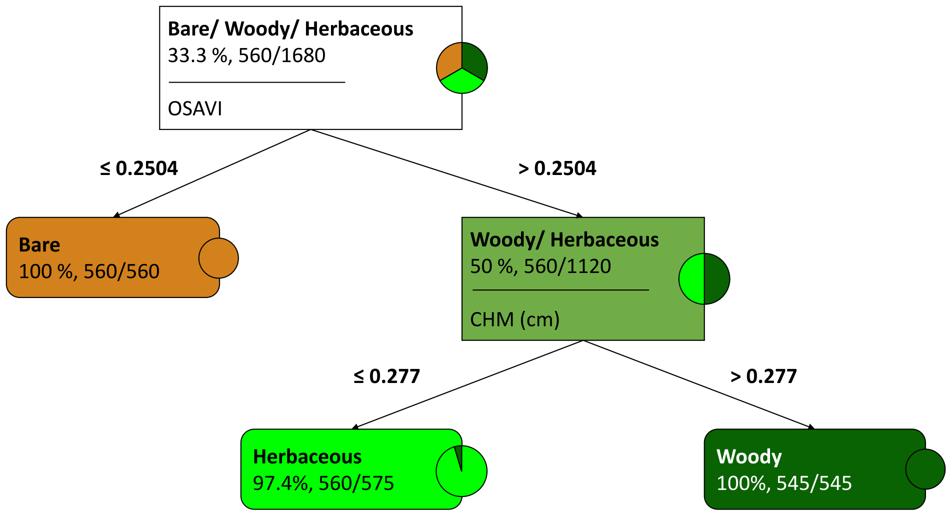

Fig. 6. The classification model showing OSAVI and CHM layers and their computed threshold values suitable for separating the three RFAs across the rangeland system.

Table 2
Error matrix of the RFAs classification from the four transects. The accuracies and kappa coefficient presented are the means derived from the four transects.

	Reference data				
Classification data	Bare	Herbaceous	Woody	Total	Users Accuracy (%)
Bare	764	–	–	764	100.0
Herbaceous	36	782	48	866	90.3
Woody	–	18	752	770	97.7
Total	800	800	800	2400	Overall Accuracy (%)
Producers Accuracy (%)	0.96	0.98	0.94		95.8
Kappa coefficient	0.94				

and the cover of the main rangeland functional attributes were quantified with high accuracies from the drone multispectral imagery. These results are comparable to or better than similar validation studies done in other ecosystems, with R^2 ranging from 0.65 to 0.92 for herbaceous biomass (Navarro et al., 2020; Théau et al., 2021) and 0.81–0.99 for land cover (Cunliffe et al., 2016; Gillan et al., 2019; Laliberte et al., 2010; Zhang et al., 2021). However, we have not come across any study that validated drone-based estimates of rangeland parameters in a dryland savannah.

4.1. Potential forage biomass indicator

Potential forage biomass was well predicted from the drone imagery with significant agreements between the four tested vegetation indices and field dry potential forage biomass (Table 1). The OSAVI had the highest prediction accuracy of the four tested vegetation indices. This is consistent with other studies (Baghi and Oldeland, 2019; Fern et al., 2018; Pourhadi et al., 2012) that also found that OSAVI was the most appropriate vegetation index for estimating plant biomass in dryland systems. Because the distribution of potential forage biomass in arid rangelands is patchy (Fern et al., 2018), it is crucial to ensure that the model is spatially robust to predict potential forage biomass across the landscape (DiMaggio et al., 2020). Thus, our model is based on data that is representative of different range conditions (i.e., very low to none in highly degraded sites to the expected potential biomass in healthy rangelands). We obtained a better model fit ($R^2 = 0.80$) than a similar model ($R^2 = 0.66$ in (Théau et al., 2021)) that was also developed using highly variable data (i.e., from low biomass to the expected biomass) acquired from a single site but from the early to late growing season. Our more accurate model makes it highly relevant for timely grazing management, especially to identify sites with very little or no herbaceous plants, particularly due to overgrazing (i.e., near water points or like in most communal sites that are highly degraded). It also allows for accurate predictions of higher potential biomass expected at the peak of the growing season or in healthier rangelands (i.e., further away from water points or in most freehold farms). This makes it applicable for characterizing potential forage availability across the rangeland sites, providing land users with timely information for pro-active management like adjusting livestock numbers. The model is however limited to the growing season, and so it would be necessary to test its suitability for predicting potential forage biomass when the herbaceous layer becomes senescent (i.e., at the end of the growing season and during the dry season) to determine the grazing capacity of the range until the next growing season.

4.2. Classification accuracy of the RFAs

Our supervised classification using thresholds of the CHM and OSAVI to obtain the cover of the three RFAs yielded high accuracies. The RFAs that we chose to estimate are those commonly assessed from remotely sensed data as important indicators of rangeland condition (Laliberte et al., 2010; Théau et al., 2021). Based on the error matrix the three RFAs were well classified across the rangeland system, with the overall accuracy and kappa coefficient obtained being better than previous drone-based land cover classification results (Barnas et al., 2019; Laliberte et al., 2010). The bare cover class showed no misclassifications, but it contained some pixels belonging to the herbaceous RFA. This is likely because herbaceous plants particularly the short-lived annual plants that are going into senescence may fall below the determined OSAVI threshold, thereby being classified as bare ground. But the former is more relevant, as more accurate quantification of bare ground allows for optimizing the management of rangelands (Gillan et al., 2020). This is because bare ground cover is deemed as one of the most reliable indicators of land degradation (Booth and Tueller, 2003). For example, it provides a good measure of soil stability (i.e., susceptibility to water and wind erosion), grazing pressure, management practices and environmental conditions, all of which affect rangeland condition (Bestelmeyer et al., 2015; Breckenridge et al., 2011). In terms of vegetation cover, there were only negligible confusions between the herbaceous plants and woody plants. These are expected due to the overlap in the characteristics of the herbaceous and woody plants (see also (Barnas et al.,

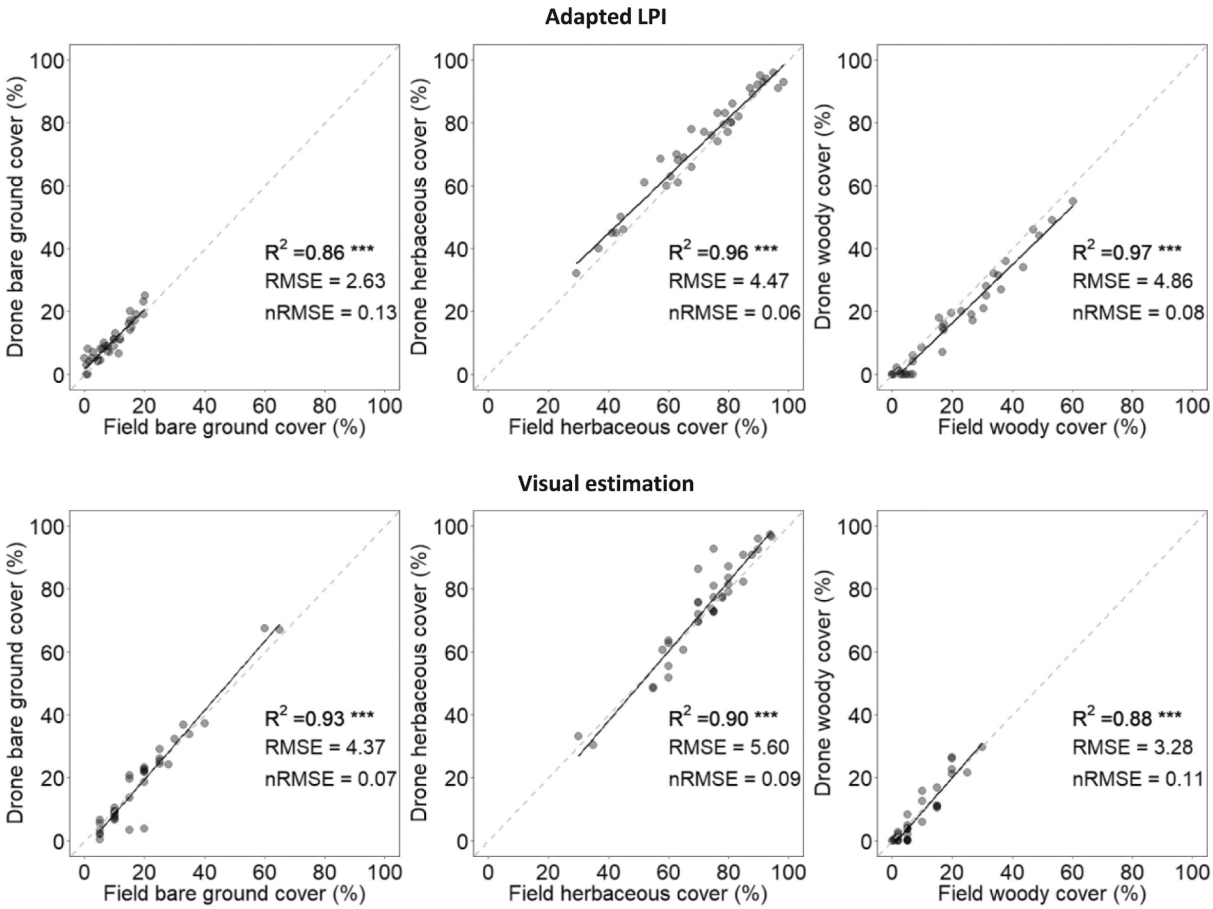

Fig. 7. Relationship between drone-based estimates and field observations for RFAs percent cover. Validation using (a) the LPI technique and (b) the visual estimation method where each point represents the plot mean ($n = 36$). Continuous black lines = linear regression, while the grey dashed lines = 1:1 agreement and the asterisks show the level of significance with a p-value <0.001.

Table 3
Median cover of the RFAs as estimated from the drone classification maps and observed in the field, the deviation of the medians between the methods and the significance from the Wilcoxon Rank-sum test.

RFA type	Median cover (%)		Deviation from median	Wilcoxon test p-value	Median cover (%)		Deviation from median	Wilcoxon test p-value
	Field LPI	Drone LPI			Field VE	Drone map		
Bare	8.09	9.00	0.91	$p = 0.454$	17.50	19.08	1.58	$p = 0.648$
Herbaceous	75.49	77.0	1.51	$p = 0.562$	75.00	75.65	0.65	$p = 0.488$
Woody	16.91	15.50	−1.41	$p = 0.252$	5.00	3.64	−1.36	$p = 0.188$

2019) depending on their respective growth stages. For example, woody seedlings and small shrubs may have similar heights and OSAVI values as the herbaceous plants. This may result in underestimating the recruitment of woody plants, a significant problem given the concern of bush encroachment in this region (De Klerk, 2004) and other dryland systems (Roques et al., 2001). To improve their separation, segmentation may be integrated as a pre-processing step before classification as it relies on other traits such as texture and shape to distinguish features (Wegmann et al., 2016) as demonstrated in other studies (Gillan et al., 2020; Laliberte et al., 2010). Nonetheless, the high accuracies achieved here are based on a classification approach that is relatively simple, robust, and transferable across the landscape, as it did not require site-specific manipulation of the determined thresholds as done in a previous study (Laliberte et al., 2010).

4.3. RFAs cover indicator

We showed how efficient drone technology is for mapping the RFAs cover by tracking and comparing the time required to obtain the estimates from the imagery against the in-situ measurements. The total time spent relative to the area covered and the required manpower was less for the drone method than the LPI and visual estimation approaches. The main benefits of drone mapping over field observations that previous studies also highlighted (Barnas et al., 2019; Laliberte et al., 2010; Navarro et al., 2020) include the ability to cover larger spatial areas in significantly less time, with only two persons required. The expertise needed for the drone-based and field approaches vary for the different stages of determining the RFAs cover. Even though all the methods require considerable training, for the data collection and data processing, the drone method is largely automated and therefore easier to conduct and repeat than the field methods. But the interpretation and the extraction of the RFAs cover requires advanced expertise for the

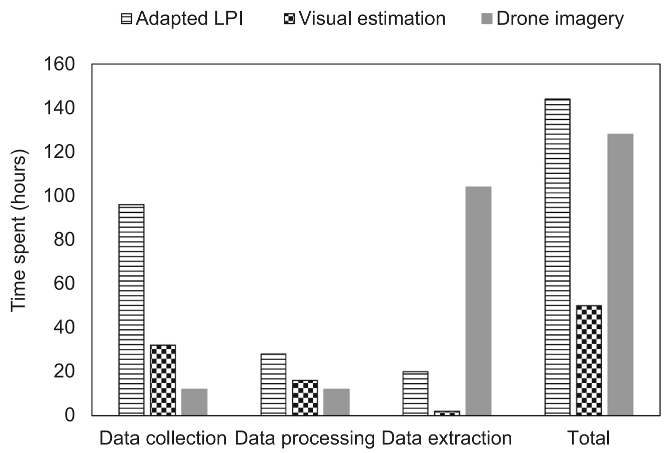

Fig. 8. Time spent (hours) for the different tasks to determine the RFAs cover indicator by the two image-truthing methods (LPI and visual estimation) and from the drone imagery.

drone data than the field data.

The time spent for the field methods decreased from data collection to data extraction, while it increased in the same direction for the drone method. Thus, the time saved to acquire the drone data comes at the cost of spending time later during the data extraction from the imagery (Barnas et al., 2019; Laliberte et al., 2010). For example, in this study a significant amount of time was spent testing different classifiers to identify a robust classification approach that is transferable across the rangeland system. But once this was done, producing the classification maps for the entire transects was relatively fast. For monitoring the parameters presented here, when considering the reliability of the data (i.e., bias), repeatability (i.e., frequency of data acquisition), and the spatial extent covered, the drone method seems more appropriate for researchers and land users.

The two image-truthing methods used to validate drone estimates of RFAs cover produced similar strong agreements with very little bias. These close agreements are to be expected, especially from high-resolution imagery as found in other validation studies (Gillan et al., 2020; Laliberte et al., 2010; Zhang et al., 2021). In dynamic systems like arid savannahs, the timing of data collection during the growing season and the time between the acquisitions of drone imagery and the field observations are critical when evaluating the performance of drone technology. For example, the high model fits are directly linked to how well the RFAs were classified (Gillan et al., 2020), which indicates that the phenological stage of the vegetation (i.e., the period of data collection) was suitable for distinguishing the rangeland features. Secondly, collecting the field data immediately after the drone flights minimized the influence of expected disturbances from grazing or climatic conditions (i.e., influences of rainfall and/or wind) that may affect the field cover estimates, and therefore the comparisons derived.

Though the field methods showed no significant deviations from the drone estimates, the herbaceous and woody cover were better related with the LPI approach, while bare ground cover was better related with the visual estimation method. These differences may be due to the inherent mechanical differences associated with field (i.e., pin drop method and subjective visual estimates) and imagery (i.e., post

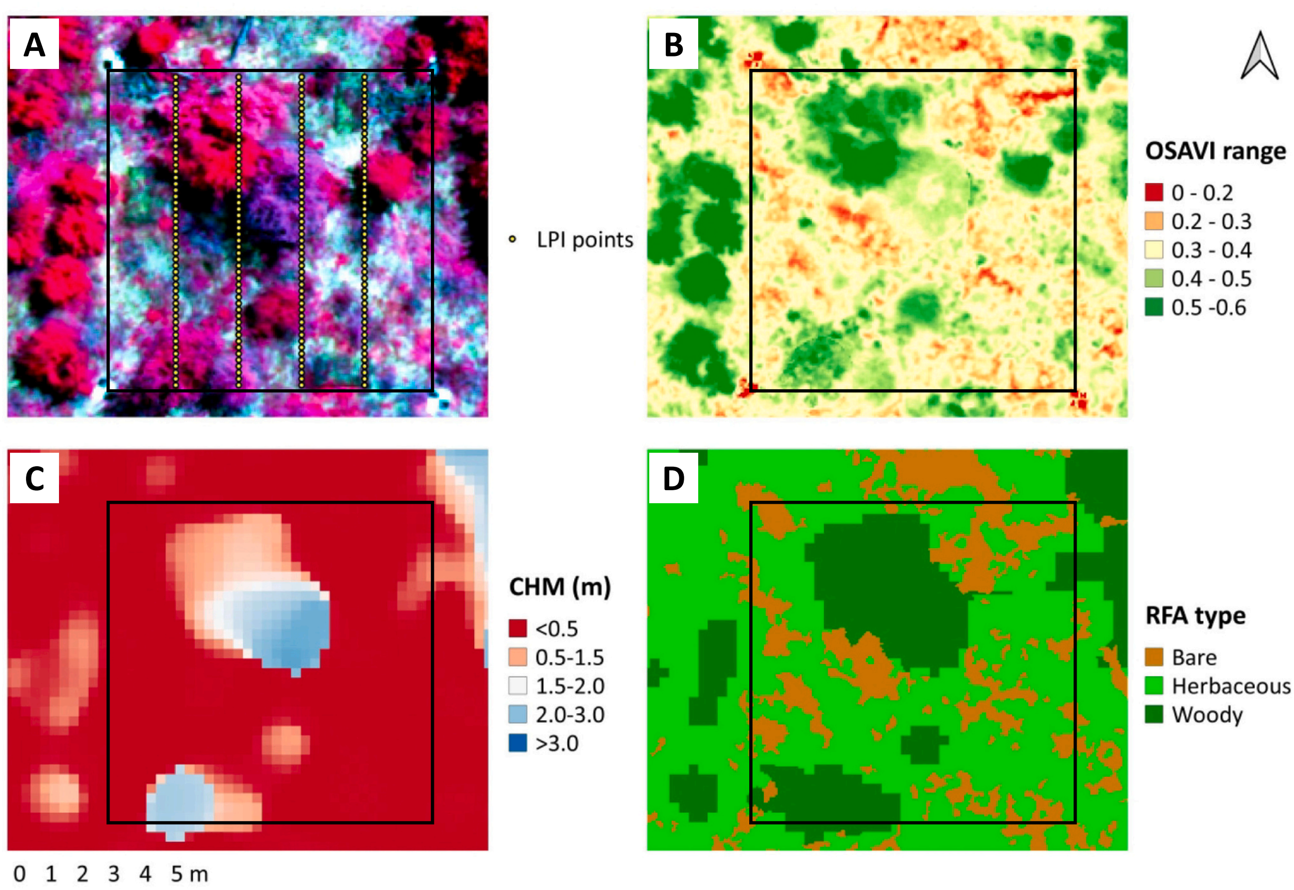

Fig. 9. Example subset from one of the observation plots showing drone data products used to extract the RFAs cover: (a) false color image composite (NIR, R and G bands) overlaid with the virtual LPI; (b) the optimized soil adjusted vegetation index map; (c) the canopy height model and (d) classification map of the three RFAs.

classification technique) methods (Gillan et al., 2020). But, employing the same approach used in the field to extract the RFAs cover from the drone imagery minimized the differences (Zhang et al., 2021). For example, although (Laliberte et al., 2010) and (Gillan et al., 2020) found very good correlations between the cover estimations from the LPI method which does not cover the entire plot and total cover derived from the classified maps in their study sites, this approach yielded much lower agreements in our study during initial data analysis exploration. Using these agreements may incorrectly reflect that drone technology is less accurate for estimating land cover in dryland savannahs. And so instead we suggest that validation studies replicate the ground-based approach on the imagery (i.e., virtual LPI on the imagery) to obtain more accurate evaluations, especially in heterogeneous landscapes as it was done in this study and by (Barnas et al., 2019) and (Zhang et al., 2021). Overall, our results corroborate the efficient and reliable assessment of land cover from drone imagery, especially because it covers larger areas in a shorter field time than ground-based approaches (Anderson and Gaston, 2013; Gillan et al., 2019; Laliberte et al., 2010).

4.4. Applicability of the drone-based rangeland monitoring workflow

The costs of drone technology are rapidly decreasing while their applicability and capacity for monitoring and research are constantly improving. Artificial intelligence and machine learning approaches are also improving imagery analysis, and this will make drone technology even more cost-effective. Therefore, the development of drone-based workflows that are efficient, repeatable, and validated with field data will ensure that they are easily adopted (Gillan et al., 2020; Sankey et al., 2019) The results achieved in this study are based on a workflow (Fig. 4) that is relatively simple and efficient for mapping the condition of rangelands in such dry savannahs.

Ensuring drone-based measurements are reflective of the ecosystem parameters of interest requires certain considerations. The main procedures are determining the timing of data collection (i.e., optimal period in the growing season), collecting samples that are representative of the expected range conditions, acquiring high quality imagery (i.e. flying within solar noon and ensuring sufficient overlap), conducting the field observations within a few days of drone data acquisition, and ensuring that observational plots can be identified in the imagery (for example using ground markers) to directly relate the estimates derived. The current limitations and advances of drone technology also need to be considered to efficiently integrate their use into the existing monitoring approaches.

For the potential forage biomass indicator, it may be necessary to identify a suitable vegetation index for the biomass prediction model, which requires destructive harvesting of plant material. While, for the land cover indicator, we showed that the validation techniques with the aid of the orthomosaics, visual estimations and the LPI method yielded equally high accuracies. Therefore, relying only on the drone imagery to quantify land cover may be sufficient, as this will save a significant amount of time spent in the field. To classify land cover in heterogeneous landscapes and for a range of conditions we suggest the use of a data mining approach to determine optimal classification thresholds for the study system. For this the spectral information alone may be insufficient and thus would require the inclusion of additional data products like the CHM and a suitable vegetation index. To obtain finer rangeland information such as further distinguishing the herbaceous layer into annuals and perennials may require integrating a temporal aspect or the use of airborne hyperspectral sensors (Knox et al., 2013). The latter is, however, costly and requires a considerable processing effort, making it potentially less suitable for rangeland managers.

Overall, our workflow is reproducible and so we encourage future drone-based studies to adopt it (and adapt it) to aid standardized sampling and spatio-temporal comparisons in other similar study systems. Drone technology may even replace some of the strenuous field measurements like determining land cover (Laliberte et al., 2010). Additionally, the spatially explicit data provided by UAVs (Sankey et al., 2019) may serve as training input for upscaling the estimated ecosystem parameters to satellite observations for improved rangeland monitoring at larger spatial scales. This has been demonstrated in Australian rangelands (Barnetson et al., 2021) and other domains like vineyards (Matese et al., 2017), crop fields (Li et al., 2022), forests (Puliti et al., 2018), and Mangroves (Navarro et al., 2019). Particularly access to full archives of pre-processed Landsat- and Sentinel-2 data along with recent advances in machine learning techniques might be the key to deploying such multi-scale applications across large areas. The developed models can continue to be used in future studies to determine the potential grazing capacity and monitor cover changes of bare ground, herbaceous and woody plants to detect potential ecosystem state shifts. Thus, it is vital to test the transferability of these models to characterize the condition of other similar rangeland systems.

5. Conclusions

Our study provides compelling evidence based on a simple but robust workflow for the use and suitability of drone technology to evaluate key indicators of rangeland condition in dryland savannahs. Both potential forage biomass and RFAs cover were predicted with a high level of confidence from the drone imagery across a rangeland system with varying conditions. Using field observations to validate the estimates obtained from the drone imagery, we achieved high accuracies and low error rates in the same range or even better than similar studies done in other ecosystems. This offers an opportunity for unbiased, repeatable, and cost-effective mapping at higher spatial and temporal resolutions in near-real time at a landscape level where management decisions of rangeland resources are made. Therefore, the workflow presented here provides the possibility for drone technology to be embedded within the larger context of ecological data collection and rangeland monitoring. This would provide complementary information at an intermediate scale between satellite and field observations. Additionally, because drone imagery offers data in a continuous way, it provides an ideal opportunity to study directional properties of ecosystems such as the classical space-for-time analysis (i.e., studying grazing-induced degradation along continuous gradients) to advance ecological research. The developed drone-based prediction models could be valuable for climate-adapted rangeland management, especially because unwanted transitions are becoming more frequent in dryland systems due to changing climatic conditions and intensifying land use.

CRediT authorship contribution statement

Vistorina Amputu: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Nichola Knox:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Andreas Braun:** Data curation, Writing – review & editing. **Sara Heshmati:** Data curation, Writing – review & editing. **Rebecca Retzlaff:** Data curation, Writing – review & editing. **Achim Röder:** Data curation, Writing – review & editing. **Katja Tielbörger:** Conceptualization, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare no conflict of interest.

Data availability

The research data used for the analysis to obtain the presented results will be made available upon request from the authors.

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Chapter II

Spatio-temporal transferability of drone-based models to predict forage supply in drier rangelands

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Article

Spatio-Temporal Transferability of Drone-Based Models to Predict Forage Supply in Drier Rangelands

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Abstract: Unmanned aerial systems offer a cost-effective and reproducible method for monitoring natural resources in expansive areas. But the transferability of developed models, which are often based on single snapshots, is rarely tested. This is particularly relevant in rangelands where forage resources are inherently patchy in space and time, which may limit model transfer. Here, we investigated the accuracy of drone-based models in estimating key proxies of forage provision across two land tenure systems and between two periods of the growing season in semi-arid rangelands. We tested case-specific models and a landscape model, with the expectation that the landscape model performs better than the case-specific models as it captures the highest variability expected in the rangeland system. The landscape model did achieve the lowest error when predicting herbaceous biomass and predicted land cover with better or similar accuracy to the case-specific models. This reinforces the importance of incorporating the widest variation of conditions in predictive models. This study contributes to understanding model transferability in drier rangeland systems characterized by spatial and temporal heterogeneity. By advancing the integration of drone technology for accurate monitoring of such dynamic ecosystems, this research contributes to sustainable rangeland management practices.

Keywords: model generality; phenological differences; rangeland monitoring; spatial variation; unmanned aerial system (UAS); validation

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1. Introduction

Remote sensing using unmanned aerial systems (UASs) (hereafter, drone technology) has become a valuable tool for effectively monitoring rangelands [1]. It provides reliable and timely estimates of key forage resources such as aboveground biomass [2–4] and vegetation cover [5,6]. However, calibrating drone-based models with field measurements, required for model fitting to ensure unbiased predictions, is often costly and time-consuming [5,7]. Rather, it would be desirable to know whether drone-based models calibrated with field data collected in a particular area, and at a certain time point (hereafter, also referred to as a scene), can be transferred to other areas or points in time [8]. Therefore, to maintain the mapping efficiency of drone technology for rangeland monitoring [1], and to save time and resources, especially, for case-specific ground-truthing, the need to evaluate the generality or transferability of developed predictive models is clear.

Transferability refers to the ability of models to effectively predict parameters of interest in locations or time periods beyond those in which they have been built (i.e., trained) [9,10]. This is essential in model development, parameterization, and application, as it determines the extent to which predictions made can be generalized and applied to different contexts. While the concept of generality is commonly investigated for ecological models [8,9,11], its relevance should also be recognized in the context of models developed from remote sensing data. Despite the increasing popularity of drone technology for rangeland applications over the past two decades [1,7,12,13], testing the transferability of derived models remains underexplored. Conducting such assessments holds immense potential for optimizing landscape-scale monitoring and, thus, minimizing the degradation of these valuable resources [14–16]. Namely, accurate and efficient prediction of forage resources is vital for adaptive rangeland management to maintain essential ecosystem services like forage supply [17].

Understanding the extent to which drone-based models can be transferred in rangeland systems will provide insights into their generality and identify potential limitations [8]. Rangeland systems, especially those in arid regions, present unique challenges that can limit the accuracy and reliability of model predictions [9] because of their inherent spatial heterogeneity [18]. This heterogeneity arises from a combination of factors, largely differences in climatic conditions (i.e., patchy rainfall), different soil types, and grazing management practices (i.e., continuous vs. rotational grazing) that result in uneven forage distribution within and across rangelands [19,20]. Therefore, although one of the main advantages of drone technology is its ability to provide high-resolution spatial-temporal data [21,22], the transferability of its models in such systems may be limited even at local scales.

Studies assessing the prediction accuracy of drone-based models beyond the calibration scenes conducted in different systems found varying results. For instance, [23] achieved similar prediction accuracy for shrubs in sagebrush steppe across different elevations but found inconsistencies in the prediction of grasses and bare ground. [24] showed how spatial heterogeneity due to diverse forest structures results in substantial differences between drone data and field measurements (more than 50%) when models were transferred to test sites for predicting forest attributes like stem volume. However, in agricultural systems, the transferability of drone-based models appears to be less affected, possibly due to their typically homogeneous setup [25]. Considering that forage resources in arid rangelands are generally patchy, dynamic throughout the growing season, and strongly influenced by grazing management [26], it is crucial to recognize that the developed models may have limitations when applied in different areas or phenological periods [9].

An alternative to testing case-specific models is to develop drone-based models with a wide range of variability, as this approach may enhance transferability. Multi-temporal models created using data collected at various times of the growing season or over several years have demonstrated sufficient accuracies in predicting forage resources across diverse systems, including arid rangelands [27], temperate grasslands [4], and floodplain vegetation [28], and in precision agricultural [29,30]. However, models that combine both multi-temporal and spatially variable information (i.e., data collected at different times from sites with different conditions) that may be more robust and generalizable in dynamic systems should also be assessed. This has been explored in temperate grasslands, yielding highly accurate results in predicting plant species composition [31]. But to our knowledge, the generalizability of models encompassing the spatial and temporal variations of rangeland resources in drylands, where livestock grazing and wildlife conservation are very important economic factors [14], has not been evaluated.

In this study, we test the accuracy of transferring four separate drone-based models in predicting forage supply in semi-arid rangelands. The tested models included three that are case-specific, (1) spatial models between two land tenure systems, (2) temporal models between two time periods in the growing season, (3) spatio-temporal models that examine the cross transfer between land tenure systems and time of the growing season, and (4) a landscape (comprehensive) model that is built with a subset of the data from all scenes. Specifically, we evaluate the transferability of the models to predict herbaceous biomass and the cover of the three main rangeland functional attributes (i.e., herbaceous cover, woody cover, and bare ground cover). Considering the spatial variations resulting from management practices and phenological differences, we hypothesized that the spatio-temporal models would have the lowest transferability, while the remaining models would provide the most reliable predictions of the forage provision indicators. Overall, we expected the highest transferability to be achieved by the landscape model, which encompasses the full range of variability present in the rangeland system.

2. Materials and Methods

2.1. Study Area

We used the semi-arid rangelands in the Greater Waterberg Landscape Conservation Area that spans an area of 19,200 km^2 [32] in central Namibia (Figure 1) as a case study of spatially and temporally heterogeneous dryland systems. The region experiences a typical dryland climate, with the average annual rainfall ranging from 350 to 400 mm and mean maximum temperatures ranging from 30 to 34 °C in the hot season (October–March); mean minimum temperatures range from 4 to 6 °C during the cold season (June–August) [33]. These climatic conditions influence the growth and productivity of vegetation, directly impacting forage availability.

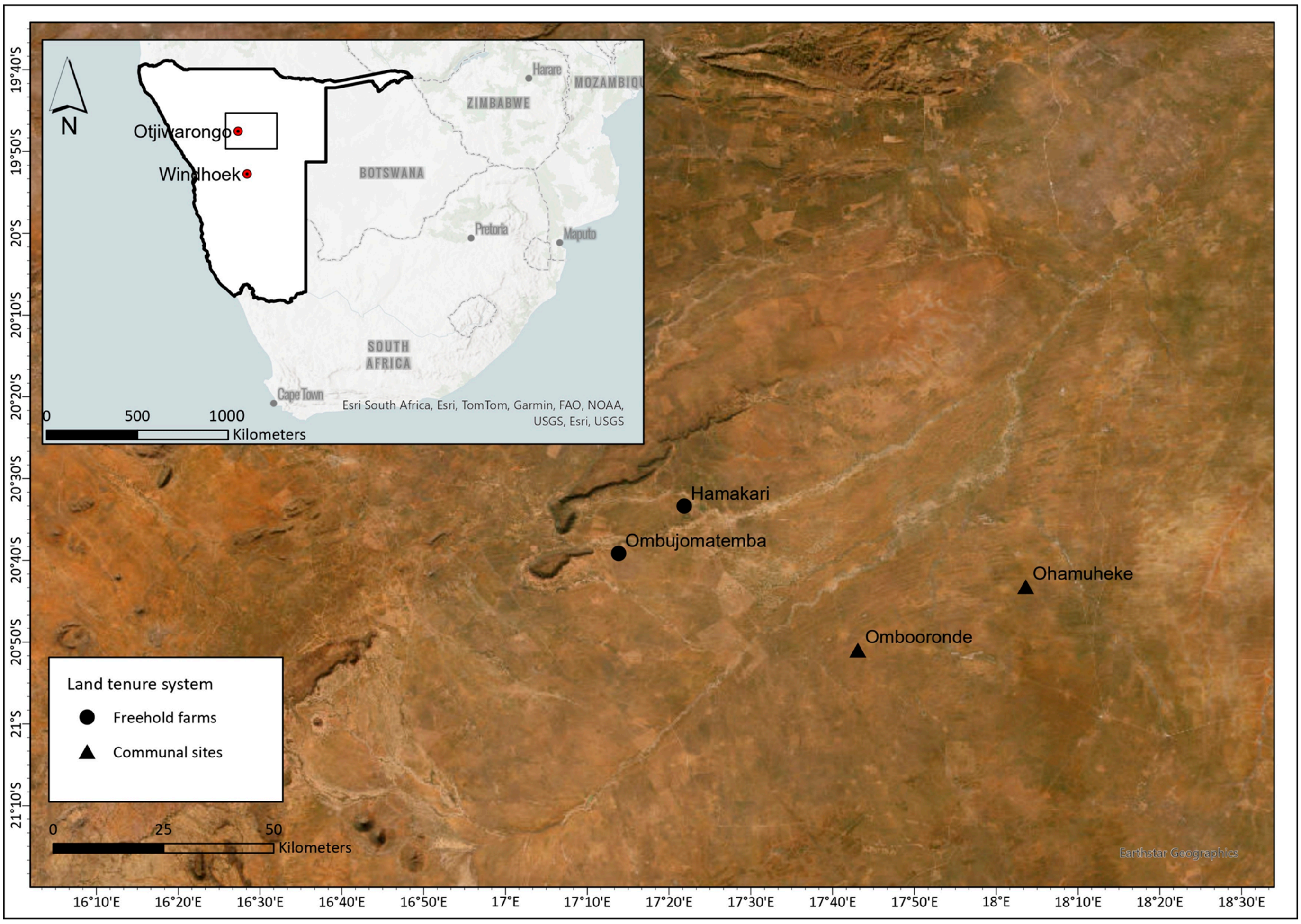

Figure 1. Location of the study area in central Namibia, with the freehold farms and communal areas where data were collected.

Forage production in the area is strongly dependent on rainfall, which typically occurs between December and May [32]. However, the rainfall patterns exhibit high intra- and interannual variability [33]. This natural variability is further exacerbated by the effects of climate change, with more frequent and intense drought events that further constrain forage production and availability. The study area is characterized by vegetation typical of the central Kalahari and thornbush shrubland, which grows on sandy soils (classified as ferralic arenosols). These soils are highly drained and as a result, nutrient-poor [33,34]. The dominant woody plants are *Senegalia mellifera* (Vahl.) and *Terminalia sericea* (Burch.), while the herbaceous layer consists mainly of annual grasses like *Urochloa brachyura* (Hack.), *Pogornathria fleckii* (Hack.), and *Melinis repens* subsp. *grandiflora* (Hochts.), as well as forbs like *Ipomoea chloroneura* (Hallier f.), *Acanthosicyos naudinianus* (Sond.), and *Tephrosia burchellii* (Burtt.) as the once common perennial grasses like *Stipagrostis uniplumis* (Licht.) and *Melinis repens* subsp. *repens* (Willd.) are diminishing due to overgrazing (plant species data provided from a parallel study by Chambara et al., unpublished).

The landscape is primarily utilized for livestock production in two different land tenure systems (Figure 1). On the one hand, there are privately owned freehold farms (FF), which are fenced off and divided into multiple camps to facilitate rotational grazing. In contrast are open communal areas (CA), which are comparatively more degraded as multiple households graze their livestock throughout the year [35].

2.2. Data Collection

We collected field data in 2021 at two key periods of the growing season in the two land tenure systems (Table 1). Our goal was to capture the temporal aspect of forage supply dynamics and to ensure that it was representative of the spatial distribution of forage in this rangeland system. In each of the four sites (two within each land tenure system), we established a line transect, along which nine 10 m × 10 m plots were demarcated with increasing distances from a permanent artificial waterpoint. The line transects were 1500 m long in the freehold farms and 1000 m longer in the communal areas. This difference is because rangeland conditions only improve much further away from the artificial waterpoints in this land tenure system. With this setup, we aimed to capture the spatial variability of forage distribution resulting from different grazing management strategies and varying grazing pressures. The transects were surveyed during the early growing season (ES), which is generally from January to early March (Figure 2a) and revisited during the peak growing season (PS) (Figure 2b), typically occurring between late March and April [33]. This enabled us to comprehensively capture the temporal dynamics of forage production throughout the growing season.

Table 1. Dates of the drone imagery acquisition and field data collection in the two land tenure systems across the two periods of the growing season.

Land Tenure System	Transect	Dates of Drone Mapping	Dates of Field Data Collection
Early season (ES)			
Communal area (CA)	CA-ES-1	16 February 21	16–17 February 2021
Communal area (CA)	CA-ES-2	8 March 21	8–9 March 2021
Freehold farm (FF)	FF-ES-1	23 February 21	23–25 February 2021
Freehold farm (FF)	FF-ES-2	24 February 21	26–27 February 2021
Peak season (PS)			
Communal area (CA)	CA-PS-1	27 March 21	27–29 March 2021
Communal area (CA)	CA-PS-2	6 April 21	6–8 April 2021
Freehold farm (FF)	FF-PS-1	23 March 21	23–24 March 2021
Freehold farm (FF)	FF-PS-2	19 April 21	19–20 April 2021

We used a Micasense RedEdge-MX sensor mounted on a DJI Matrice 200v2 quadcopter to acquire multispectral imagery along the transects. The sensor simultaneously captured spectral reflectance at a 90° angle (nadir orientation) in the blue (475 nm), green (560 nm), red (668 nm), red-edge (717 nm), and near-infrared (840 nm) regions [36]. The imagery was captured using the Pix4DCapture (version 4.13.1, Pix4D SA, Prilly, Switzerland)mission planning application with a front and side overlap of 80%, which is considered sufficient for processing multispectral imagery [37]. The grid dimensions of the flight plans were 50 m wide by the length of the transects, resulting in a total of 3315 images per transect in the freehold farms and 5425 images per transect in the communal areas. The reflectance was radiometrically corrected with the aid of an integrated light sensor and a calibrated panel that was captured before and after each flight. The quadcopter was flown at 80 m above the ground to provide data with a ground sampling distance of 5.6 cm/pixel, a suitable resolution for estimating the sparsely distributed and relatively small-sized herbaceous plants in the study system [7,31]. Ground control point (GCP) targets were placed in each of the four corners of all plots during drone flights for later identification to directly overlay the drone and field information. However, these could not be used for georeferencing because of the lack of a Global Navigation Satellite System (GNSS) receiver or a total station to measure their positions. All flights were carried out within 2 h of local solar noon to minimize shadowing effects.

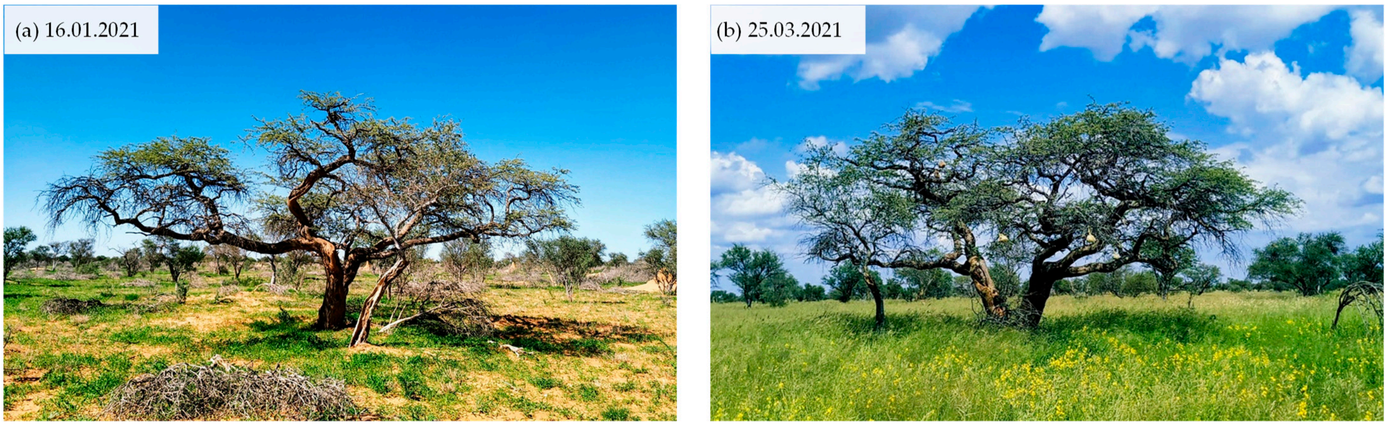

Figure 2. Examples of the vegetation condition during the (**a**) early season (mid-February) and (**b**) the peak season (late March).

After conducting the drone flights, we collected field data from the nine plots along the transects (Table 1) with the perspective of the drone (i.e., considering only the top of the canopy). Within each plot (100 m^2), we estimated the percentage cover of herbaceous plants, woody plants, and bare ground, hereafter collectively termed rangeland functional attributes (RFA) as described in [7]. Additionally, we harvested herbaceous biomass in 1 m $\times$ 5 m subplots adjacent to 100 m^2. The locations of the plots were marked with a GPS and physically with metal rods at each corner to facilitate revisiting them during the peak season. These data served as the ground-truth information to provide a reliable reference for the predicted estimates derived from the drone imagery. A detailed account of the data acquisition can be found in [7].

2.3. Data Processing to Develop the Transferability Assessment Workflow

The raw imagery for all the transects was pre-processed in Pix4DMapper (version 4.6.4, Pix4D SA, Prilly, Switzerland). The resulting drone data products for each transect were a calibrated reflectance map for each of the five spectral bands, a digital terrain model (DTM), and a digital surface model (DSM). The DTM was subtracted from the DSM in QGIS (version 3.16.16, QGIS Development Team, Boston, MA, USA) to produce the canopy height model (CHM), which is effective for distinguishing the herbaceous plants from the woody plants during the classification process [7]. Further analysis was conducted in ENVI version 5.3 (Exelis, Boulder, CO, USA) based on the workflow provided in [7] to produce the optimized soil-adjusted vegetation index (OSAVI) maps and classification maps to extract the drone-based estimates of forage biomass and the RFA cover, respectively, from the field reference areas (Figure 3).

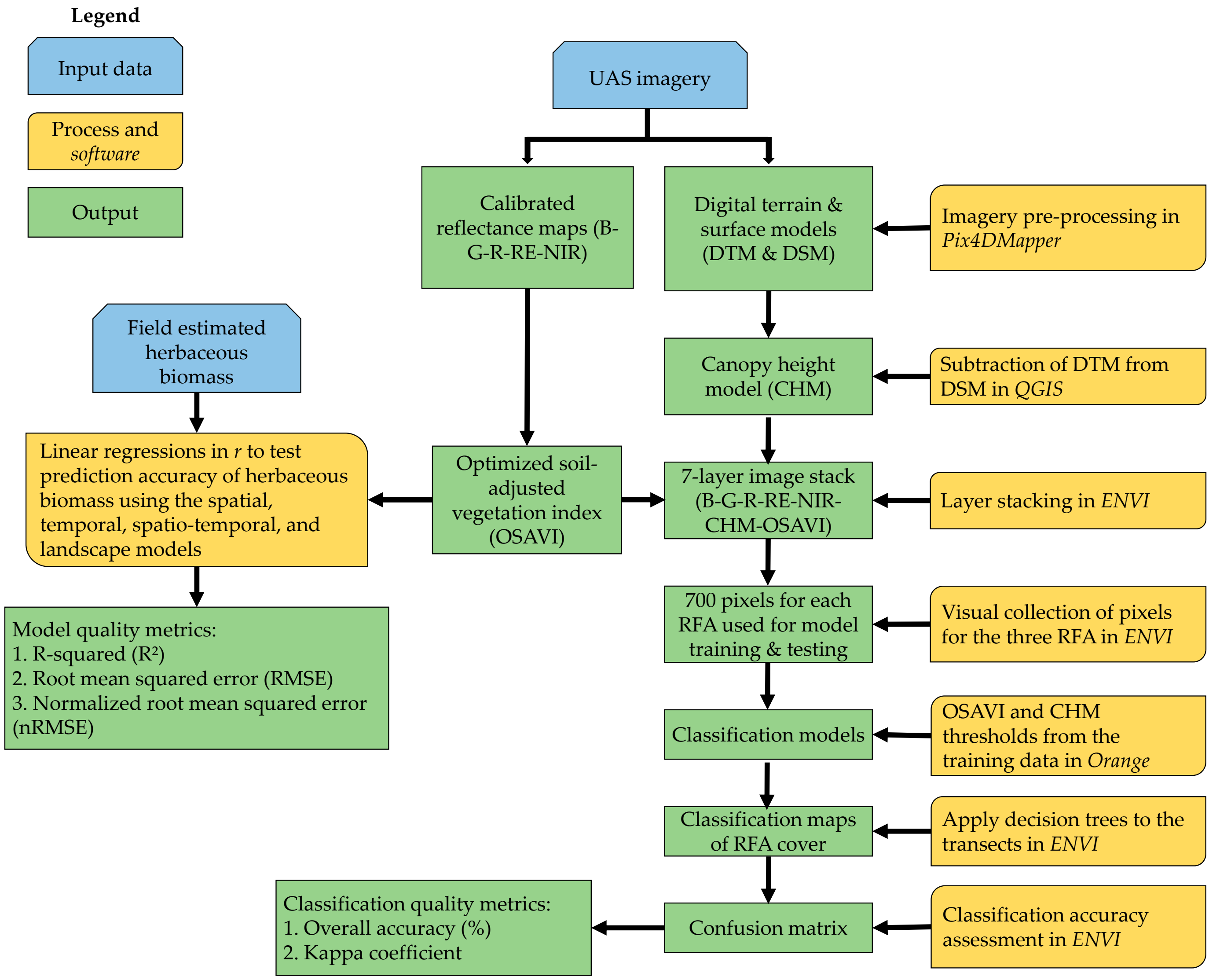

Figure 3. Transferability assessment workflow of drone-based models for predicting forage provision attributes.

To classify the RFA cover, we employed data mining techniques in Orange software (version 3.31.1, Ljubljana, Slovenia) [35]. We determined thresholds for the OSAVI and the CHM based on visually collected pixels (700 pixels for each of the three RFA types/transect). The OSAVI and the CHM were previously identified [7] as suitable features for distinguishing the three main RFA that characterize this rangeland system. The derived thresholds were then used to construct decision trees (Appendix B: Figures A1–A4) in ENVI version 5.3 (Exelis, Boulder, CO, USA) that were applied to classify the transects, ensuring a robust classification process.

2.4. Spatial, Temporal, Spatio-Temporal, and Landscape Model Transfers

Before conducting model transfers, we validated the classification models of RFA cover within their respective contexts using a 70/30 partitioning, with 70% training data and 30% independent validation data. Specifically, this was done with the following numbers of training and validation pixels for the four different model types (Figure 4): (1) spatial models: a model for each of the two land tenure systems (700 pixels × 3 RFA types × four transects = 8400), trained with 5880 pixels and validated with 2520 pixels, (2) temporal models: a model for each of the two periods of the growing season (700 pixels × 3 RFA types × four transects = 8400), trained with 5880 pixels and validated with 2520 pixels,

(3) spatio-temporal models: a model for each of the four combinations of the two land tenure systems at the two periods of the growing season (700 pixels × 3 RFA types × two transects = 4200), trained with 2940 pixels and validated with 1260 pixels, (4) landscape model: a model using all the data (700 pixels × 3 RFA types × eight transects = 16,800), trained with 11,760 pixels and validated with 5040 pixels. This allowed us to assess case-specific prediction accuracies (Appendix A: Tables A1–A9). We assumed similar prediction accuracies for the herbaceous biomass models, given the use of OSAVI in the RFA cover classification models.

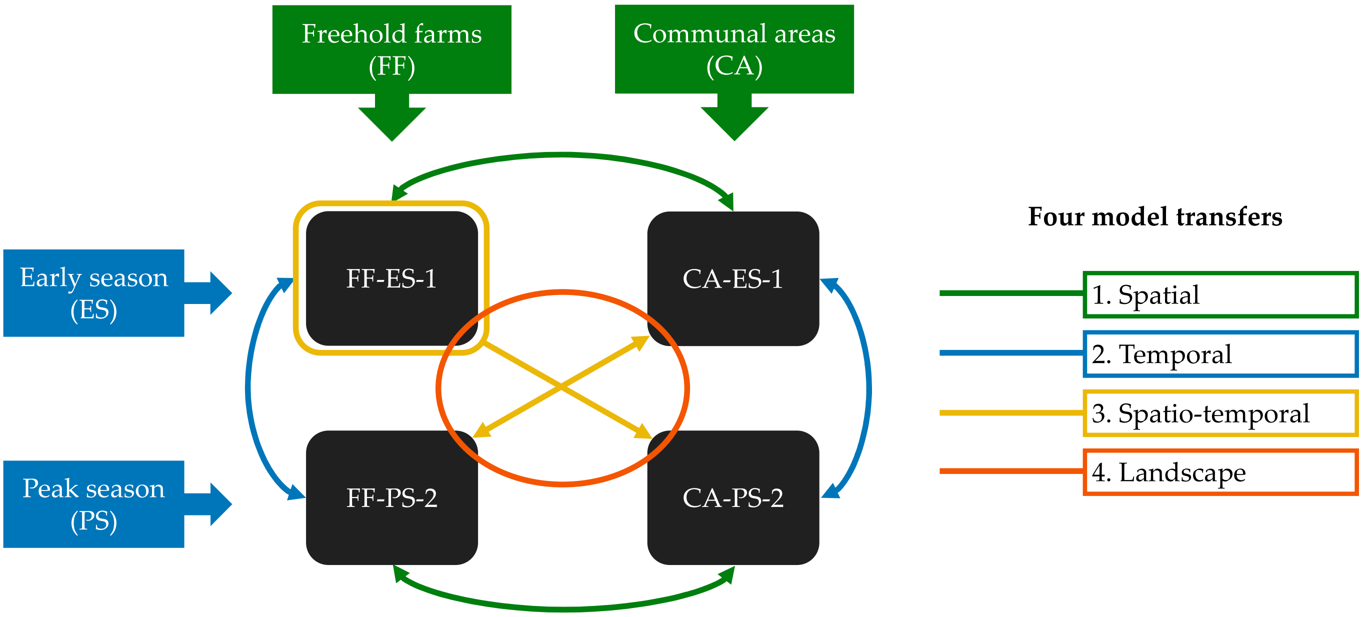

Figure 4. Schematic diagram of the four model transfers conducted across the two land tenure systems and the two periods of the growing season. Note: for the spatio-temporal model transfer we only illustrate one of the four comparisons.

To evaluate the transferability of the models for predicting proxies of forage supply in this dynamic rangeland system, we performed full model comparisons (Figure 4). We conducted four separate comparisons, with the first three based on case-specific model comparisons, while the fourth model utilized the full dataset. The forage supply proxies we predicted with these models were herbaceous biomass and the three main RFA cover types, namely, herbaceous cover, woody cover, and bare ground cover (Figure 5). We used the cross-validation method, an approach that is popular in statistical validation and proposed for transferability assessments [11]. In this method, the data are split into distinct subsets using a relevant factor, in our case, by land tenure system or time of the growing season. In each scenario, one subset was used for developing the model (e.g., freehold farm model), then the model was applied (i.e., transferred) to the other subset (e.g., communal areas), and then the process was reversed [11]. This was done as follows for the case-specific models: (i) for spatial comparisons, the dataset was split by land tenure system (freehold farms and communal areas), (ii) for temporal comparisons it was split by time of growing season (early season and peak season), and (iii) for spatio-temporal comparisons, the data were split into four subsets, one for freehold farms during the early season, one for communal areas during the early season, one for freehold farms during the peak season, and one for communal areas during the peak season.

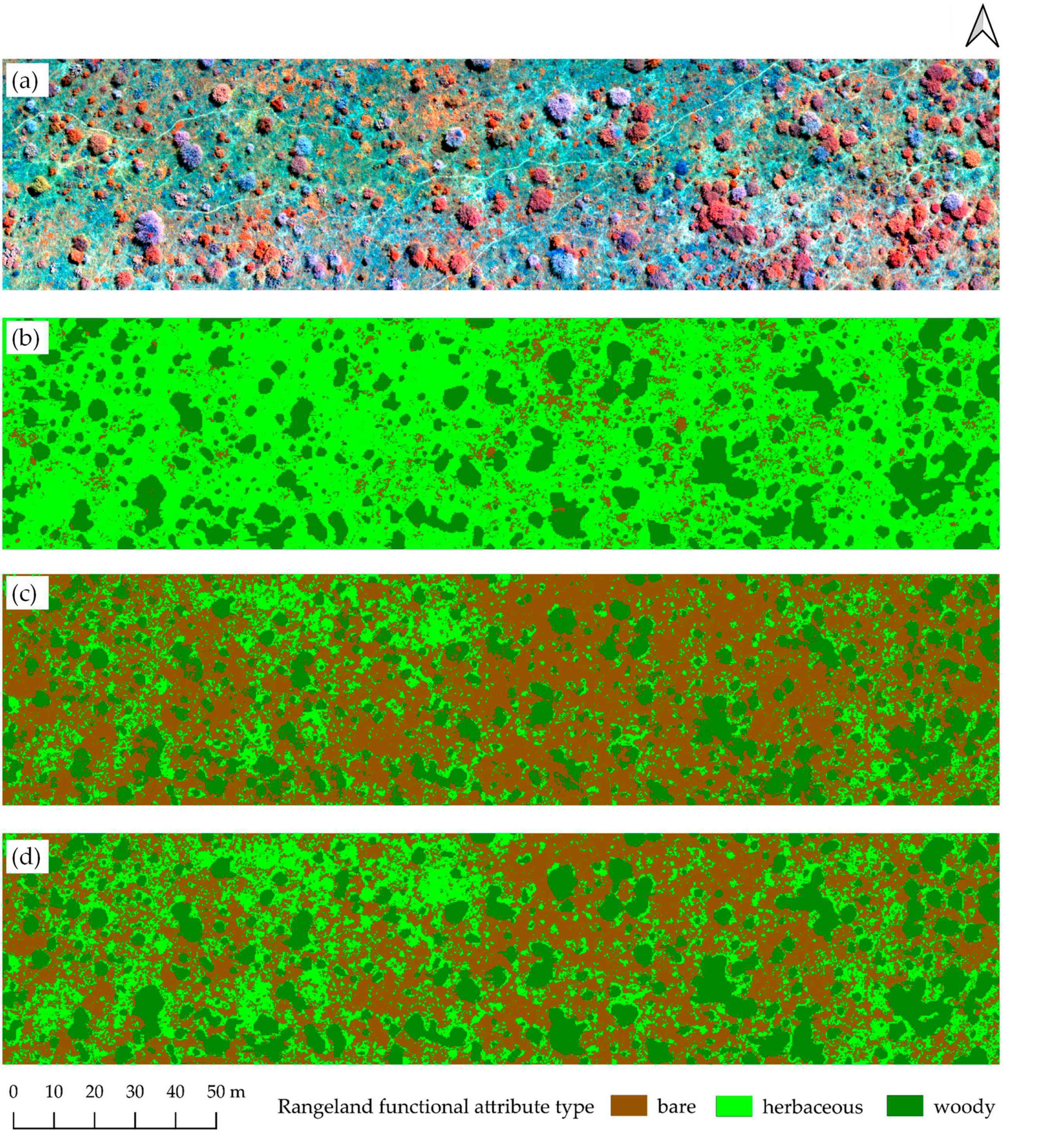

Figure 5. Visualization of a transect example from freehold farms captured at the peak growing season, showing (**a**) false color composite (NIR-G-B), (**b**) classification of the RFA types with the communal area model (spatial transfer), (**c**) classification of the RFA types with the early season model (temporal transfer), and (**d**) classification of the RFA types with the landscape model.

To assess how grazing management strategies affect model transfer, we conducted spatial comparisons between the two land tenure systems. For this, we developed prediction models using data from the freehold farms (FF) and then tested their performance in the communal areas (CA), and vice versa. Similarly, we conducted temporal comparisons to assess the impact of phenological variations on model transfer between the early growing season and peak growing season. Additionally, we conducted spatio-temporal comparisons to explore the combined effect of grazing management strategies and phenological variations on model transfer. In this approach, we developed models in one land tenure system at a particular period of the growing season (e.g., model trained using all the data from the freehold farms during the early season) and then tested it on the rest of the data, repeating this for the four combinations. Finally, to test the landscape model, with the assumption that it captures the full range of potential forage supply, we applied the five-fold cross-validation in which the full dataset was randomly divided into five portions, with a fourth of it used for model training, and the remaining portion withheld to evaluate the performance of the model (Figure 4).

2.5. Statistical Analysis

We assessed the accuracy of the four model transfers, as described above in Section 2.4, in predicting herbaceous biomass and RFA cover. For herbaceous biomass, we used three widely accepted quality metrics: (i) the coefficient of performance (R^2), (ii) the root mean squared error (RMSE), and (iii) the between-minimum-and-maximum range normalized RMSE (nRMSE) of the predicted compared to the observed values. The analysis was performed using the stats package in the R statistical environment version 4.2.2 (R Core Team 2022, Vienna, Austria). Meanwhile, for RFA cover, we compared the actual (i.e., true) RFA with the RFA predicted by the models by generating error matrices [38] (Appendix C: Tables A10–A18) in ENVI version 5.3 (Exelis, Boulder, CO, USA). From this, the commonly used classification accuracy metrics were calculated to quantify the accuracy and the reliability of the produced classification maps. These metrics included the user's accuracy, (i.e., the probability that a pixel predicted as a certain RFA is correct), producer's accuracy (i.e., the ability of the models to recognize the different RFA), overall accuracy (i.e., total proportion of correctly classified RFA), and kappa coefficient (i.e., a measure of the agreement between classification and truth values that ranges from 0 (no agreement) to 1 (perfect agreement)) [38].

3. Results

3.1. Transferability When Predicting Herbaceous Biomass

All four models tested consistently achieved acceptable accuracies ($R^2 > 0.798$, RMSE ≤ 323.95, nRMSE ≤ 0.195) in predicting herbaceous biomass. However, most of them were limited when predicting herbaceous biomass greater than 1500 kg/ha (Figure 6). But, as expected, the landscape model was able to make the most accurate predictions of herbaceous biomass, with the lowest prediction error ($R^2 = 0.868$, RMSE = 168.418, nRMSE = 0.102), outperforming the case-specific models.

Within the case-specific models, spatial comparisons differed slightly, with the freehold farm model estimating herbaceous biomass in the communal areas with similar accuracies ($R^2 = 0.843$, RMSE = 207.521, nRMSE = 0.129) to the communal area model when transferred to the freehold farms ($R^2 = 0.862$, RMSE = 141.297, nRMSE = 0.11). More distinct differences were exhibited within the temporal comparisons, with the model developed during the peak season ($R^2 = 0.80$, RMSE = 189.771, nRMSE = 0.17) resulting in lower predictive errors than the early season model ($R^2 = 0.90$, RMSE = 225.015, nRMSE = 0.136). Among the four spatio-temporal comparisons, the model developed in the freehold farms during the peak season demonstrated better predictive ability ($R^2 = 0.889$, RMSE = 176.173, nRMSE = 0.106) compared to the other three transfers. Meanwhile, in contrast to this, the model developed in the communal areas during the peak season underpredicted herbaceous biomass greater than 500 kg/ha.

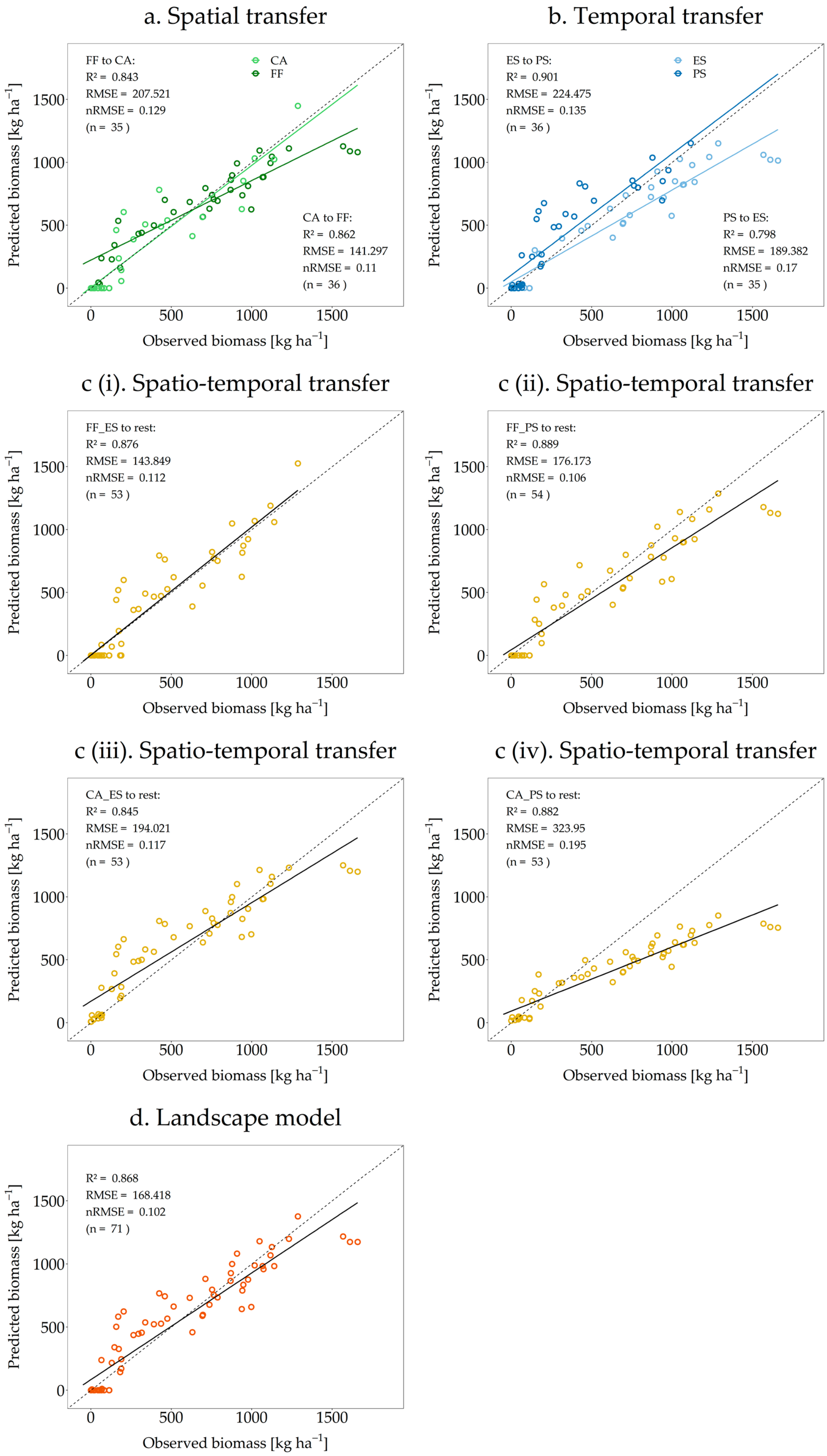

Figure 6. Relationship between predicted herbaceous biomass and that observed in the field based on the transfer of the (**a**) spatial transfers (CA = communal areas; FF = freehold farms), (**b**) temporal

transfers (ES = early season; PS = peak season), ((**c**). (i–iv)) spatio-temporal transfers, and (**d**) the landscape model. The solid line indicates the regression line of the model, while the dashed line represents the 1:1 agreement.

3.2. Transferability When Predicting RFA Cover

The four models exhibited consistently high prediction accuracies when classifying the RFA cover in the different scenes they were evaluated in (Table 2). The landscape model classified the RFA cover with an overall accuracy of 97.1% and a high level of agreement (kappa coefficient = 0.875) that was better than or similar to the case-specific models (Table 2).

Table 2. Mean (±standard error) of overall classification accuracy and kappa coefficient of the predicted RFA cover based on the transfer of the spatial models, temporal models, spatio-temporal models, and the landscape model.

Model Type	Model Transfer	Overall Accuracy (%)	Kappa Coefficient
1. Spatial	FF to CA	88.9 (±9.047)	0.819 (±0.136)
	CA to FF	82.5 (±9.033)	0.703 (±0.142)
2. Temporal	ES to PS	80.2 (±9.470)	0.703 (±0.142)
	PS to ES	88.0 (±9.078)	0.819 (±0.136)
3. Spatio-temporal	FF-ES to rest	90.4 (±6.087)	0.856 (±0.091)
	CA-ES to rest	93.9 (±2.338)	0.908 (±0.035)
	FF-PS to rest	91.1 (±6.308)	0.866 (±0.095)
	CA-PS to rest	91.7 (±6.419)	0.876 (±0.096)
4. Landscape	To all scenes	91.7 (±4.659)	0.875 (±0.070)

Among the case-specific models, the transfers with the lowest accuracies were observed within the temporal and spatial model types (Table 2). Specifically, when the early season model was applied to classify the RFA cover in the peak season scenes, it obtained an overall accuracy of 80.2%. Similarly, when the communal area model was applied to the freehold farm scenes to classify the RFA cover, it achieved an overall accuracy (82.5%) in the same range. For the spatio-temporal comparisons, the differences between the classification accuracies achieved were negligible and highly comparable to those achieved by the landscape model.

The classification accuracy of the four separate models, when applied to predict the cover of the three rangeland functional attributes (RFA), consistently underestimated herbaceous cover (Figure 5), with the producer's accuracy ranging from 71.7 to 86.3% (see error matrices in Appendix C: Tables A10–A18). Namely, the lowest producer's accuracy was achieved within the spatial comparisons when the freehold farm model was tested in the communal areas (Appendix C: Table A10), whereas the best producer's accuracy was obtained by the landscape model (Appendix C: Table A18). In contrast, all the models consistently classified the woody cover RFA the most accurately (Figure 5), with the producer's accuracy ranging from 92.4 to 99.1%.

4. Discussion

Our overall findings show that drone-based models developed using data from two distinct land uses and at two key periods of the growing season are transferable across the spatial and temporal contexts in this dryland savannah. Namely, they were able to predict proxies of forage supply (herbaceous biomass and the cover of rangeland functional attributes) with acceptable accuracies. Moreover, we show how rapid phenological changes and grazing management practices that drive heterogeneity in dryland systems can affect model generality. We found consistent evidence that the landscape model that encompassed the highest variability of the system predominantly outperformed the case-specific models in predicting the two forage supply proxies. Our evaluation sheds light on the performance of drone-based predictive models and their implications for monitoring resources in dynamic rangelands.

Most of the models showed a decreased accuracy in predicting larger amounts of herbaceous biomass, particularly those that exceeded 1500 kg/ha. This is not surprising, as such high quantities of herbaceous biomass are generally no longer common in most of the study area, due to extensive land degradation, particularly in the communal areas [34,35,39]. However, our analysis consistently revealed that the landscape model achieved the highest accuracy in predicting the two tested proxies of forage supply, especially herbaceous biomass. In the case of predicting RFA cover, the landscape model also achieved better accuracies than most of the case-specific models. For instance, while all the models underestimated herbaceous cover by misclassifying it as bare ground or woody cover, the landscape model still attained better results. This finding aligned with our expectation, suggesting that this model indeed effectively captured the spatial and temporal variations within this rangeland system. It also supports the recommendation by [8] about the value of incorporating the entire range of potential ecosystem variation when developing predictive models. In our study system, this meant obtaining forage distribution data that is representative of various rangeland conditions, both within (due to varying grazing pressure) and across (due to management practices) land tenure systems throughout the growing season. This resulted in more accurate predictions than those achieved by the case-specific models, which enhances the efficiency of drone technology to map forage supply at larger scales.

Within the case-specific models, the spatial comparisons obtained similar prediction accuracies, especially for estimating herbaceous biomass. This suggests that models tailored to a particular land tenure system can be effectively transferred to predict forage supply in other land tenure systems, potentially streamlining model development and, consequently, monitoring efforts. Generally, some of the case-specific models performed in the same range as the landscape model, but most of them exhibited lower predictive accuracies of herbaceous biomass and RFA cover. Specifically, lower accuracies for predicting herbaceous biomass were achieved within the temporal and the spatio-temporal comparisons, while lower accuracies of RFA cover were achieved within the spatial and temporal transfers. The limitation of these models is likely attributed to the rapid phenological changes of the herbaceous vegetation that result in varying biomass quantities and spectral features [40,41]. Particularly, this variance occurs because the herbaceous layer in the study area is dominated by annual plants [42,43] that grow rapidly upon the onset of the rains (early season), flower by late March (onset of the peak season), and quickly go into senescence [44]. These fast changes in the herbaceous layer may be the reason for the increased predictive errors of herbaceous biomass as well as the misclassification of herbaceous plants (i.e., more senescent plant material later in the season) when, for example, the early season models are applied to the peak season. Other studies using multi-temporal data [4,41] to predict plant biomass also observed a reduced predictive ability as they found vegetation biomass to be estimated better at certain growth stages than others. These observations underline the importance of temporal considerations in model development in such rangelands, where vegetation, specifically herbaceous plants, undergo rapid changes over a short period.

The spatio-temporal comparisons showed better generality and very similar accuracies to the landscape model, specifically for predicting RFA cover. This could be explained by the high variability of the training data as it incorporates the spatial and temporal dynamics of RFA cover. Additionally, this variability appears to be well-captured by the machine learning (data mining) approach used to determine the classification thresholds that were adequate for predicting RFA cover in the test data. Our result aligns with [4], who also achieved adequate accuracies for estimating vegetation cover from classification thresholds derived using machine learning. Therefore, our results underline the robustness of a data mining approach, as it generates objective and generalizable thresholds from the combined datasets (e.g., spatial, temporal, spectral, and structural information) that are often required for classification. However, for the purposes of long-term monitoring, the limitation to this is that such a dataset needs to be updated occasionally, which requires time and a certain level of expertise [1,5].

To our knowledge, our study presents the first comprehensive evaluation of the main factors likely to limit the transferability of drone-based models for predicting rangeland resources in dryland savannahs. Seeing that monitoring rangeland conditions generally relies on making inferences beyond the dataset used for model fitting [8–10], our study provides an essential baseline. We show that the landscape model achieved higher accuracies with the lowest prediction errors, confirming our expectation that it adequately accounts for forage supply variability in our system. However, transferability was limited for the case-specific models, particularly those that incorporate a temporal aspect, due to the rapid phenological changes, especially of the herbaceous layer. However, it is worth noting that all models sufficiently captured the inherent variation within our study system, highlighting their generalizability beyond their specific contexts.

While our models demonstrated high transferability, further research is needed to explore their applicability to different times of the year and to other savannahs in different climatic zones, and consideration should be given to integrating these models with high-resolution satellite data. Firstly, given that our data was collected only in the growing season, an essential next step would be to evaluate how well these models transfer to the dry season. This could reveal further insights into the potential and limitations of quantifying forage supply throughout the year, which is crucial for determining grazing capacity and optimizing proactive rangeland management. Secondly, a broader evaluation of the potential of transferring drone-based predictive models to savannahs with different climatic conditions would enhance the utility of this technology in characterizing the dynamic nature of rangeland resources. Finally, combining remotely sensed data products (i.e., drone and satellite data) [45] could provide enhanced rangeland information, resulting in more accurate estimations of forage resources over larger areas. This could align with existing efforts like the Rangeland Early Warning System [46].

5. Conclusions

Our study on transferability in a dryland savannah evaluated the performance of drone-based models in conditions different from those in which they were developed, an important but often overlooked aspect of model implementation. The findings from our study offer valuable insights into the generality of drone-based models for predicting rangeland resources like forage supply, with direct implications for resource management. Our comprehensive evaluation demonstrated the robustness and reliability of predicting herbaceous biomass and the cover of rangeland functional attributes, considering both spatial (land use) and temporal (phenological periods) variations, demonstrating the importance of incorporating such heterogeneity for accurate resource estimation in these dynamic ecosystems. The model transfer was mainly constrained in temporal comparisons, due to phenological variations of the herbaceous layer between the early (green vegetation) and peak growing season (senescent plant matter). But as anticipated, the landscape model, which incorporated data from all land tenure systems and phenological periods, consistently achieved prediction accuracies that were higher or in the same range as the case-specific models in estimating forage supply proxies. Such a model has the potential to reduce the necessity for time-consuming and expensive ground-truthing, facilitating more frequent and comprehensive data collection and enhancing monitoring efforts. Therefore, this research not only addressed the critical issue of transferability, but also revealed the potential limitations associated with case-specific models when applied beyond their training contexts. By advancing the integration of drone technology for accurate monitoring of dynamic ecosystems, this research contributes to improved resource management practices in diverse ecological settings.

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Appendix A. Error Matrices for the Validation of the RFA Cover Classification Models within the Spatial, Temporal, Spatio-Temporal, and Landscape Models

Appendix A.1. Error Matrix for the Validation of the RFA Cover Classification Model within the Spatial Models (i.e., within the Two Land Tenure Systems)

Table A1. Validation results of the RFA cover classification model for the freehold farms.

Reference Data	Bare Ground	Herbaceous	Woody	Total Pixels
Classified data				
Bare ground	99.3%	0.5%	0.4%	840
Herbaceous	0.2%	98.8%	0.7%	840
Woody	0.5%	0.7%	98.9%	840
Total pixels	839	842	839	2520

The diagonal cells highlighted in grey indicate the percentage of correctly classified pixels.

Table A2. Validation results of the RFA cover classification model for the communal areas.

Reference Data	Bare Ground	Herbaceous	Woody	Total Pixels
Classified data				
Bare ground	100.0%	0.1%	0.6%	840
Herbaceous	0.0%	97.6%	3.1%	840
Woody	0.0%	2.3%	96.4%	840
Total pixels	834	834	859	2520

Appendix A.2. Error Matrix for the Validation of the RFA Cover Classification Model within the Temporal Models (i.e., within the Two Periods of the Growing Season)

Table A3. Validation results of the RFA cover classification model for the early season.

Reference Data	Bare Ground	Herbaceous	Woody	Total Pixels
Classified data				
Bare ground	98.8%	0.0%	1.0%	840
Herbaceous	0.1%	97.5%	2.9%	840
Woody	1.1%	2.5%	96.2%	840
Total pixels	842	836	842	2520

Table A4. Validation results of the RFA cover classification model for the peak season.

Reference Data	Bare Ground	Herbaceous	Woody	Total Pixels
Classified data				
Bare ground	100.0%	0.0%	0.0%	840
Herbaceous	0.0%	98.7%	1.3%	840
Woody	0.0%	1.3%	98.7%	840
Total pixels	840	840	840	2520

Appendix A.3. Error Matrix for the Validation of the RFA Cover Classification Model within the Spatio-Temporal Models (within the Two Land Tenure Systems during the Two Periods of the Growing Season)

Table A5. Validation results of the RFA cover classification model for the freehold farms during the early season.

Reference Data	Bare Ground	Herbaceous	Woody	Total Pixels
Classified data				
Bare ground	99.8%	0.0%	0.7%	420
Herbaceous	0.0%	100.0%	0.9%	420
Woody	0.2%	0.0%	98.4%	420
Total pixels	418	416	426	1260

Table A6. Validation results of the RFA cover classification model for the communal areas during the early season.

Reference Data	Bare Ground	Herbaceous	Woody	Total Pixels
Classified data				
Bare ground	100.0%	0.5%	0.0%	420
Herbaceous	0.0%	98.3%	1.7%	420
Woody	0.0%	1.2%	98.3%	420
Total pixels	418	420	422	1260

Table A7. Validation results of the RFA cover classification model for the freehold farms during the peak season.

Reference Data	Bare Ground	Herbaceous	Woody	Total Pixels
Classified data				
Bare ground	100.0%	0.0%	0.0%	420
Herbaceous	0.0%	98.3%	1.4%	420
Woody	0.0%	1.7%	98.6%	420
Total pixels	420	421	419	1260

Table A8. Validation results of the RFA cover classification model for the communal areas during the peak season.

Reference Data	Bare Ground	Herbaceous	Woody	Total Pixels
Classified data				
Bare ground	100.0%	0.0%	0.0%	420
Herbaceous	0.0%	98.3%	2.4%	420
Woody	0.0%	1.7%	97.6%	420
Total pixels	420	417	423	1260

Appendix A.4. Error Matrix for the Validation of the RFA Cover Classification Model within the Landscape Model (i.e., All the Scenes)

Table A9. Validation results of the RFA cover classification model for the landscape model.

Reference Data	Bare Ground	Herbaceous	Woody	Total
Classified data				
Bare ground	99.3%	0.1%	0.4%	1680
Herbaceous	0.5%	98.4%	2.6%	1680
Woody	0.2%	1.5%	97.0%	1680
Total	1684	1654	1702	5040

Appendix B. Classification Models for Assessing the Spatial, Temporal, Spatio-Temporal and Landscape Transferability for Mapping the RFA Cover

Appendix B.1. Spatial Classification Models for the Two Land Tenure Systems

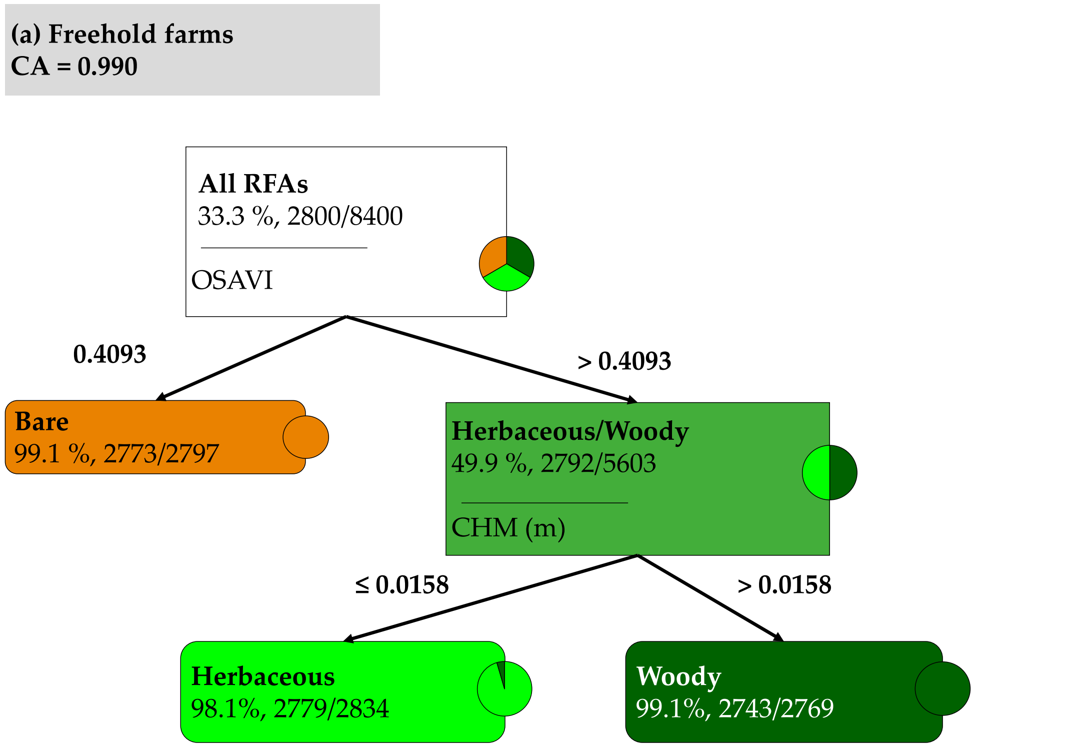

Figure A1. Classification models (i.e., thresholds of the OSAVI and the CHM) based on the training data from the (**a**) freehold farms and the (**b**) communal areas for assessing the spatial transferability for mapping the RFA cover. CA in grey boxes refers to the classification accuracy of the models.

Appendix B.2. Temporal Classification Models for the Two Periods of the Growing Season

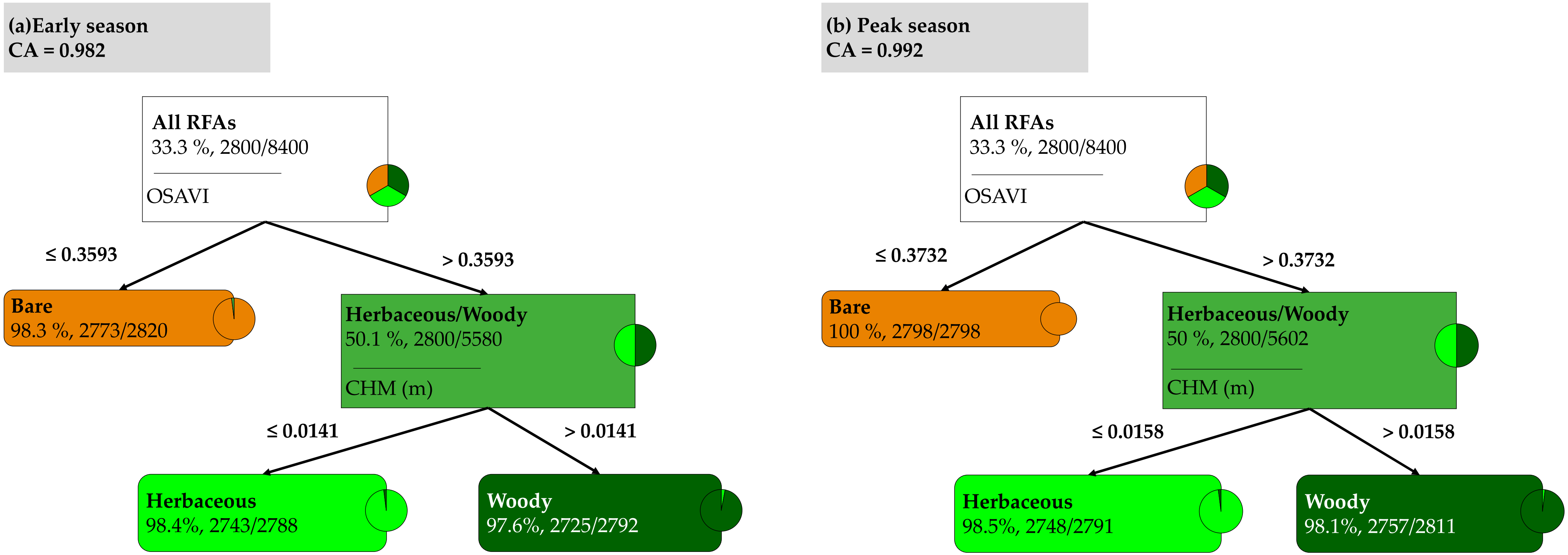

Figure A2. Classification models based on the training data from the (**a**) early season and the (**b**) peak season for assessing the temporal transferability for mapping the RFA cover. CA in grey boxes refers to the classification accuracy of the models.

Appendix B.3. Spatio-Temporal Classification Models for the Four Different Scenes

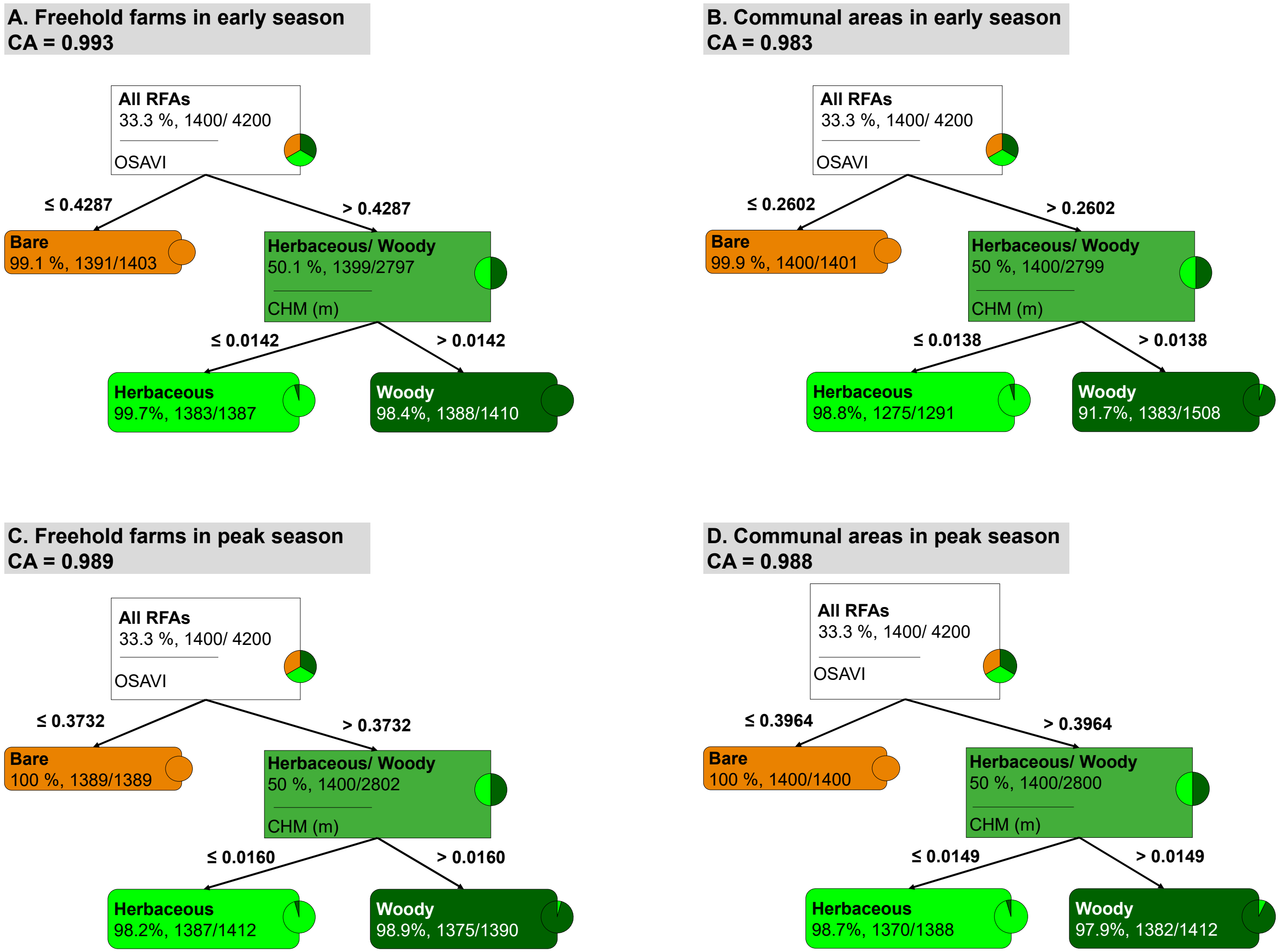

Figure A3. Classification models based on training data from the four scenes in the two land tenure systems during the two periods of the growing season for assessing the spatio-temporal transferability for mapping the RFA cover. CA in grey boxes refers to the classification accuracy of the models.

Appendix B.4. Landscape Classification Model

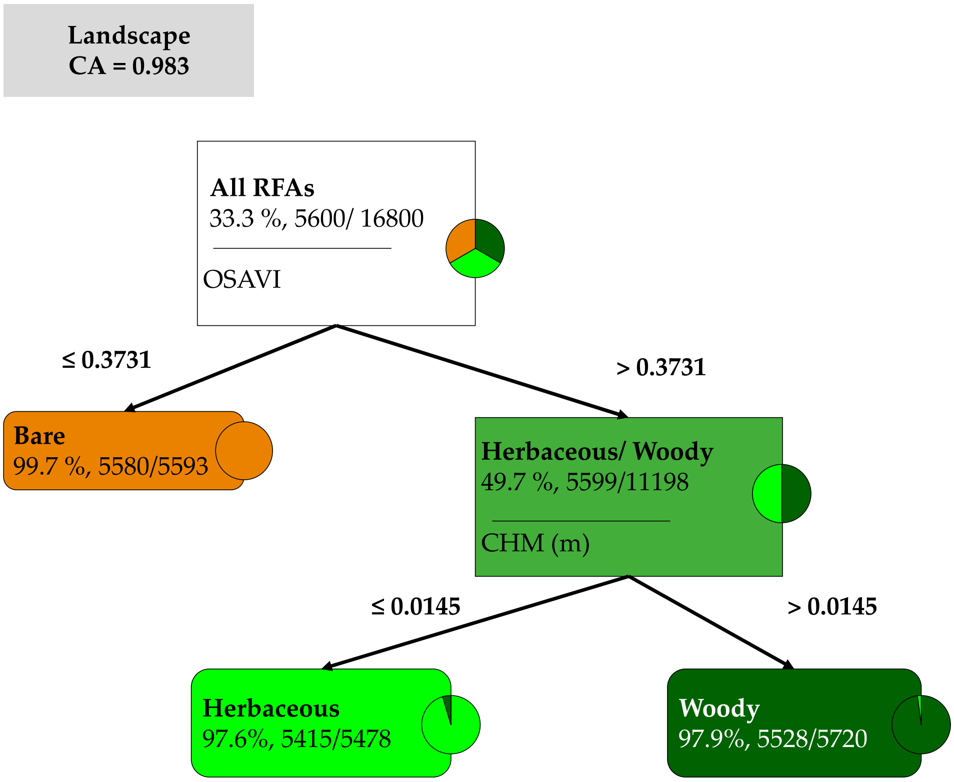

Figure A4. Classification model based on a subset of the entire dataset from the landscape for capturing the combined effect of grazing management and phenological variations for mapping the RFA cover. CA in grey boxes refers to the classification accuracy of the model.

Appendix C. Error Matrices for the Classification of the RFA Cover Based on the Transferability of the Spatial, Temporal, Spatio-Temporal, and Landscape Models

Appendix C.1. Error Matrix for the Classification of the RFA Cover When Testing the Spatial Models (i.e., between the Two Land Tenure Systems)

Table A10. Classification model of the RFA cover derived in the freehold farms and applied to the communal areas.

Reference Data	Bare Ground	Herbaceous	Woody	Total	User's Accuracy (%)
Classified data					
Bare ground	2796	677	98	3571	78.3
Herbaceous	0	2007	39	2046	98.1
Woody	4	116	2663	2783	95.7
Total	2800	2800	2800	8400	
Producer's accuracy (%)	99.9	71.7	95.1		

The diagonal cells highlighted in grey indicate the number of correctly classified pixels.

Table A11. Classification model of the RFA cover derived in the communal areas and applied to the freehold farms.

Reference Data	Bare Ground	Herbaceous	Woody	Total	User's Accuracy (%)
Classified data					
Bare ground	1432	0	0	1432	100
Herbaceous	1028	2725	25	3778	72.1
Woody	340	75	2775	3190	87.0
Total	2800	2800	2800	8400	
Producer's accuracy (%)	51.1	97.3	99.1		

Appendix C.2. Error Matrix for the Classification of the RFA Cover When Testing the Temporal Models (i.e., between the Two Periods of the Growing Season)

Table A12. Classification model of the RFA cover derived in the early season and applied to the peak season.

Reference Data	Bare Ground	Herbaceous	Woody	Total	User's Accuracy (%)
Classified data					
Bare ground	1400	21	34	1455	96.2
Herbaceous	1322	2611	40	3973	65.7
Woody	78	168	2726	2972	91.7
Total	2800	2800	2800	8400	
Producer's accuracy (%)	50.0	93.3	97.4		

Table A13. Classification model of the RFA cover derived in the peak season and applied to the early season.

Reference Data	Bare Ground	Herbaceous	Woody	Total	User's Accuracy (%)
Classified data					
Bare ground	2697	681	122	3500	77.1
Herbaceous	73	2031	17	2121	95.8
Woody	30	88	2661	2779	95.8
Total	2800	2800	2800	8400	
Producer's accuracy (%)	96.3	72.5	95.0		

Appendix C.3. Error Matrix for the Classification of the RFA Cover When Testing the Spatio-Temporal Model (between the Two Land Tenure Types and the Two Periods of the Growing Season)

Table A14. Classification model of the RFA cover derived in the freehold farms during the early season and applied to the other three scenes.

Reference Data	Bare Ground	Herbaceous	Woody	Total	User's Accuracy (%)
Classified data					
Bare ground	4150	736	255	5141	80.7
Herbaceous	0	3356	63	3419	98.2
Woody	50	108	3882	4040	96.1
Total	4200	4200	4200	12,600	
Producer's accuracy (%)	98.8	79.9	92.4		

Table A15. Classification model of the RFA cover derived in the communal areas during the early season and applied to the other scenes.

Reference Data	Bare Ground	Herbaceous	Woody	Total	User's Accuracy (%)
Classified data					
Bare ground	3532	0	0	3532	100.0
Herbaceous	554	4149	55	4758	87.2
Woody	114	51	4145	4310	96.2
Total	4200	4200	4200	12,600	
Producer's accuracy (%)	84.1	98.8	98.7		

Table A16. Classification model of the RFA cover derived in the freehold farms during the peak season and applied to the other scenes.

Reference Data	Bare Ground	Herbaceous	Woody	Total	User's Accuracy (%)
Classified data					
Bare ground	4047	695	147	4889	82.8
Herbaceous	73	3444	70	3587	96.0
Woody	80	61	3983	4124	96.6
Total	4200	4200	4200	12,600	
Producer's accuracy (%)	96.4	82.0	94.8		

Table A17. Classification model of the RFA cover derived in the communal areas during the peak season and applied to the other scenes.

Reference Data	Bare Ground	Herbaceous	Woody	Total	User's Accuracy (%)
Classified data					
Bare ground	4139	696	156	4991	82.9
Herbaceous	39	3417	42	3498	97.7
Woody	22	87	4002	4111	97.3
Total	4200	4200	4200	12,600	
Producer's accuracy (%)	98.5	81.4	95.3		

Appendix C.4. Error Matrix for the Classification of the RFA Cover When Testing the Landscape Model (i.e., All the Scenes)

Table A18. Error matrix for the classification of the RFA cover when applying the landscape model.

Reference Data	Bare Ground	Herbaceous	Woody	Total	User's Accuracy (%)
Classified data					
Bare ground	5211	708	147	6066	85.9
Herbaceous	26	4830	95	4951	97.6
Woody	363	62	5358	5783	92.7
Total	5600	5600	5600	16,800	
Producer's accuracy (%)	93.1	86.3	95.7		

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Gradual rather than abrupt responses to grazing pressure of rangeland conditions revealed from high-resolution drone imagery

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Abstract

Rangeland degradation remains a major global environmental and socio-economic challenge. In drier rangelands, degradation is often evident around artificial water points where intense grazing activities drastically reduce forage resources, resulting in the formation of 'piosphere patterns' or grazing gradients. While these grazing gradients provide valuable insights into rangeland responses to grazing pressure, past studies have relied on spatially discontinuous field data, limiting their ability to accurately capture piosphere patterns and associated ecological tipping points. Here, we leveraged high-resolution drone data to assess piosphere dynamics and potential abrupt shifts in rangeland conditions across two contrasting land tenure systems. Our findings revealed significant contrasts between freehold and communal rangelands, largely due to differing grazing management strategies. In freehold farms, rotational grazing coupled with bush control maintained healthier conditions, with herbaceous vegetation dominating the landscape. In contrast, continuous grazing without bush management in communal areas resulted in extensive bush encroachment, particularly by woody plants shorter than two meters. This divergent vegetation structure influenced the response of rangeland parameters along grazing gradients, such that expected trends of an increase in bare ground and a decline in herbaceous plants toward water points, were only observed in freehold farms. Notably, we did not observe sharp threshold-like shifts along grazing gradients; instead, rangeland parameters exhibited gradual responses to grazing pressure. This suggests that spatial heterogeneity in forage distribution and consequently, grazing patterns may obscure tipping points in semi-arid systems. Overall, our findings underscore the critical role of sustainable grazing practices in maintaining the long-term functioning of these vital ecosystems and demonstrate the value of drone remote sensing for advancing rangeland monitoring.

1. Introduction

Rangeland degradation, driven by the dual forces of climate change and unsustainable grazing practices (Cipriotti *et al.*, 2019; Maestre *et al.*, 2022), remains a significant issue in drylands. For centuries, this problem was worsened by the concentration of grazing pressure around limited resources, such as artificial water points and mineral blocks (Andrew, 1988; Washington-Allen *et al.*, 2004; Todd, 2006). As a result of herbivory activities including trampling, grazing, and excretion, these landscapes are scarred with distinct ecological zones known as "piospheres", that radiate from these focal areas (Andrew, 1988; Linstädter *et al.*, 2016). A piosphere (hereafter, also referred to as grazing gradients or distance gradients) consists of a "sacrifice zone" closest to the resource focal point, where vegetation is nearly absent, because of excessive grazing, trampling, and soil compaction. Then comes the transition zone, which is extensively grazed, which then merges into a region that is minimally affected by herbivore activities (Manthey and Peper, 2010). However, the spatial extent of the different piosphere zones can vary both locally and at a landscape scale due to factors such as patchy forage resources (Adler, Raff and Lauenroth, 2001; Manthey and Peper, 2010; Oñatibia and Aguiar, 2023), and differing grazing management practices (Todd, 2006).

The distribution of grazing activities is strongly influenced by the availability of forage, with livestock often concentrating in areas with abundant resources and selecting the most palatable options, especially during the growing season (Adler, Raff and Lauenroth, 2001; Bailey and Brown, 2011). Sustainable grazing practices, like rotational grazing, can help minimize the spatial extent of piospheres by allowing areas to recover and replenish forage resources (Rothauge, 2007; Stehn, 2008; Mudongo *et al.*, 2016). In contrast, continuous grazing can lead to the depletion of available forage patches, leading to an increased degradation of these landscapes and an expansion of piosphere zones, especially the sacrifice and transition zones, that are more noticeable in the dry season and at the onset of the rains (i.e., in the early rainy season) (Heshmatti, Facelli and Conran, 2002; Reis and Şen, 2017). This variability highlights the complex interplay among the spatial and temporal forage dynamics, grazing activities, and applied management practices in shaping rangeland ecosystems. Understanding these dynamics is crucial to prevent further deterioration of these ecosystems that are highly relevant for sustaining billions of livelihoods and for accurately predicting how they will respond under changing environmental conditions (Reynolds *et al.*, 2007; Maestre *et al.*, 2022; Biancari *et al.*, 2024).

Ecologists have long utilized grazing gradients as natural laboratories to understand the effects of varying grazing pressure on rangeland attributes and to gain insight into ecological thresholds. Research using grazing gradients has focussed on various ecological attributes including vegetation structure and function (Makhabu, Marotsi and Perkins, 2002; Todd, 2006; Katjiua and Ward, 2012), plant species composition (Peper *et al.*, 2011; Egeru *et al.*, 2015), soil seed banks (Dreber, Oldeland and van Rooyen, 2011; Kassahun, Tegegne and Aberra, 2012), soil dynamics (Kassahun, Tegegne and Aberra, 2012; Katjiua and Ward, 2012; Sandhage-Hofmann *et al.*, 2015; Zimmer *et al.*, 2024), and ecosystem service delivery (Maestre *et al.*, 2022). These studies provided valuable insights into how the different parameters are affected by grazing and their responses to it; however, because they were largely based on field observations that provide spatially discontinuous data, their findings are generally extrapolated, which may not be reflective in heterogeneous rangeland ecosystems. This may hinder the detection of subtle piosphere effects and signals of approaching thresholds, particularly due to different land use systems and patchy grazing activities.

Remote sensing techniques provide spatially and temporally continuous data that has been leveraged to monitor ecological indicators that overlap with those mentioned above, i.e., vegetation and soil dynamics (Tueller, 1989; Booth and Tueller, 2003; Wu, 2009; Jones and Vaughan, 2010; Boswell, 2015; Retallack *et al.*, 2023). This approach, complemented by ground-truthing, has contributed to a more comprehensive understanding of rangeland dynamics and degradation from landscape to global scales (Raymond, Wasantha and Douglas, 2016; Yao, Qin and Chen, 2019). Studies largely based on satellite data have demonstrated the effectiveness of remotely sensed data in capturing the impacts of herbivory activities and characterising piospheres, enabling the identification of degraded areas and distinguishing between climate-induced and grazing-induced degradation (Pickup and Chewings, 1994; Washington-Allen *et al.*, 2004; Chamaillé-Jammes, Fritz and Madzikanda, 2009). One remote sensing tool that has become popular in ecological research is drone technology. This mapping tool offers high-resolution rangeland information at the sufficient spatio-temporal scales necessary for implementing targeted grazing management strategies (Gallacher, 2019). Rangeland parameters such as vegetation cover, bare patches, and biomass production can be mapped easily, rapidly, and with high accuracy, providing valuable insights into grazing impacts on rangelands (Cunliffe, Brazier and Anderson, 2016;

Gillan, Karl and van Leeuwen, 2020; Roser *et al.*, 2022; Amputu *et al.*, 2024). However, despite their suitability for various rangeland applications, the use of spatially continuous drone data that offers an ideal opportunity to study grazing gradients and tipping point behaviour has, to our knowledge, not yet been explored.

Here, we used spatially continuous data from high-resolution drone imagery to assess piosphere effects in semi-arid rangelands under two different land tenure systems during the growing season. Specifically, we analysed for changes in rangeland condition indicators as a function of distance from livestock water points, a proxy for grazing pressure. We hypothesized that: (1) rangeland conditions are poorer in communal areas due to unsustainable grazing management compared to freehold farms, with stronger differences in the early growing season; (2) within land use types, bare ground cover and cover of woody plants shorter than 2 m increase with proximity to livestock water points, while herbaceous plants (cover and biomass) and cover of woody plants taller than 2 m decrease; and (3) that there are clear shifts from severely degraded to healthier rangeland conditions, most evident in abrupt changes in herbaceous vegetation and bare ground cover along the distance gradients from spatially continuous drone data.

2. Materials and methods

2.1 Study area

The research was conducted within the semi-arid rangelands of central Namibia, as a case study of dryland ecosystems (Figure 1). The region receives on average between 350 and 400mm annual rainfall between December and May, but experiences significant intra- and inter-annual variations and frequent droughts (Ministry of Environment and Tourism, 2013; Atlas of Namibia Team, 2022). Mean maximum temperatures range from 30 – 34°C in the hot season (October to April), while mean minimum temperatures drop to 4 – 6°C in the cold season (June to July) (Atlas of Namibia Team, 2022).

The study area is dominated by Arenosols, sandy soils with low clay content (Atlas of Namibia Team, 2022; Zimmer *et al.*, 2024). The vegetation growing on this nutrient-poor soil is predominantly thornbush shrubland, including species like *Senegalia mellifera* (Vahl.) and *Terminalia sericea* (Burch.), which are also the main culprits of bush encroachment in the region (De Klerk, 2004; Brinkmann *et al.*, 2023). The herbaceous layer consists largely of annual grass species like *Urochloa brachyura* (Hack.), *Pogornathria fleckii* (Hack.), and *Melinis repens* subsp. *grandiflora* (Hochts.), as well as forbs such as *Ipomoea chloroneura* (Hall. f.), *Acanthosicyos naudinianus* (Sond.), and *Tephrosia burchellii* (Burtt.) (Strohbach, 2014). Perennial grasses like *Stipagrostis uniplumis* (Licht.), *Eragrostis rigidior* (Pilg.) and *Melinis repens* subsp. *repens* (Willd.) have declined significantly due to unsustainable grazing.

The region is mainly used for livestock production. Cattle are the main livestock, but there are also smaller livestock such as sheep and goats. Two contrasting land tenure systems are present, each with distinct grazing management practices (Figure 1). Freehold farms are fenced and divided into several camps to facilitate rotational grazing. Livestock are provided with water and mineral supplements at artificial water points that are strategically positioned to cater to several camps (Figure 1c). In contrast, communal land typically follows an open-access grazing system, where forage resources and a common water point are shared in a village among multiple households. As a result, communal rangelands tend to be more degraded on average, often suffering from severe bush encroachment (Brinkmann et al., 2023; De Klerk, 2004; Heita et al., 2024). (Figure 1).

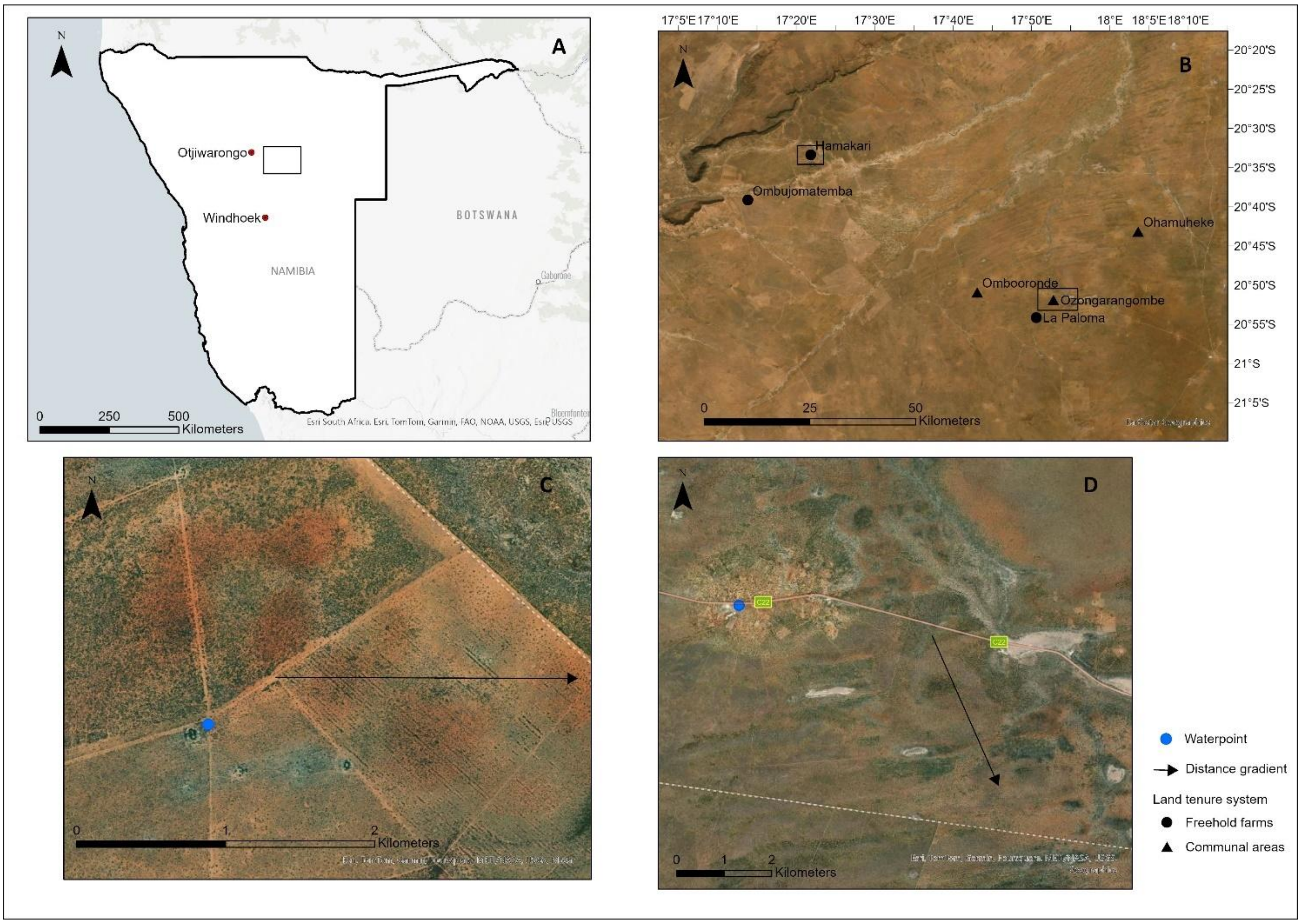

Figure 1. Overview of the study area in the semi-arid rangelands in central Namibia, its land use types, and the study design. (a) Map showing the location of the study area in Namibia; (b) Location of freehold farms and communal areas within the study site; (c) Example of a grazing gradient established with increasing distance from a water point shared by four camps on a freehold farm; and (d) In a communal area away from a water point shared commonly by a village. Modified from (Amputu *et al.*, 2024).

2.2 Study design

To investigate the effects of grazing pressure on rangeland conditions and to test the presence of a tipping point from severely degraded to healthier rangeland condition in semi-arid rangelands, we established five transects in each of the two land use types, freehold farms and communal areas (Figure 2; Table S1). These transects (hereafter, also distance gradients) were placed with increasing distance from livestock water points, starting after the sacrifice zone (i.e. area where vegetation was absent) (Manthey and Peper, 2010) (Figure

3). Distance from water points served as a proxy for grazing pressure, a common assumption in rangeland ecology (Andrew, 1988; Todd, 2006; Sasaki *et al.*, 2008; Hoshino *et al.*, 2009; Wesuls *et al.*, 2013; Reis and Şen, 2017). The length of the transects in freehold farms was 1500m, while those in the more degraded communal areas were extended to 2000m, and all transects had a consistent width of 80 m. The starting point of the transects in communal areas were on average 1200m away from water points as they were placed from the edge of villages, and in freehold farms about 800m away to avoid demarcated corridors that guide livestock to the water points. Hence, except these sacrifice zones, we captured the whole area where grazing diminishes with distance from the water point, creating a gradient of vegetation cover and other ecosystem characteristics (Figure 3). The transects were surveyed at two distinct periods of the growing season: early (16 January to 10 March 2021) and peak (23 March to 24 May 2021), to capture different phenological stages that may play a role in revealing subtle piosphere effects and consequently, detecting tipping point dynamics.

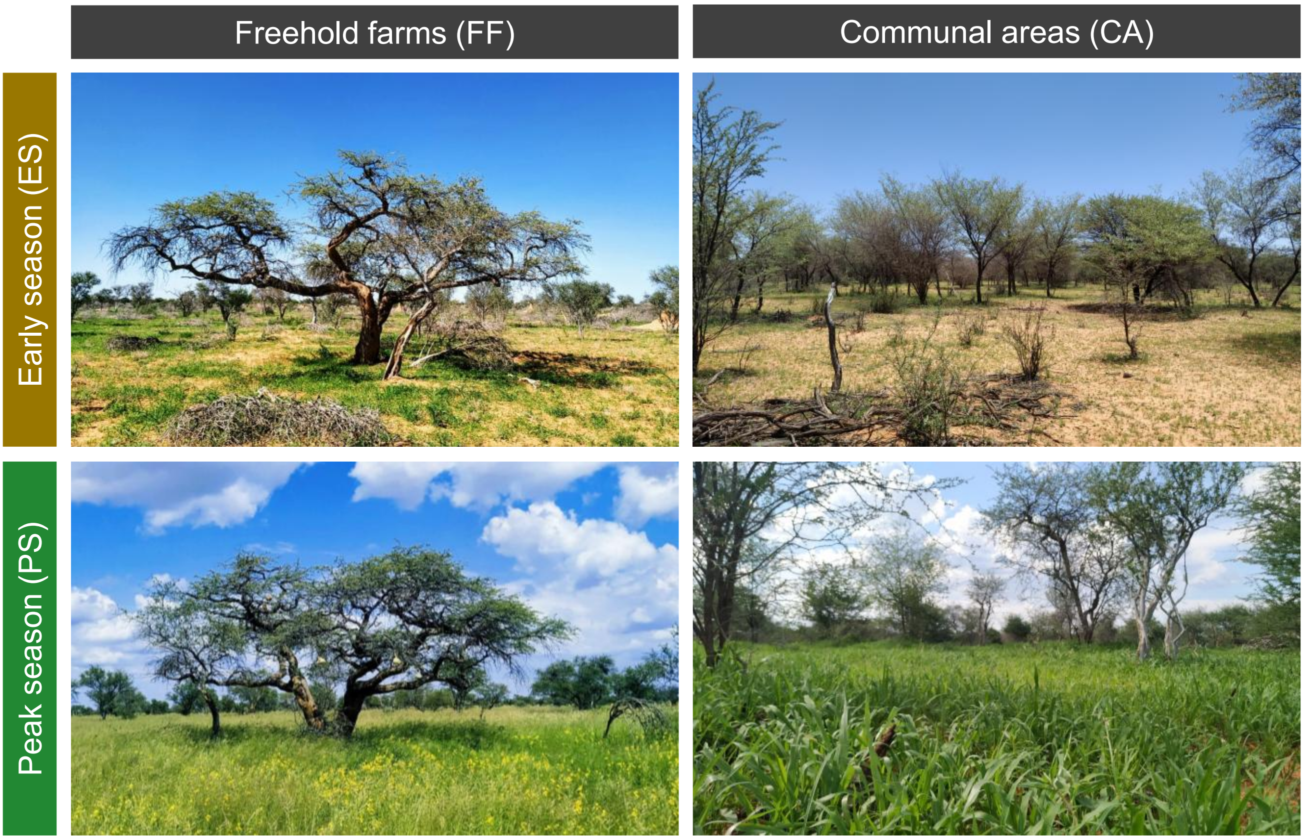

Figure 2. Examples of vegetation at different phenological stages in the growing season in freehold farms (left) and communal areas (right).

2.3 Data collection

Drone-based imagery was collected with a MicaSense RedEdge-MX RX01 multispectral sensor mounted on a DJI Matrice 200 Series V2 quadcopter (for detailed descriptions of the equipment, see Amputu et al., (2023). Flight missions were conducted using the Pix4DCapture software and scheduled within two hours of local solar noon to minimize shadowing effects and ensure consistent lighting conditions. A Downwelling Light Sensor (DLS) and a Calibrated Reflectance Panel (CRP) were used for radiometric correction to obtain surface reflectance. The drone was flown at 80m above the ground with 80% front and side overlap, providing multispectral imagery with a ground sampling distance of approximately 6 cm/pixel, sufficient for estimating the annual dominated herbaceous layer (i.e., relatively small and sparsely distributed plants). Two flight missions were conducted per transect during the growing season. The first round (early growing season) occurred from 16 January to 10 March 2021, followed by the second round (peak growing season) from 23 March to 24 May 2021 (Figure 2; Table S1).

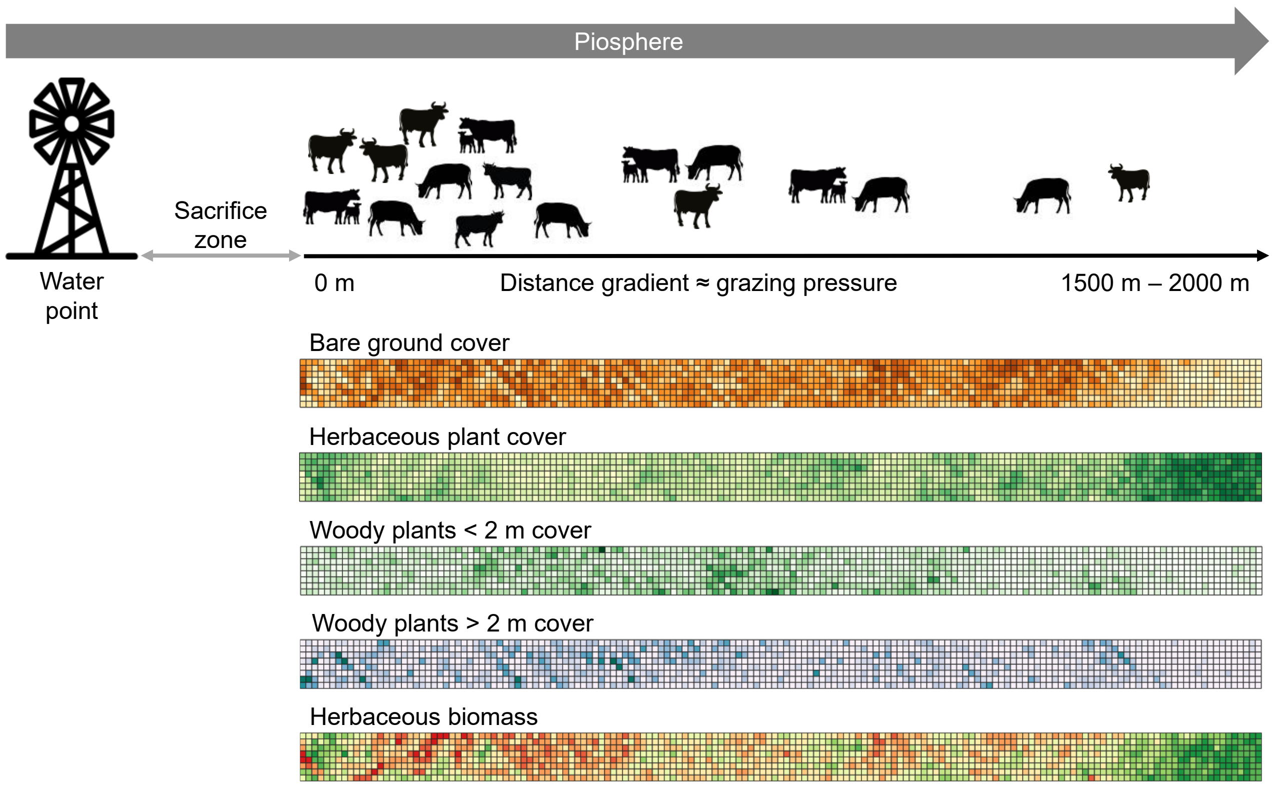

Figure 3. Schematic representation of the transect design used to assess rangeland condition indicators within piospheres (modified from Knopf and Samson, 1997). Transects started close to

livestock water points, excluding the sacrifice zone, extending throughout the piosphere to areas with lower grazing pressure (1500 – 2000 m away from water points). Examples of how five rangeland condition indicators vary with grazing pressure, analysed from drone imagery, are shown. Each grid cell (10 m x 10 m) represents a sampling unit, with darker tones indicating higher cover and for herbaceous biomass, greener cells represent higher biomass values than redder cells.

2.4 Data processing

Drone images were processed using Pix4DMapper version 4.6.4 (Pix4D SA, Prilly, Switzerland), a Structure-from-Motion (SfM) software. This process generated mosaicked, calibrated surface reflectance images, digital surface models (DSMs), and digital terrain models (DTMs) for each transect, following the workflows outlined in (Amputu *et al.*, 2023, 2024). A herbaceous biomass model and classification thresholds developed in (Amputu *et al.*, 2024), were used to predict the following five rangeland condition indicators: herbaceous biomass; cover of bare ground; herbaceous plant cover, cover of woody plants <2 m, and cover of woody plants >2 m. Then using QGIS (version 3.16.16, QGIS Development Team, Boston, USA) we extracted data for these indicators along the transects in a grid with 10 m × 10 m cells (Figure 3), an optimal plot size in rangeland studies (Herrick *et al.*, 2017), that also facilitated comparisons with several other studies along the same transects (Chambara et al. in prep. (perennial plant species), Hamunyela et al. in prep. (soil seedbanks), Männer et al. in prep. (forage quality), Schwarz et al. in prep. (plant functional traits), Zimmer et al. 2024 (soil characteristics)). Average values were calculated at 10 m distance intervals (i.e., an average of 8 grid cells) to obtain the mean of herbaceous biomass and of the four cover-based indicators along all distance gradients. The extracted spatially continuous data were then analysed as detailed in subsection 2.5.

2.5 Statistical analysis

To identify the best predictors of rangeland condition among distance from water points, land use type, and time of season, the full models incorporated interactions among all predictor variables and included transect as a random effect to account for potential spatial and temporal dependencies in the data because of repeated measures.

Generalized Linear Mixed Models (GLMMs) with beta-family distribution were fitted using the *glmmTMB* package in R (Brooks et al. 2017) to analyse the proportional cover of bare ground, herbaceous plants, and woody plants (< 2 m and > 2 m). For woody plants taller than 2 m, which contained several proportional cover values close to zero resulting in overdispersion, a common transformation of adding 0.001 to all values was applied to meet the assumptions of the beta family distribution before GLMM analysis. Additionally, bare ground cover and woody plant cover data were square root transformed prior to analysis to improve the normality of residuals. Herbaceous biomass was analysed using a Linear Mixed Effects Model (LMM) with Gaussian distribution within the *lme4* package in R (Bates et al. 2015) maintaining the same model structure. Marginal (R^2m) and conditional (R^2c) R^2 values (Nakagawa and Schielzeth, 2013) were calculated to quantify the proportion of variance explained by fixed and combined fixed and random effects, respectively.

Differences in rangeland condition indicators between land use types and time of the growing season were assessed with Tukey's HSD post-hoc tests (Tukey 1953) using the *emmeans* package in R after fitting the GLMMs (Lenth 2024). To explore potential tipping points, we fitted piecewise regressions to identify thresholds in rangeland condition indicators along the distance gradients (Sasaki *et al.*, 2008), using the *segmented* package in R (Muggeo, 2008). We then compared the performance of piecewise models to linear models using AIC (Table S3). All statistical analyses were performed in the RStudio statistical environment v.4.4.1 (Posit Team, 2024).

3. Results

The state of rangelands in freehold farms was significantly better than in communal areas throughout the entire growing season. Mainly, freehold farms had more herbaceous plants and less woody plants shorter than 2 m, while communal areas had significantly higher cover of woody plants shorter than 2 m, (Figure 4). Although communal areas were also expected to have higher bare ground cover, indicating less healthy rangelands, both land use types had similar levels. However, the contrasting composition of vegetation between the two land use types was the key distinction.

There were no clear responses in rangeland condition indicators to grazing pressure in communal areas, indicated by a general lack of slopes in the linear regression lines (Figure 4A). In contrast, evident trends were observed for most of the rangeland condition indicators in freehold farms (Figure 4A), aligning with our expectations. These findings suggest that the effect of grazing pressure on vegetation characteristics strongly depends on the overall condition of rangelands, which is highly influenced by management practices. Consequently, we primarily found significant interactions between distance from water points and land use type for all parameters (Table 1). We also observed a significant temporal influence in communal areas (Figure 4), which resulted in a significant interaction between land use type and time of the season (Table 1). Specifically, we found that communal rangelands slightly improved with the progression of the growing season, with 7% more herbaceous plant cover and 9.6% less bare ground cover in the peak season compared to the early season.

Bare ground cover in freehold farms significantly decreased with increasing distance from water points during both early and peak growing seasons (Figure 4A; Table 1), while showing little variation in communal areas (Figure 4A). Unexpectedly, bare ground cover in communal areas during the peak growing season was lower by 9.6% compared to the early season, while the opposite trend was found in freehold farms with the peak growing season having about 4% more bare ground cover than the early growing season (Figure 4B). Despite these seasonal differences, overall bare ground cover was similar between the two land use types (z = -1.231, P = 0.218).

Table 1. GLMM results to test for the effects of distance from water points (D), land use type (L) (freehold farms *vs*. communal areas), time of the growing season (T) (early *vs*. peak) and their interactions on the proportional cover of bare ground, herbaceous plants, woody plants shorter than 2 m, and woody plants taller than 2 m. The reference categories for land use type and time of the growing season are communal areas and early season, respectively. Significant results ($p < 0.05$) are shown in bold.

Rangeland condition indicators	Bare ground cover		Herbaceous plant cover		Woody plants <2 m cover		Woody plants >2 m cover	
Fixed effects	*z* value	*P* value	*z* value	*P* value	*z* value	*P* value	*z* value	*P* value
Distance from water points (D)	-0.936	0.349	-0.884	0.377	1.470	0.142	-1.184	0.236
Land use type (L)	-1.231	0.218	**3.374**	**0.001**	**-2.414**	**0.016**	0.036	0.972
Time of growing season (T)	**-10.709**	**<0.001**	**6.716**	**<0.001**	**2.146**	**0.032**	**6.116**	**<0.001**
D × L	**-3.806**	**<0.001**	**7.642**	**<0.001**	**-2.350**	**0.019**	**-5.649**	**<0.001**
D × T	1.864	0.062	-1.086	0.278	-0.035	0.972	1.325	0.185
L × T	**9.740**	**<0.001**	**-6.305**	**<0.001**	**-2.631**	**<0.001**	**-4.207**	**<0.001**
D ×L × T	-1.650	0.099	0.724	0.469	0.962	0.336	-0.240	0.811

Herbaceous plant cover in freehold farms was almost 20 % more than in communal areas (Figure 4B) and exhibited an inverse pattern to bare ground cover, as it increased with distance from water points (Figure 4A), reflecting the expected improvement in rangeland condition with decreasing grazing pressure. In contrast, communal areas showed nearly no variation in herbaceous vegetation along the distance gradient, indicating similar rangeland conditions closer to and further away from water points.

The expected negative effect of higher grazing pressure on herbaceous biomass was observed in freehold farms (Figure 5A; Table 2). Additionally, there were clear seasonal differences within the land use types (Figure 5B; Table S2e), even though the overall herbaceous biomass was not significantly different between the two land use types (Table 2), likely as it exhibits considerable variability within each land use type and season (Figure 5). Such variability can be seen in both land use types in Figure 5A, where some transects that had higher herbaceous biomass.

Table 2. LMM results to test for the effects of distance from water points (D), land use type (L) (freehold farms *vs*. communal areas), time of the growing season (T) (early *vs*. peak) and their interactions on herbaceous plant biomass. The reference categories for land use type and time of the growing season are communal areas and early season, respectively. Significant results ($p < 0.05$) are shown in bold.

Rangeland condition indicator	Herbaceous biomass	
Fixed effects	*t* value	*P* value
Distance from water points (D)	-1.138	0.255
Land use type (L)	1.771	0.111
Time of growing season (T)	**2.676**	**0.007**
D × L	**4.379**	**<0.001**
D × T	-0.500	0.617
L × T	**-3.728**	**<0.001**
D ×L × T	-0.063	0.949

Contrary to our prediction for woody plants shorter than 2 m, no clear patterns in their cover were observed with distance from water points in either land use type (Figure 4A). However, communal areas had 8.9 % more cover of woody plants shorter than 2 m than freehold farms ($z = -2.414$, $P = 0.016$; Figure 4A), likely due to the implementation of active bush control in freehold farms but not in communal areas. While the cover of woody plants taller than 2 m did not differ between the two land uses ($z = 0.036$, $P = 0.972$; Figure 4B), in freehold farms a slight but significant decline was found with increasing distance away from water points (Figure 4A; Table 1).

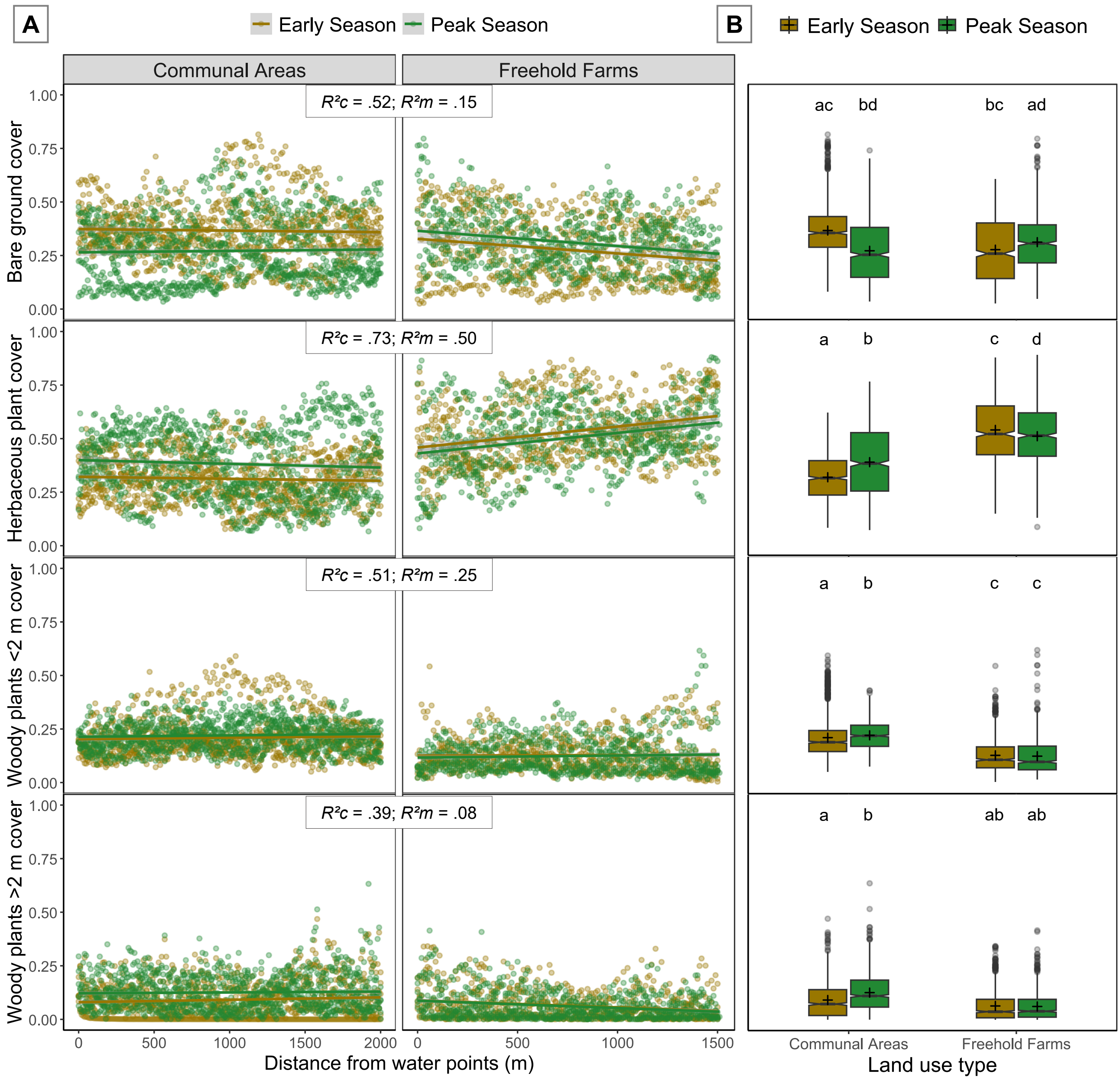

Figure 4. (A) Relationship between distance from water points (m) and the proportional cover of bare ground, herbaceous plants, woody plants < 2 m, and woody plants > 2 m in communal areas (left) and freehold farms (right) during the early and peak growing seasons. Marginal (R^2m) and conditional (R^2c) R^2 values are shown in the boxes. Solid lines represent linear regression models with 95% confidence intervals in grey. (B) Differences in the proportional cover of the same rangeland condition indicators in relation to land use type across two periods of the growing season. The letters denote Tukey statistical differences. The median is shown as a bold line, while the mean is represented by the cross and the 95% confidence interval as a notch.

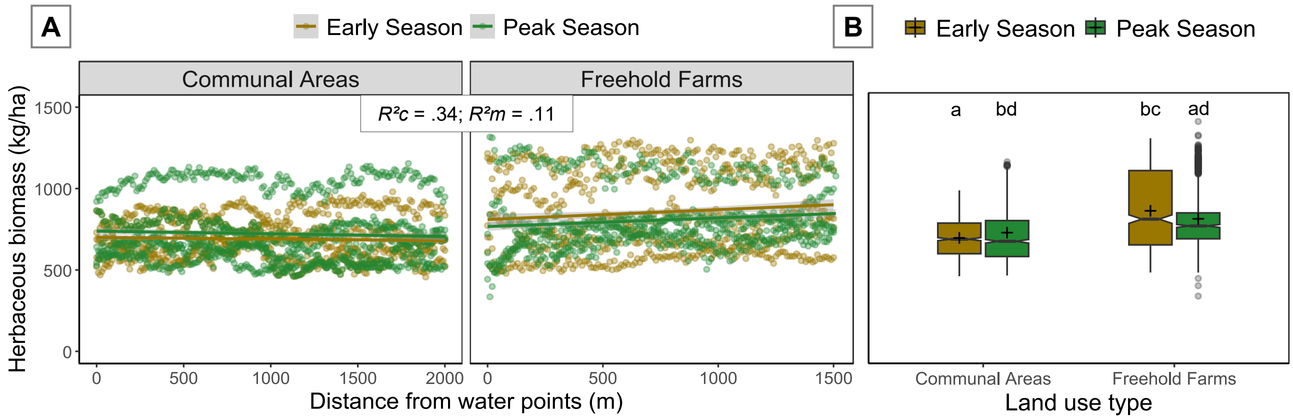

Figure 5. (A) Herbaceous biomass (kg/ha) in relation to distance from water point (m) in communal areas (left) and freehold farms (right) during the early and peak growing seasons. Solid lines represent linear regression models with 95% confidence intervals in grey. (B) Differences in herbaceous biomass (kg/ha) in relation to land use type across two periods of the growing season. The letters denote Tukey statistical differences that are also presented in Table S2e. The median is shown as a bold line, while the mean is represented by the cross and the 95% confidence interval as a notch.

The breakpoint analysis did not provide clear evidence for the presence of abrupt shifts in any of the five rangeland condition indicators across the two land-use types and both periods of the growing season. Additionally, segmented models performed worse than linear models (Table S3), supporting the absence of tipping point behaviour in the spatially continuous drone data.

4. Discussion

Our results indicate the critical role of grazing management practices in shaping rangeland conditions, with freehold farms showing significantly healthier states compared to communal areas. Specifically, freehold farms supported a more herbaceous-dominated plant community, indicative of better rangeland health, while communal areas exhibited higher levels of bush encroachment, characterized by an increased cover of woody plants shorter than 2 m. This divergent vegetation structure influenced the response of rangeland condition indicators to grazing pressure: while expected trends were observed in freehold farms, no significant variation was found in communal areas.

Moreover, our analysis revealed no clear evidence of ecological tipping points along the spatially continuous distance gradients. This suggests that the five rangeland condition indicators responded to grazing pressure in a gradual rather than sharp, threshold-like shift from healthier rangelands to a degraded state, typically associated with tipping points in semi-arid ecosystems. However, we acknowledge the limitations of drone data, which may have limited the detection of potential tipping point dynamics. Specifically, only canopy-level information is reflected, and it was not possible to distinguish plant functional types, especially within the herbaceous layer. Nonetheless, these findings reinforce existing research on piosphere effects (Makhabu, Marotsi and Perkins, 2002; Todd, 2006; Katjiua and Ward, 2012; Linstädter *et al.*, 2016) and highlight the utility of drone technology as a powerful tool for rangeland monitoring.

4.1 Rangelands in healthier states exhibit piosphere patterns

The clear increase of bare ground cover, and the decrease in cover and biomass of herbaceous plants in response to increasing grazing pressure is supported by previous studies (Ward, Saltz and Ngairorue, 2004; Todd, 2006; Sasaki *et al.*, 2008; Peper *et al.*, 2011; Wesuls *et al.*, 2013; Maestre *et al.*, 2022). An increase in bare ground cover at the expense of herbaceous plants is a direct consequence of grazing activities, primarily through livestock foraging and trampling (Mphinyane, 2001; Sasaki *et al.*, 2008; Reis and Şen, 2017). However, in our case, we expected these patterns only in freehold farms and not in communal areas, as the latter were (already) extensively degraded (De Klerk, 2004; Zimmermann, 2009; Ministry of Agriculture water and forestry, 2012; Menestrey Schwieger and Mbidzo, 2020; Zimmer *et al.*, 2024). It is not surprising that rangelands need to be in a relatively good state for piosphere patterns to be detectable. And this ability to determine the impact and spatial extent of grazing is crucial for rangeland managers, as it enables them to adapt grazing regimes to maintain desirable conditions (i.e. ecosystem service delivery of forage) and to prevent undesirable states (Sasaki *et al.*, 2008; Maestre *et al.*, 2022).

Generally, sustainable rangeland management practices like the rotational grazing strategy implemented in freehold farms has maintained rangeland health under the long history of grazing and climatic extremes, like intense droughts that have characterized these rangelands for millennia (Rothauge, 2007; Shrum *et al.*, 2018). In contrast, in communal areas, pastoralists who historically practised nomadism by moving livestock between grazing areas to prevent rangeland degradation were forced to settle in the mid-1800s due to socio-political factors (Menestrey Schwieger and Mbidzo, 2020). As a direct consequence of this grazing regime change, areas that were previously left to recover are now permanently grazed. The observed lack of piosphere patterns is therefore likely due to severe degradation from overgrazing and woody plant expansion (Weber and Horst, 2011; Shikangalah and Mapani, 2020; Heita *et al.*, 2024), that may not have occurred if pastoralists would have maintained their nomadic nature.

We did not observe strong responses in woody plant cover to grazing pressure in both land-use types, likely because the distribution of woody plants is relatively homogeneous. In freehold farms there is active management of encroacher woody plants through debushing (Brinkmann *et al.*, 2009; Lukomska, Quaas and Baumgärtner, 2014; Birch *et al.*, 2017). In this sense, the slight decline in the cover of woody plants taller than 2 m that we found further away from water points may simply be an artifact of debushing. By reducing woody plants and allowing rangelands to rest from grazing, freehold farms are thus able to maintain sufficient forage provision (Lukomska, Quaas and Baumgärtner, 2014). In comparison, the absence of debushing in communal areas, combined with overgrazing, has led to the extensive spread of woody plants at the expense of herbaceous vegetation (De Klerk, 2004; Rothauge, 2007; Ministry of Agriculture water and forestry, 2012; Bestelmeyer *et al.*, 2015). This expansion of woody plants, commonly referred to as bush encroachment, is a well-known issue in dryland ecosystems that has adverse effects for the environment, economy and society (De Klerk, 2004; Maestre, 2011; Angassa, 2014; Lukomska, Quaas and Baumgärtner, 2014; Ward, Hoffman and Collocott, 2014; Stevens *et al.*, 2016; Koch *et al.*, 2023). It is extensively documented in Namibia as it affects over 40 million hectares of rangelands, with our study region experiencing particularly severe impacts (Strohbach, 2001; De Klerk, 2004; Schröter *et al.*, 2009; Shikangalah and Mapani, 2020).

4.2 Spatially continuous drone data show no evidence of abrupt shifts along grazing gradients

Our analysis of spatially continuous gradients did not reveal evidence of ecological thresholds in rangeland condition indicators. Instead, we observed gradual linear responses of rangeland parameters to grazing pressure in freehold farms, and a lack of variation in communal areas, indicating extensive rangeland degradation that is well-documented (Ward *et al.*, 1998, 2000; Ward and Ngairorue, 2000; Strohbach, 2001; Zimmermann, 2009; Menestrey Schwieger and Mbidzo, 2020; Zimmer *et al.*, 2024). These gradual responses align with findings from other studies (Bastin *et al.*, 1993; Pickup and Chewings, 1994; Hoshino *et al.*, 2009; Manthey and Peper, 2010; Rajabov, 2010) which also identified linear rather than nonlinear changes along distance gradients. However, it should be noted that this does not imply tipping points are absent or completely undetectable in our study area.

Our approach has limitations that may obscure subtle signals of tipping point behaviour in rangeland parameters. For one, our study design was setup in such a way that transects were placed after the assumed sacrifice zone, which varied greatly between the two land-use types, and so abrupt shifts that likely occurred within this piosphere area might have been overlooked. Secondly, the indicators assessed through drone imagery may be too coarse, making it difficult to identify potential tipping point behaviour. Specifically, we were unable to distinguish between different herbaceous plant functional types such as forbs, annual grasses, and perennial grasses, all of which have been shown to respond differently along distance gradients due to varying grazing tolerance (Rothauge, 2007; Stehn, 2008; Linstädter *et al.*, 2014; Oñatibia and Aguiar, 2023). For example, nonlinear responses in forbs and perennial grasses with higher grazing pressure have been observed in other regions, like Mongolian rangelands (Sasaki *et al.*, 2008), signalling the presence of ecological thresholds.

It is worth highlighting that the spatial distribution of grazing activities is highly driven by the patchy distribution of forage resources in drylands (Adler, Raff and Lauenroth, 2001; Manthey and Peper, 2010). Our results, specifically herbaceous biomass show this very well (Figure 5a), with a clear dichotomy between some more-productive and some less-productive sites in both land use systems. In general, grazing is typically selective toward palatable forage, particularly during the growing season (Vesk and Westoby, 2001; Neely, Bunning and Wilkes, 2010; Peper *et al.*, 2011). Therefore, the patchiness of forage and livestock choosing what to eat makes it even more difficult to detect tipping points along linear distance gradients. Additionally, long-term unsustainable grazing practices, exacerbated by increasingly harsh climatic conditions may have already pushed rangelands in communal areas beyond a tipping point. While there is substantial evidence of previous tipping points in various dryland systems (Arnalds and Archer, 2000; Darkoh, 2003; Bestelmeyer *et al.*, 2015; Peters *et al.*, 2015; Berdugo *et al.*, 2017; Saco *et al.*, 2018; Lopez *et al.*, 2019), it remains hard to recognize tipping points before they have been crossed (Andersen *et al.*, 2009; Ditlevsen and Johnsen, 2010; Scheffer, 2010; Bestelmeyer *et al.*, 2013).

4.3 Implications of leveraging drone technology for mapping forage resources and detecting tipping points in dryland rangelands

The increasing urgency to enhance informed and adaptive management of rangeland resources necessitates integrating innovative tools like drone technology (Gillan, Karl and van Leeuwen, 2020). Drone mapping offers a valuable complement to traditional field methods, significantly streamlining data collection and enabling more efficient assessments (Laliberte, 2009; Amputu *et al.*, 2023). It can quantify herbaceous biomass and land cover dynamics, reducing the time required for data collection and processing. This approach is non-destructive, fast, repeatable, covers relatively large areas, and provides spatially continuous data, making it an effective tool for mapping overall rangeland health, quantifying bush encroachment, and monitoring bush control measures (Rango *et al.*, 2006; Themistocleous, 2017; Knox, Strohbach and De Cauwer, 2018; Zhang *et al.*, 2021). Consequently, field efforts can then focus on assessing fine-scale information, such as herbaceous plant functional types, species composition, and seedling counts, which is still challenging to derive from drone data.

The robustness of inferences about piosphere effects and the detection of ecological tipping points can be enhanced in future research by expanding the spatial (i.e., different climatic zones and diverse soils) and temporal (i.e., several growing seasons and dry season surveys) scope. Larger spatio-temporal studies that integrate data from the field, drone and satellite imagery could provide valuable insights into the vulnerability of dryland ecosystems to grazing intensification and changing environmental conditions. Another limitation of our study design was that transects did not start directly at livestock waterpoints; therefore, further research could investigate the dynamics within this area (i.e., sacrifice zone) to gain a more complete understanding of piosphere effects and optimize the detection of tipping point behaviour.

Other rangeland metrics derived from drone imagery that can serve as indicators of ecological threshold should be considered. Vegetation patch-size distribution is one such metric proposed to signal the onset of degradation processes and the proximity of abrupt shifts (Maestre *et al.*, 2009; Berdugo *et al.*, 2017). However, this may also only be feasible in healthier rangelands, as Oñatibia & Aguiar (2023) showed that it can highly depend on the ratio of forage to non-forage vegetation. In dryland systems dominated by non-forage plants (i.e., shrubs), as seen in communal areas, vegetation patchiness may not serve as a suitable early warning indicator. In general, exploring cost-effective early warning indicators is crucial to prevent unwanted transitions and maintain ecosystem services, even more so in the face of escalating climate change and human pressure.

5. Conclusion

Our study, based on spatially continuous drone data, highlights the critical role of management practices in maintaining rangeland health. Rangelands in better condition exhibited predictable responses to grazing pressure, while those suffering from extensive degradation – particularly in communal areas – showed little to no variation, preventing us from detecting piosphere patterns. In addition, the homogeneous distribution of woody plants reflects either active shrub control or its absence, which further shapes the vegetation structure on rangelands. The lack of tipping point behaviour in our indicators suggests a gradual response to grazing pressure on freehold farms, while communal areas may have already transitioned into a more advanced degraded state. However, the patchy distribution of forage resources, and consequently foraging patterns, complicates the detection of tipping points along distance gradients. Other rangeland parameters, such as vegetation patch dynamics, which can be analysed from drone imagery may therefore be better suited to reveal threshold responses along grazing gradients. Overall, our findings underscore the importance of rotational grazing and bush control in maintaining rangeland health and ensuring the long-term sustainability of these ecosystems. Furthermore, the integration of drone technology with on-the-ground monitoring can further enhance our ability to manage and restore these vital landscapes.

Conflict of interest

The authors declare no conflict of interest.

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To enhance the readability of this manuscript, DeepL-Write was used, after which the authors reviewed the text and edited it as needed and therefore take full responsibility of its contents.

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Supplementary information

Table S1. Dates of drone flights in the two land use types conducted at two periods of the growing season

Transect	ID	Land use type	Date of drone flight
		Early season	
1	ES_FF_1	Freehold farm	16-Jan
2	ES_FF_2	Freehold farm	19-Jan
3	ES_FF_3	Freehold farm	9-Feb
4	ES_FF_4	Freehold farm	23-Feb
5	ES_FF_5	Freehold farm	25-Feb
6	ES_CA_1	Communal area	24-Jan
7	ES_CA_2	Communal area	1-Feb
8	ES_CA_3	Communal area	16-Feb
9	ES_CA_4	Communal area	8-Mar
10	ES_CA_5	Communal area	10-Mar
		Peak season	
1	PS_FF_1	Freehold farm	23-Mar
2	PS_FF_2	Freehold farm	25-Mar
3	PS_FF_3	Freehold farm	19-Apr
4	PS_FF_4	Freehold farm	15-May
5	PS_FF_5	Freehold farm	16-May
6	PS_CA_1	Communal area	27-Mar
7	PS_CA_2	Communal area	6-Apr
8	PS_CA_3	Communal area	5-May
9	PS_CA_4	Communal area	21-May
10	PS_CA_5	Communal area	24-May

Table S2. Pairwise comparisons of rangeland condition indicators across land tenure systems and two periods of the growing season. SE represents the standard error.

a. Bare ground cover

Contrasts	Estimates	SE	*z* value	*P* value
CA-ES and FF-ES	0.476	0.216	2.207	0.121
CA-ES and CA-PS	**0.484**	**0.025**	**19.073**	**<0.001**
CA-ES and FF-PS	0.316	0.216	1.462	0.461
FF-ES and CA-PS	0.008	0.216	0.037	1.000
FF-ES and FF-PS	**-0.161**	**0.033**	**-4.871**	**<0.001**
CA-PS and FF-PS	-0.169	0.216	-0.782	0.863

b. Herbaceous plant cover

Contrasts	Estimates	SE	*z* value	*P* value
CA-ES and FF-ES	**-0.979**	**0.170**	**-5.744**	**<0.001**
CA-ES and CA-PS	**-0.297**	**0.024**	**-12.241**	**<0.001**
CA-ES and FF-PS	**-0.855**	**0.171**	**-5.013**	**<0.001**
FF-ES and CA-PS	**0.682**	**0.170**	**4.004**	**<0.001**
FF-ES and FF-PS	**0.124**	**0.029**	**4.228**	**<0.001**
CA-PS and FF-PS	**-0.558**	**0.170**	**-3.272**	**0.006**

c. Woody plants shorter than 2m

Contrasts	Estimates	SE	*z* value	*P* value
CA-ES and FF-ES	**0.478**	**0.165**	**2.901**	**0.019**
CA-ES and CA-PS	**-0.066**	**0.014**	**-4.550**	**<0.001**
CA-ES and FF-PS	**0.492**	**0.165**	**2.983**	**0.015**
FF-ES and CA-PS	**-0.544**	**0.165**	**-3.300**	**0.005**
FF-ES and FF-PS	0.014	0.019	0.698	0.8979
CA-PS and FF-PS	**0.558**	**0.165**	**3.381**	**0.004**

d. Woody plants taller than 2m

Contrasts	Estimates	SE	*z* value	*P* value
CA-ES and FF-ES	0.307	0.349	0.88	0.816
CA-ES and CA-PS	**-3.811**	**0.026**	**-14.89**	**<0.001**
CA-ES and FF-PS	0.284	0.349	0.811	0.849
FF-ES and CA-PS	-0.688	0.349	-1.97	0.199
FF-ES and FF-PS	-0.024	0.035	-0.676	0.906
CA-PS and FF-PS	0.665	0.349	1.902	0.227

e. Herbaceous plant biomass

Contrasts	Estimates	SE	*z* value	*P* value
CA-ES and FF-ES	**-173.000**	**60.730**	**-2.849**	**0.023**
CA-ES and CA-PS	**-32.900**	**7.330**	**-4.488**	**<0.001**
CA-ES and FF-PS	-122.900	60.730	-2.024	0.179
FF-ES and CA-PS	140.100	60.730	2.307	0.096
FF-ES and FF-PS	**50.100**	**8.750**	**5.725**	**<0.001**
CA-PS and FF-PS	-90.000	60.730	-1.483	0.448

Table S3. Akaike Information Criterion (AIC) comparisons between linear and piecewise models used to assess the response of rangeland condition indicators along distance gradients from livestock water points

a. Freehold farms

Rangeland condition indicators	Linear	Piecewise
Bare ground cover	-5168.769	-1627.902
Herbaceous plant cover	-4766.766	-1532.934
Woody plants <2 m cover	-7975.063	-3151.894
Woody plants >2 m cover	-6357.155	-3825.568
Herbaceous biomass	24954.44	20524.01

b. Communal areas

Rangeland condition indicators	Linear	Piecewise
Bare ground cover	-5168.769	-2063.633
Herbaceous plant cover	-4766.766	-2257.725
Woody plants <2 m cover	-7975.063	-4274.489
Woody plants >2 m cover	-6357.155	-4196.226
Herbaceous biomass	24954.44	26067.94

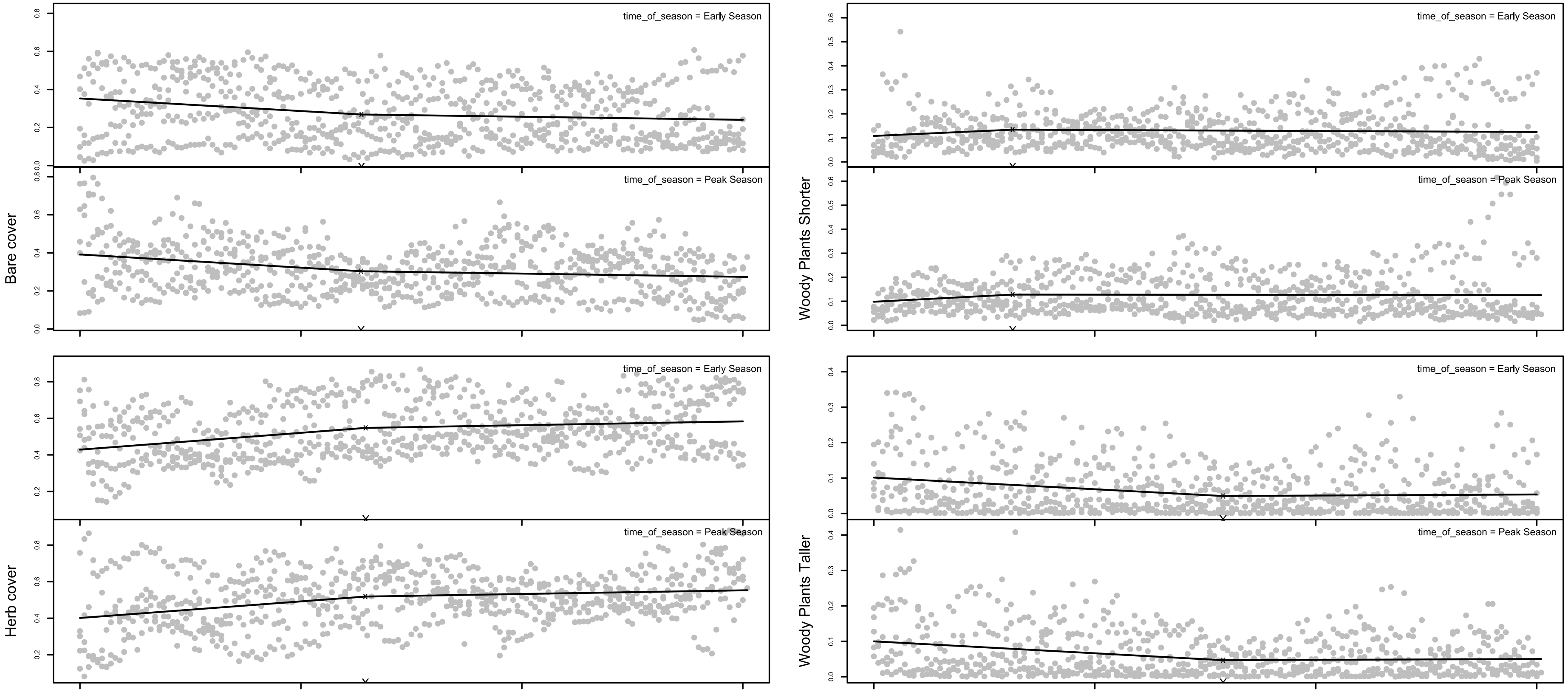

Figure S1. Breakpoint analysis of the five rangeland condition indicators along distance gradients in freehold farms

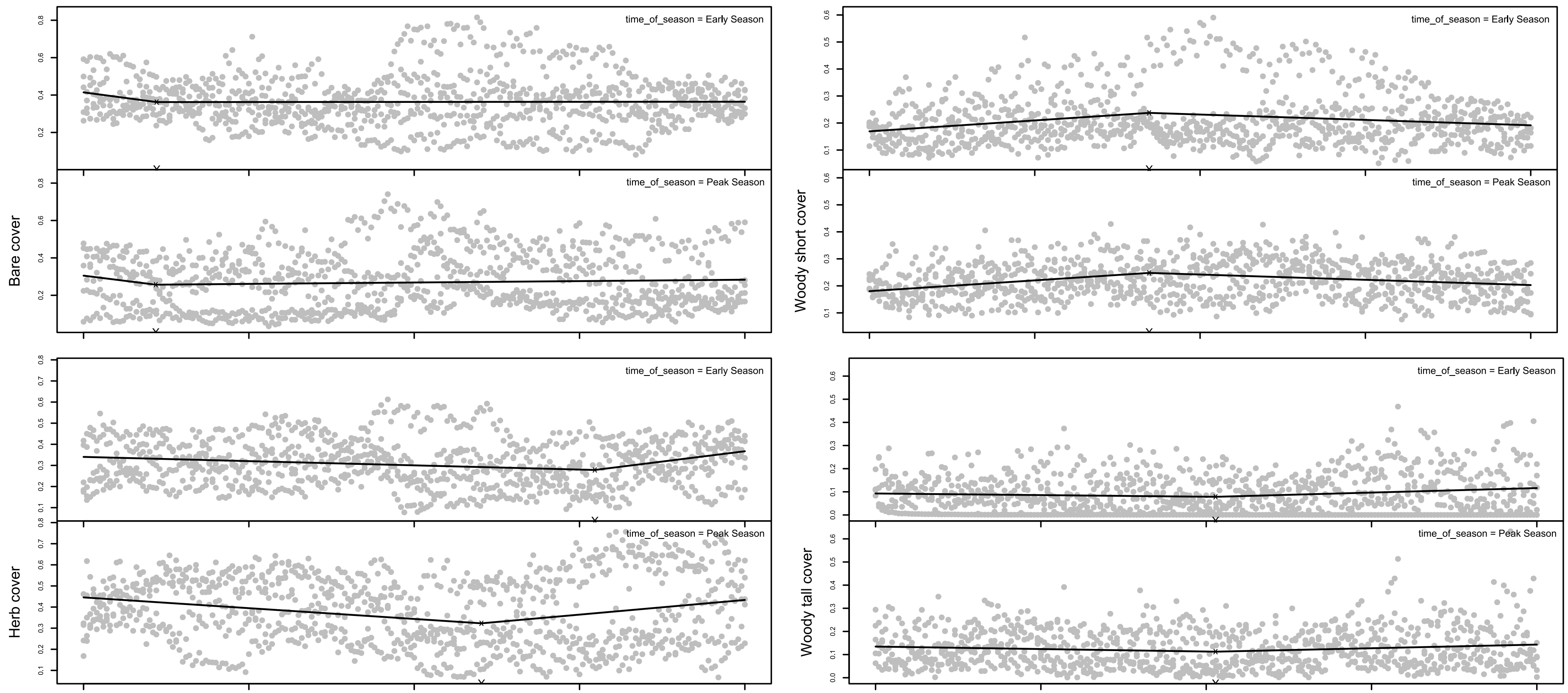

Figure S2. Breakpoint analysis of the five rangeland condition indicators along distance gradients in communal areas

General Conclusions

As global change accelerates undesirable and often irreversible transitions in rangeland systems, advanced tools such as drone technology emerge as cost-effective monitoring solutions. By delivering high-resolution data that bridge the gap between field measurements and satellite observations, drones enable flexible, frequent, and management-oriented monitoring. While drone technology has been widely tested and applied in fields such as precision agriculture and forestry, its potential in rangeland systems is still underexplored. Leveraging drone technology holds great promise for optimising rangeland monitoring, as illustrated by this case study from Namibia's dryland savannah.

In this thesis, I tested the applicability of drone technology to assess the spatio-temporal dynamics of rangeland conditions, evaluate the impacts of grazing pressure and grazing management on rangelands, and detect potential tipping points. For this I used Namibia's semi-arid rangelands, which are representative of many drylands, to make the following contributions in three interconnected chapters that could advance the integration of drone mapping for rangeland monitoring and understanding the ecological impacts of, for example, grazing-induced degradation.

In Chapter I, entitled "**Unmanned Aerial Systems (UAS) accurately map rangeland condition indicators in a dryland savannah**" (Amputu *et al.*, 2023). *Ecological Informatics*, doi: 10.1016/j.ecoinf.2023.102007), I demonstrate the effectiveness of drone technology in predicting key rangeland indicators, such as potential available forage and rangeland functional attribute cover. The high accuracy and low error rates achieved in this study, validated with field observations, highlight the reliability of drone mapping for near-real-time monitoring of rangeland status. This approach provides an opportunity for unbiased, repeatable, and cost-effective rangeland assessments at spatial and temporal resolutions relevant to inform and adapt grazing strategies. The simple, replicable drone-based workflow presented in this chapter provides a basis to enhance adaptive rangeland management in global drylands. This is particularly crucial as these vital ecosystems become increasingly vulnerable to the impacts of changing climatic conditions and intensifying land use.

An important aspect to consider is the generality of derived prediction models beyond their training context in such ecosystems. Semi-arid rangelands and other dryland rangelands are characterized by rapid temporal dynamics and spatial variability, largely due to different land tenure systems and rapid phenological changes during the short growing season, which may limit the reliability of resource predictions. In Chapter II "**Spatio-temporal transferability of drone-based models to predict forage supply in drier rangelands**" (Amputu *et al.*, 2024). *Remote Sensing*, doi: 10.3390/rs16111842), I therefore tested the prediction of proxies of available forage at different times of the growing season and across two contrasting land tenure systems. The results presented in this chapter showed that context-specific models, specifically those developed for certain time periods, achieved limited accuracy when extrapolated, which may restrict their broader applicability across such variable ecosystems. This shows the need to develop prediction models using data that sufficiently capture the spatial and temporal variability inherent in rangelands to better guide grazing management decisions. Overall, the work in this chapter underscored the need for identifying robust, transferable predictive models, as these contribute to better informed management by providing an accurate account of forage resources.

Finally, in Chapter III, entitled "**Gradual rather than abrupt responses of rangeland conditions to grazing pressure revealed from drone imagery**" (in prep.), I leveraged the spatially continuous drone data to test the response of rangeland condition to grazing pressure in two contrasting land tenure systems during the growing season and whether rangeland parameters, including bare ground cover, herbaceous plant cover & biomass, and woody plants, changed abruptly (i.e., indicative of a tipping point behaviour) along grazing gradients established from artificial waterpoints. The results showed the expected response of improving rangeland condition (i.e., more herbaceous plants and less bare ground) with decreasing grazing pressure, but only in the healthier freehold farm rangelands, while no variation (i.e., likely due to uniform, widespread degradation) was found in the more degraded communal areas. In addition, semi-arid rangelands that are continuously grazed, as those in communal areas, vegetation structure diverged from predominantly herbaceous to woody dominated, in line with the well-known phenomenon of bush encroachment. Contrary to my expectation, I found no evidence for the presence of abrupt, threshold-like shifts typically associated with tipping points. However, this does not mean that tipping points are not present in the study system. Factors like patchy forage resources may obscure their detection; and alternative parameters that can be derived from drone imagery, such as vegetation patch size dynamics, which have been shown to signal abrupt changes, should be explored.

Overall, this thesis presents a compelling case for the adoption of drone technology as a cost-effective and scalable tool to optimize rangeland monitoring. Its ability to capture high-resolution, spatially explicit data at user-defined frequencies and relatively large spatial coverage offers immense potential to guide adaptive management strategies and to contribute to the understanding of drivers of rangeland degradation, such as the impacts of grazing management, which are critical to maintaining and restoring the health and resilience of rangeland ecosystems.

Future Research Directions

While this study provides a comprehensive assessment of the potential contribution of drone technology for assessing rangeland dynamics in the growing season, there are several other areas which could be explored to further this work.

Dry season assessments

The research in this thesis was limited to the growing season and the ability of drone technology to assess rangeland condition during the dry season was not tested. The dry season is a critical period when grazing capacity declines significantly due to reduced forage availability as annual plants (which often dominate the forage base in the study system) die back (Stehn, 2008; Knox *et al.*, 2011). It is therefore important that land users plan for this period, when forage resources are limited, to ensure that their rangelands can sustain their livestock. This urges the need to improve the utility of drone technology for year-round rangeland monitoring. For this, further research is needed to evaluate its effectiveness beyond the growing season, when the herbaceous layer is senescent. Key challenges in assessing rangelands in the dry season using remotely sensed data include distinguishing between vegetation and bare soil, which is more difficult due to reduced vegetation contrast (i.e., lower chlorophyll content) and sparser vegetation cover (Smith *et al.*, 2019). Additionally, senescent vegetation has low moisture content that limits the effectiveness of commonly used vegetation indices, which consequently affects the estimation of forage resources and the classification of rangeland parameters. The classification of rangeland features presented in this thesis partly relied on spectral information, which may be limited by the above-mentioned factors. Therefore, alternative approaches, such as image segmentation that is based on traits like texture and shape rather than spectral information (Oldeland *et al.*, 2021), may be more suitable for distinguishing rangeland features during the dry season.

Drone-based forage resource assessments in the dry season would further support land users to adapt their grazing strategies, such as determining appropriate stocking rates or the amount of supplementary fodder needed until the next growing season. Overall, by optimizing the management of forage resources, land users can prevent overgrazing, reduce emergency measures such as selling livestock when prices are unfavourable, minimize the risk of land degradation, and ultimately ensure the ecological health and the socio-economic benefits derived from their rangelands.

Expediting the monitoring of bush encroachment and bush control measures

Bush encroachment remains a prominent issue across global rangelands, and in Namibia about 45 million hectares of rangelands are severely affected (United Nations Industrial Development Organization, 2019). While bush encroachment is associated with increased soil fertility and carbon sequestration (Sandhage-Hofmann *et al.*, 2020), the most concerning consequence is the replacement of the herbaceous layer with woody plants and bare soil patches, reducing the rangeland's carrying capacity for livestock (De Klerk, 2004; Nghikembua *et al.*, 2021). In terms of monitoring this ‘unwanted greening’ of rangelands that is projected to expand with climate change (Bravo-García *et al.*, 2024), drone mapping could greatly expedite quantifying the extent of bush encroachment and support the tracking of restoration efforts like bush thinning.

Woody plant characteristics such as plant cover, height, canopy size, and biomass can be easily measured from drone imagery (Rango *et al.*, 2006; Knox, Strohbach and De Cauwer, 2018; Zhang *et al.*, 2021). In this thesis, woody plant cover was accurately distinguished into two height classes: those shorter than 2m (indicative of saplings and shrubs) and those taller than 2m (indicative of trees) (Chapter III). A few other studies (Oldeland *et al.*, 2017; Kattenborn *et al.*, 2019; Oddi *et al.*, 2021) have also shown the possibility to identify woody plant species from drone imagery based on a combination of plant traits (e.g., leaf size and canopy shape), spectral signatures (e.g. as shown in the drone image in Figure 3), and phenology (i.e., early leaf shedding/ greening species vs. late leaf shedding species). The above demonstrate how drone technology can be used to cost-effectively quantify bush encroachment, identify species of concern, and guide targeted restoration measures.

Figure 3. Distinct spectral signatures of different woody plants visible in a false colour composite (NIR-G-B) captured using drone technology during the growing season in the study system.

Integrating drone data to refine a satellite-based rangeland monitoring system

Integrating drone data with satellite-based monitoring systems, like the Namibia Rangeland Early Warning System, is another way that can enhance adaptive rangeland management. The early warning tool currently disseminates national-level vegetation condition maps every 10 days between October and the end of May (i.e. from the start of the growing season to the start of the dry season). The maps compare current vegetation greenness with historical greenness, providing land users with insights into trends in vegetation condition and the expected rangeland productivity. Specifically, the maps highlight areas with stressed vegetation conditions and those with better than normal vegetation conditions, allowing land users to proactively plan their grazing strategies and to implement timely interventions. While these maps provide a comprehensive and up-to-date view of rangeland condition, they lack the resolution to disentangle vegetation greenness into specific vegetation types, like woody and herbaceous plants, which is necessary to estimate available forage in mixed-woodland-grassland ecosystems like savannahs.

As an alternative to traditional field sampling for reference data, high-resolution imagery obtained by drones has proven to be suitable as training and validation data for satellite information. For example, previous studies have used drone data to train satellite data to map invasive species with acceptable accuracies (Kattenborn *et al.*, 2019) and to distinguish between grass and non-grass canopy reflectance in grasslands (Hu *et al.*, 2024). Drone data have also been used to validate satellite outputs, for example to confirm identified stressed trees in forests (Dash, Pearse and Watt, 2018) or to verify fractional cover maps for woody, herbaceous, and bare ground in Namibian rangelands (Harkort et al. under review). Their finer-scale information could therefore be used to disentangle "general greenness" maps, like those produced by the Namibia Rangeland Early Warning System into woody and herbaceous plants. This refinement will enable the monitoring of forage availability to complement the overall vegetation condition trends, enabling land users to further improve their grazing management. Ultimately, integrating different approaches is crucial to adequately monitor rangelands across various spatial and temporal scales, as this will ensure the sustainability and resilience of these important ecosystems under the pressures of global environmental change.

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