Remote sensing of grazing-induced changes of Mongolian Steppe

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SUMMARY

The Mongolian grasslands, particularly the Eastern Steppe, represent one of the largest remaining intact temperate rangeland ecosystems in the world. Over recent decades, increasing anthropogenic pressures—especially from livestock grazing and land use intensification—have raised growing concerns about grassland degradation, ecological resilience, and sustainable pastoral livelihoods. Despite their ecological importance, large-scale monitoring and understanding of vegetation dynamics and degradation drivers remain limited, largely due to the vast extent of the steppe and its spatial heterogeneity. In particular, the effects of nomadic grazing patterns and their interaction with environmental variability have not been systematically assessed across broad regions using high-resolution observational data. This dissertation addresses this knowledge gap by integrating multi-source remote sensing data, process-based modeling, and machine learning approaches to (i) estimate aboveground biomass (AGB) across central and eastern Mongolia, (ii) detect grazing-induced vegetation breakpoints associated with herder movement, and (iii) assess the ecological impact of livestock and wildlife on steppe productivity and vegetation dynamics. The key research statements and findings are summarized below.

The first part of this thesis focuses on quantifying grassland aboveground biomass (AGB) across the heterogeneous landscapes of Eastern and Central Mongolia, where diverse grassland types—including typical steppe, desert steppe, meadow steppe, and forest steppe—create a complex ecological mosaic. This spatial diversity leads to strong heterogeneity in biomass distribution, posing significant challenges for large-scale monitoring and management. To address this, a machine learning approach using random forest (RF) was developed to integrate multi-source remote sensing data, including multi-temporal optical imagery (WorldView-2, Sentinel-2, Landsat-8) and Synthetic Aperture Radar (SAR) from Sentinel-1. The model was trained and validated against over 600 field samples, providing one of the most robust AGB estimations for the region to date. Furthermore, a novel dissimilarity index (DI) was applied to quantify the area of applicability (AOA), ensuring spatial reliability of the model outputs. Results demonstrated that the combination of Sentinel-1 and Sentinel-2 achieved the highest predictive accuracy, and the model was applicable to more than 70% of the steppe area. Areas with low model transferability were mostly located at the ecological boundaries of grassland types. This study contributes a new, validated AGB mapping framework for the Mongolian steppe, highlighting the value of integrating SAR and optical data for monitoring biomass in large area.

Building upon the foundational mapping of aboveground biomass (AGB), the second part

of this thesis explores the dynamic interactions between vegetation condition and nomadic grazing patterns through time-series analysis. Given the critical role of herder mobility in sustaining livestock and pasture use in Mongolia's traditional nomadic systems, this study investigates whether vegetation changes—particularly those driven by grazing—can be detected using time-series satellite data. A novel machine learning-based breakpoint detection algorithm was developed, leveraging Interferometric Synthetic Aperture Radar (InSAR), optical vegetation indices, and weather data. This method was specifically designed to distinguish vegetation changes caused by grazing from those induced by natural climatic fluctuations such as snow and rainfall. Compared to the widely used BFAST (Breaks For Additive Season and Trend) algorithm, the new method demonstrated superior performance in capturing temporal breakpoints linked to seasonal herder movements, particularly in summer and winter pastures. Field-based validation across Eastern Mongolia confirmed the method's effectiveness, with detection rates of 44% and 28% for random forest and BFAST, respectively, in summer pastures. Temporally, grazing-induced breakpoints were mainly observed in April–June and October–March, aligning with traditional migration cycles. Spatially, the random forest model revealed pasture-use patterns consistent with known herder behavior in productive and heavily grazed areas, while results were less conclusive in more arid, sparsely populated regions.

Finally, based on the satellite-derived AGB maps from 2019 to 2021 developed in the first study, I further assessed the ecological impact of grazing by comparing observed AGB with simulated AGB from the process-based dynamic global vegetation model LPJ-GUESS. This comparison enabled us to evaluate the extent to which grazing activities and wildlife foraging explain discrepancies between modeled and observed biomass. The analysis was conducted across Eastern Mongolia at a 0.1° spatial resolution, integrating field surveys, satellite products, and socio-ecological data on human population, livestock density, and wildlife distribution. The results revealed that livestock grazing had a detectable and systematic influence on vegetation dynamics, whereas changes in wildlife populations—particularly gazelles—exhibited no clear correlation with biomass variability. Weak positive correlations were found between model-data agreement and human/wildlife population densities, while livestock numbers, adjusted into animal units, showed a weak negative correlation with consistency. These findings suggest that livestock grazing acts as a dominant anthropogenic driver affecting grassland productivity, serving as a visible human footprint on vegetation.

Overall, this thesis provides novel insights into the monitoring and interpretation of biomass dynamics and grazing-induced vegetation changes in the Mongolian steppe ecosystem by integrating multi-source remote sensing data, field observations, and advanced machine learning approaches. Through the development of a large-scale, validated AGB mapping framework, this work advances the methodology for assessing grassland productivity across heterogeneous and sparsely monitored rangelands. For the first time, grazing movement patterns were inferred at regional scale using InSAR time series and breakpoint detection models, offering a new avenue to understand seasonal pasture use in nomadic systems. Furthermore, the comparative analysis between LPJ-GUESS simulations and empirical data revealed the distinct ecological impact of livestock grazing on vegetation dynamics, which had previously been underexplored in studies of land use impacts in Mongolia. By linking remote sensing observations with socio-ecological variables such as livestock distribution and settlement patterns, this thesis contributes to a more comprehensive understanding of how human activities alter grassland functioning across space and time. Collectively, the findings of this dissertation not only advance remote sensing-based monitoring techniques for rangeland ecosystems but also provide an empirical foundation for developing targeted and evidence-based grassland management strategies in Mongolia and other dryland regions undergoing similar socio-environmental transformations.

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Introduction

CHAPTER 1

INTRODUCTION

1.1 Grassland ecosystem

The world's grazing lands are a key element of livestock production systems (Bouwman et al., 2005; Erb et al., 2016) providing food security for millions of people who depend on livestock for their livelihoods (Galvin et al., 2008; O'Mara, 2012). Grassland ecosystems fulfill critical ecological roles that underpin both biogeochemical cycles and biodiversity, rendering them indispensable components of terrestrial environments (White et al., 2000). These biomes, characterized by herbaceous vegetation with minimal woody plant cover, exert significant influence on carbon dynamics, acting as sinks through photosynthetic uptake of atmospheric CO_2 (Dass et al., 2018). In temperate grasslands, such as the North American Great Plains or Eurasian steppes, perennial grasses with extensive root systems facilitate substantial soil organic carbon (SOC) storage, often exceeding 100 Mg C ha^{1} in the top meter of soil (Conant et al., 2017). This sequestration capacity mitigates atmospheric CO_2 concentrations, with estimates suggesting grasslands globally store approximately 343 Pg C, or roughly one-third of terrestrial carbon stocks (FAO, 2010). Ecologically, grasslands sustain high species richness, supporting trophic networks that include large herbivores (e.g., *Bison bison, Equus quagga*), apex predators (e.g., *Canis lupus, Acinonyx jubatus*), and pollinators critical for angiosperm reproduction (Burkle et al., 2013; Estes et al., 2011; Knapp et al., 1999). Socioeconomically, grasslands and cultivated forage crops play a crucial role in improving rural livelihoods and alleviating poverty, particularly in regions where livestock farming is a primary economic activity. They provide a stable source of income for pastoral and agro-pastoral communities by supporting livestock production, which supplies meat, milk, wool, and hides for both subsistence and market trade (Herrero et al., 2009). Well-managed grasslands enhance food security by improving livestock nutrition, leading to higher productivity and resilience against climatic shocks (Thornton et al., 2009). Sustainable grassland management contributes to environmental health, reducing land degradation and increasing carbon sequestration, which can provide financial benefits through carbon credit schemes and ecosystem service payments (Follett & Reed, 2010; Stringer et al., 2012). Promoting improved pasture management and forage crop cultivation is thus a vital strategy for poverty reduction in rural areas. However, anthropogenic pressures—overgrazing, tillage, and climate-induced shifts in precipitation—reduce SOC stocks by up to 50% and erode biodiversity, with grassland conversion rates estimated at 1-2% annually (Gibson & Gibson, 2008). Grasslands thus represent a nexus of climate regulation, biodiversity conservation, and human dependence, warranting rigorous study and conservation prioritization (Y. Zhao et al., 2020a).

Grasslands occur in almost all climatic zones, except the poles, extreme arid zones, and the highest mountains (Figure 1.1). Temperate grassland habitats include Eurasian steppes, North American prairies, the pampas lowlands of South America, and Patagonian steppe. Tropical and subtropical grasslands (savannas) occur mostly in Africa and Australia, but are also found in the north of South America, in the southern United States, South Asia, and Southeast Asia (Petermann & Buzhdygan, 2021). With over 13 million km^2, the grasslands of Eurasia form one of the largest continuous terrestrial biomes. They predominantly represent environments with low productivity and a long evolutionary history of natural grazing. Over the last few decades, increasing population sizes and socio-economic changes have subjected these steppes to growing pressure and associated degradation (Werger & Staalduinen, 2012). The degradation of these vast biomes is a complex process that involves both gradual changes—such as a slow decline in vegetation greenness over time—and abrupt state shifts, like the conversion of grassland to sparse vegetation (G. Zhang et al., 2018). While some studies suggest a net increase in grassland area in the Eurasian steppe due to conversions from other land types, grasslands still account for the highest proportion of degraded land within the region (Du et al., 2024). This ongoing degradation is driven by a complex interplay of climatic and anthropogenic factors.

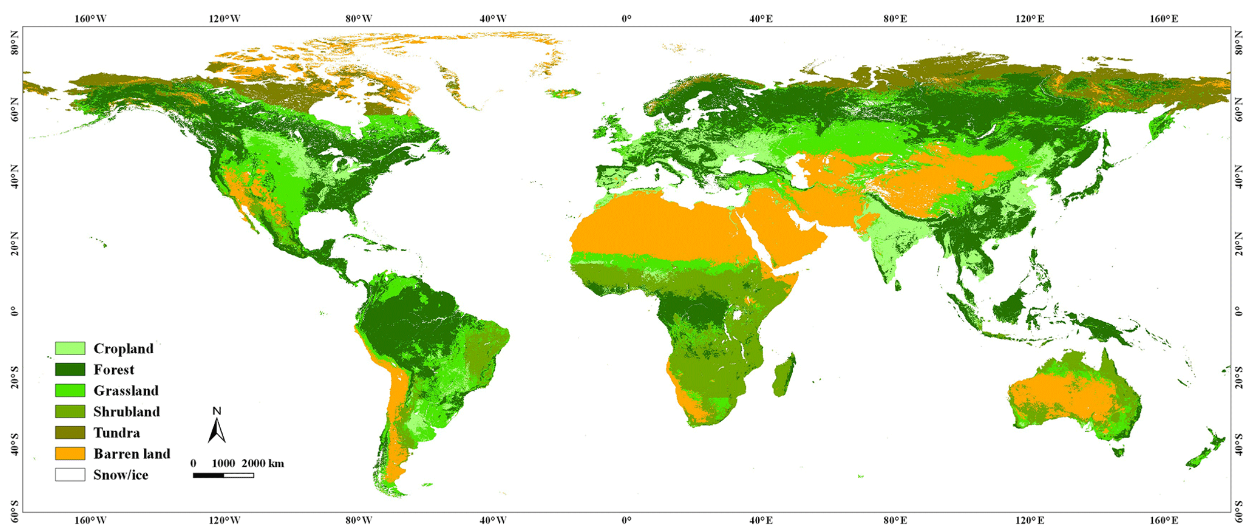


Figure 1.1: GLASS-GLC (annual dynamics of global land cover) CDRs (climate data records) results in 2015 (H. Liu et al., 2020).

Climate change is a primary driver of grassland degradation and desertification, particularly in Central Asia. Persistent drought and the combination of decreasing precipitation and rising temperatures are consistently identified as the main culprits, impacting grasslands, forests, and sparse vegetation alike (L. Jiang et al., 2019; G. Zhang et al., 2018). Studies have quantified this influence, showing that climate variation accounts for over half (53.8%) of the total degraded grassland area in Central Asia (Y. Yang et al., 2023). Interestingly, in some regions like Mongolia, climate change can actually act as a driver of grassland recovery, while human activities are the primary cause of degradation, highlighting a nuanced and region-specific relationship between climate and vegetation dynamics (Y. Yang et al., 2016). Beyond climatic factors, a variety of human activities contribute to degradation. While intensive grazing is a well-known factor that adversely affects grassland resilience (J. Wu et al., 2023), other less-documented disturbances are also significant. For example, research on Russian steppes has revealed that while large-scale agricultural abandonment in the post-Soviet era led to grassland recovery, this positive trend was offset by fragmentation from new, smaller-scale disturbances. These included the proliferation of informal roads, oil and gas exploration, shrub encroachment, and waste dumps, which together severely fragmented the landscape (Prishchepov et al., 2021). Other key anthropogenic drivers of degradation in the broader Eurasian steppe include urbanization, mining, and cropland expansion (Du et al., 2024; L. Jiang et al., 2019). The role of human activity is particularly pronounced in regions with high population density, such as Inner Mongolia, where the decline in ecological resilience has been shown to be more severe compared to less-populated areas (J. Wu et al., 2023). The specific drivers and patterns of degradation are not uniform across the vast Eurasian biome. Studies have identified desertification hotspots, such as in southern and northern Kazakhstan, where a state shift from grassland to sparse land was observed between 2000 and 2014 (G. Zhang et al., 2018). In a comparative assessment of four countries, research found that while climate change and human activities both play significant roles, their relative importance differs markedly. For instance, in Mongolia, climate is the dominant factor in grassland recovery, while human activities are the main driver of degradation.

Grassland degradation results in multifaceted impacts, affecting not only the environment but also socioeconomic systems. Ecologically, a decline in vegetation cover is the primary manifestation of degradation, which leads to exposed soil and a significant reduction in biomass (Dong et al., 2012a). This loss of vegetation-soil connectivity triggers a cascade of effects, including a reduced soil water retention capacity and increased soil hardness. More severely, desertification processes driven by wind erosion cause a loss of soil fine particles, which are the main carriers of soil organic carbon (OC) and total nitrogen (TN). This results in a substantial decrease in the content of these essential nutrients, compromising soil fertility (H.-L. Zhao et al., 2009). Research also indicates that even with the re-establishment of artificial grasslands, it is challenging to fully restore the original soil quality and nutrient reserves of degraded areas (Dong et al., 2012a). Beyond these direct impacts on vegetation and soil, grassland degradation causes a loss of both above- and belowground biodiversity. This biodiversity loss is a key driver for the decline in ecosystem multifunctionality (EMF), which encompasses vital ecological processes such as nutrient cycling and biomass production (Cui et al., 2022). As an important carbon sink, healthy grasslands lose their carbon sequestration capacity when degraded. The degradation process breaks down stable soil aggregates, releasing stored carbon and nitrogen as greenhouse gases into the atmosphere. This can turn grasslands from a carbon sink into a carbon source, exacerbating climate change (G. Zhang et al., 2011). These ecological changes have direct economic consequences for herding communities. In China, for example, the Grassland Ecological Protection Award Policy (GEPAP) was implemented to curb degradation by subsidizing herders to reduce livestock numbers. However, a study in Inner Mongolia found that while the policy led to a slight increase in total household income, herders' net income actually decreased significantly. This highlights that livestock revenue remains the primary source of income for these households, with off-farm income playing only a supplementary role (Y. Yin et al., 2019). The findings underscore the complex challenge of balancing ecological conservation with the economic sustainability of pastoral livelihoods.

Natural grasslands occur around the world and have been characterized using a number of methods. For global characterizations, the methods can be grouped into four types: vegetation composition; ecological and economic assessment; ecosystem mapping; and remote sensing classification (Dixon et al., 2014). Given the vast and often remote nature of these ecosystems, remote sensing has become an indispensable tool for monitoring and understanding grassland dynamics. A wide array of methods has been developed to estimate key biophysical parameters, including aboveground biomass (AGB), a direct measure of vegetation growth and carbon storage (G. Zhang et al., 2011), and net primary productivity (NPP), which reflects the ecosystem's carbon absorption capacity (G. Zhang et al., 2011; H.-L. Zhao et al., 2009). Other fundamental parameters such as fractional vegetation cover (FVC) and leaf area index (LAI) are also routinely estimated using a combination of ground-based and satellite data (Dong et al., 2012b; Imran et al., 2017; Z. Luo et al., 2017). These estimation techniques span from traditional statistical regression models that link vegetation indices (e.g., NDVI) to biophysical parameters, to more advanced, non-parametric machine learning models (e.g., Random Forest, Support Vector Machines) and process-based models like CASA and PROSAIL (Clementini et al., 2020; Danner et al., 2021; Naidoo et al., 2012). The application of these remote sensing methods extends beyond simple parameter estimation to address critical operational needs. These include the long-term monitoring of grassland degradation (J. Li et al., 2015; Zhou et al., 2021), the assessment of utilization intensity through grazing and mowing activities (Junges et al., 2019; Kolecka et al., 2018), the analysis of disaster impacts such as fires and droughts (S. Chen et al., 2022; F. Li, Liu, et al., 2013), and the critical task of monitoring carbon cycling to understand grasslands' role as carbon sinks or sources (Berberoglu et al., 2010; G. Zhang et al., 2011). Together, these methodologies provide the foundation for a data-driven approach to grassland science, management, and policy-making.

1.2 Study area

Mongolia host one of the largest extra-tropical grasslands worldwide. Usage of these vast grasslands have undergone and still undergo changes in terms of land-use practices and intensities. Therfore, this section provides a foundational overview of the geographical characteristics of the eastern Mongolian steppe. Additionally, it examines the socio-economic conditions of the region following the transition from a planned economy to a market-oriented system in the 1990s.

1.2.1 Background of Mongolia

Mongolia, a vast landlocked country in East Asia, presents a striking tapestry of natural and socio-economic complexities. Situated between 41°35'N and 52°09'N latitudes and 87°44'E and 119°56'E longitudes, it covers an expansive 1,564,000 square kilometers, stretching 2,392 km from west to east and 1,259 km from north to south, with an average altitude of 1,580 meters above sea level (Batima et al., 2005). Its diverse landscape, largely untouched by dense human settlements, is a product of millennia of internal and external geological processes, resulting in a unique physical-geographical mosaic. This includes the towering Altai Mountains in the west, the expansive Mongolian-Manchurian steppe in the east, and the arid Gobi Desert stretching across its southern reaches. It also features forested areas, particularly in the north, acting as a transition zone between the Siberian taiga and the Asian deserts. This varied topography gives rise to a harsh continental climate characterized by extreme seasonal temperature fluctuations and low precipitation (Yembuu, 2021). Mongolia has already observed significant climate change, with rising temperatures and uncertain rainfall patterns exacerbating the frequency and magnitude of climate variability and extremes (Batima et al., 2005). These climatic conditions profoundly shape the country's six main natural zones and belts, as illustrated in Figure 1.2: alpine and mountain taiga, mixed and deciduous forests, forest steppe, steppe, Gobi (desert steppe), and desert zones (Doljin & Yembuu, 2021). These natural divisions, often defined by vegetation cover and refined through modern physical geography, dictate distinct physical patterns across the country, influencing its water resources, soils, and rich biodiversity (Yembuu, 2021). The significant dependence of the country's population and economy on climate-sensitive sectors like animal husbandry makes it particularly vulnerable to these environmental shifts (Batima et al., 2005).

Following the dissolution of the Soviet Union in 1991, Mongolia embarked on a dramatic shift from a centrally planned economy to a market-oriented system. This transition has profoundly reshaped its human and economic landscape. While traditional nomadic animal husbandry remains a vital part of the national identity and rural livelihoods, accounting for a significant portion of agricultural GDP and employing a substantial segment of the workforce (National Statistical Office of Mongolia, 2017; (Y. Xu et al., 2019)), its relative contribution to the national economy (GDP) has diminished. This shift is largely due to the rapid ascent of the mining sector, which now dominates the economy, contributing approximately 30% of GDP and over 70% of total export value through the extraction of resources like copper, gold, and coal (Suzuki, 2013). This dual economic structure, however, has led to increasing conflicts between mining operations and nomadic herding, particularly over access to pastureland and precious water resources, as surface mining frequently occurs beneath traditional grazing lands (Suzuki, 2013). By the end of 2023, Mongolia's mining sector accounted for 29% of GDP, a 5% increase from 2020. In contrast, agriculture's contribution fell to 10%, a 3% decrease, and manufacturing's contribution decreased to 7%, a 2% decrease. Furthermore, mining products accounted for 86% of exports, while light industrial products and agricultural products accounted for only 5% and 2%, respectively (NSO2003,NSO2024c). The economic pressures have influenced herding practices, with a notable shift from sheep to goats due to the global demand for cashmere, exacerbating pasture degradation as goats are more detrimental to vegetation regeneration (Dorj et al., 2013). Coupled with a warming climate and increased frequency of natural disasters like "dzuds" (severe winters causing livestock loss) (Y. Xu et al., 2019), these anthropogenic impacts accelerate land degradation and desertification across the country's vast pasturelands, posing significant challenges to both environmental sustainability and the traditional nomadic way of life (Dorj et al., 2013; Y. Xu et al., 2019).

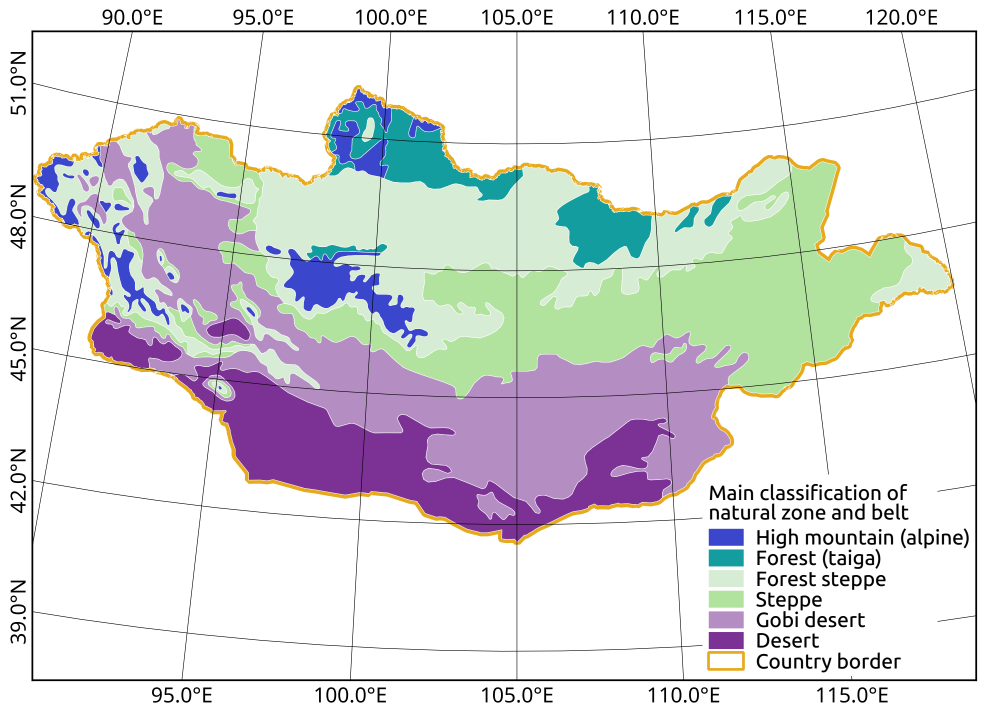


Figure 1.2: The main classification of natural zonalization of Mongolia. (Mohamed & Kimura, 2014)

1.2.2 Eastern Mongolia

Among the vast expanse of the Mongolian Steppe, the eastern region stands out due to its ecological sensitivity and its exposure to intensified human activities. Therefore, this thesis centers on the eastern Mongolian Steppe. The eastern Mongolian grasslands represent the eastern extension of the Eurasian steppe and are situated in the southeastern part of the Mongolian Plateau, spanning latitudes 44°– 48°N and longitudes 109°–118°E (Herbert et al., 2019; B. Nandintsetseg et al., 2021; Török et al., 2020). The region is characterized by a temperate continental climate, with an annual precipitation ranging from 200 to 350 mm, predominantly concentrated in the summer months. The mean annual temperature varies between -1°C and 3°C, with harsh winters, short summers, and pronounced diurnal temperature fluctuations (Jacoby et al., 2003; L. Jargalsaikhan, 2013; Ni, 2003). The topography primarily consists of expansive plateaus interspersed with low mountains and hills (Doljin & Yembuu, 2021). The dominant soil types are Kastanozems and dark Kastanozems, which exhibit moderate fertility but are susceptible to wind erosion (Khadbaatar, 2021). The vegetation is dominated by perennial xerophytic grasses, particularly *Leymus chinensis* and various species of the genera *Stipa* and *Artemisia*, forming a continuous steppe landscape that serves both as an ecological barrier and a repository of biodiversity (Danzhalova et al., 2023; Ogureeva et al., 2019; Takatsuki et al., 2018). Seasonal rivers and lakes are widely distributed across the region, providing essential water resources for pastoral activities. However, these water bodies are increasingly subject to hydrological imbalances due to climate variability and anthropogenic influences (Davi et al., 2013; Sugita et al., 2015).

Since Mongolia's transition to a market economy in the 1990s, the socioeconomic structure of the eastern grasslands has undergone profound transformations (Janzen, 2011; Mearns, 2004). The formerly state-controlled pasture system, characteristic of the planned economy era, gradually disintegrated, leading to the privatization of pastureland management rights (Edström, 1993; Mearns, 1993). However, the absence of comprehensive planning has resulted in pasture fragmentation and exacerbated overgrazing (Gantuya et al., 2021; Tomita, 2013). Traditional nomadic livelihoods have increasingly shifted toward semi-settled or fixed-point grazing systems, while livestock populations have surged in response to market-driven demand, surpassing ecological carrying capacity and contributing to localized grassland degradation and desertification (Houle, 2024b; Janzen, 2005). Concurrently, the expansion of mineral resource extraction and infrastructure development has further encroached upon pastoral lands, intensifying land-use conflicts (Baas et al., 2012; Lahiri-Dutt & Dondov, 2017). Eastern Mongolia is not only the main livestock gathering place in Mongolia, but also an important wildlife habitat, supporting rich biodiversity, especially ungulates. The number of gazelles is about 2.14 million (Buuveibaatar et al., 2024), and they migrate over a large area every year, covering a distance of more than 18,000 kilometers (Dejid et al., 2022). As human activities in the region intensify, the escalating traffic volume presents significant challenges to the movement patterns of gazelles (Mendgen et al., 2023). The area is also home to other globally and regionally threatened species, including mammals such as the manul, gray wolf, and red fox, and birds such as the white-naped crane, gray crane, white-tailed sea eagle, hunting falcon, vulture, swan, quail, black-tailed godwit, Asian sandpiper, and yellow-breasted bunting (Food and Agriculture Organization, 2020).

1.3 Grassland degradation

1.3.1 Grassland degradation in Mongolia

Mongolia's vast rangeland ecosystems, fundamental to both its ecological integrity and the sustenance of its nomadic pastoral society, are facing escalating degradation. This decline is largely attributed to a complex interplay of anthropogenic factors and climatic shifts, creating a pressing environmental and socio-economic challenge (Chuluun et al., 2017). Anthropogenic pressures, primarily stemming from the country's extensive nomadic herding system, are widely recognized as a dominant driver of vegetation change. Livestock populations have seen a dramatic increase, soaring from 25.8 million in 1990 to 43 million by 2009 (Tuvshintogtokh, 2014), and reaching over 71 million by 2022 (UNDP, 2023). This unprecedented growth has led to livestock populations exceeding pasture-

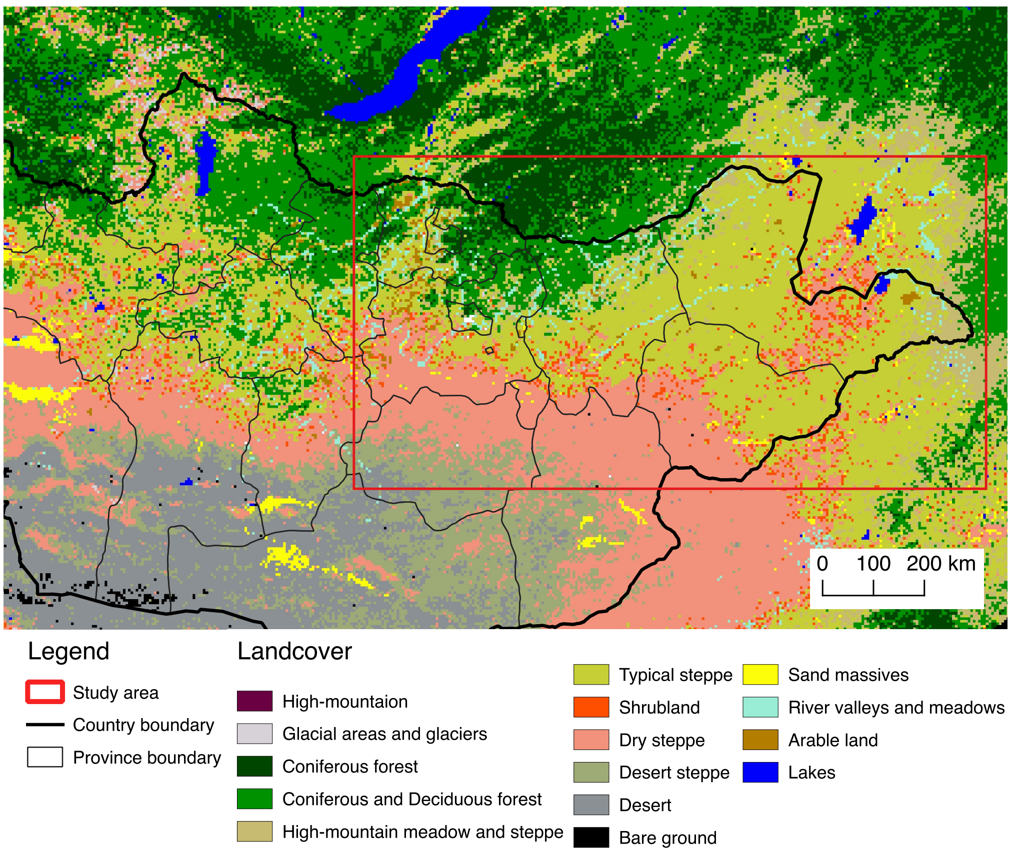


Figure 1.3: Land cover map of eastern Mongolia. *Data source: Environmental Information center Mongolia* (Environmental Information Center Mongolia, 2021).

land capacity by an estimated 2.6 times, intensifying grazing pressure across the steppes (UNDP, 2023). This overgrazing results in a reduction in palatable species, a decrease in vegetation cover, and a decline in overall rangeland health (Bazha et al., 2012; Lkhagvajav et al., 2022). The shift in herding practices, particularly the increased preference for goats due to the lucrative cashmere market, exacerbates degradation, as goats are more damaging to vegetation regeneration than sheep, feeding on roots and flowers and disturbing the pasture's regenerative capacities (Dorj et al., 2013). This intensified pressure results in observable ecological transformations, including the spread of unpalatable and weed species like *Artemisia frigida, Caragana pygmaea, Cleistogenes squarrosa, Allium polyrrhizum, and Ephedra sp.*, and can lead to a reduction in species diversity and changes in dominant plant communities (Bazha et al., 2012; Lkhagvajav et al., 2022; Tuvshintogtokh, 2014).

Beyond vegetation changes, Mongolia's soils have been significantly impacted by a wide range of degradation phenomena, including soil erosion, desertification, nutrient depletion, and various forms of soil pollution (Batkhishig, 2013; Han et al., 2021b; Hofmann et al., 2016). This multifaceted soil degradation is driven by the combined effects of climate change and diverse anthropogenic activities, which include mining, overgrazing, agriculture, urbanization, and off-road transportation (Batkhishig, 2013; Batkhishig & Lehmkuhl, 2003; Chonokhuu et al., 2019). Overgrazing demonstrably impacts soil properties, leading to decreased soil organic matter (30-50% lower in overgrazed areas), reduced fertility, altered chemical properties (e.g., 40-60% lower exchangeable calcium), and increased soil compaction, all of which compromise the ecosystem's resilience (Q. Wang, 2014). The scale of this issue is substantial, with approximately 72% of the country's land considered degraded (Darbalaeva et al., 2020; Eckert et al., 2015; Liang et al., 2021). Mongolia faces severe desertification, which, according to some scientists, affects up to 90% of its total pastureland. Historically confined to regions bordering the Gobi desert, land degradation has in recent years increasingly impacted central Mongolia and, to a lesser extent, extended northward (J. Wang et al., 2020). The combined annual cost of land degradation in the country is estimated at around 2.1 billion USD, or 43% of the country's GDP (UNCCD, 2018), underscoring the severe economic consequences alongside the ecological damage. This highlights the critical need for accurate estimation of soil erosion and a clearer understanding of its spatiotemporal patterns and driving factors (Batkhishig, 2013). While the influence of human activities is profound, the role of climate change, characterized by rising temperatures and altered precipitation patterns, cannot be overlooked in this complex narrative of degradation (Batima et al., 2005; Chuluun et al., 2017). Mongolia's temperature has increased by 2℃ and rainfall has declined over the past 70 years, creating a vicious cycle where herders increase livestock numbers to compensate for reduced pasture productivity, further stressing natural resources (World Bank, 2024). The Mongolian Plateau is identified as highly sensitive to climate change, and its pastoral economies are particularly vulnerable to extreme weather events such as "dzuds"—severe winters leading to massive livestock mortality (Y. Xu et al., 2019). Dzuds, characterized by extreme cold, heavy snow, and unforgiving ice, can wipe out entire herds, leading to mass livestock deaths, poverty, and long-term economic instability. The 2009–2010 dzud, for instance, killed over 28% of the national livestock population, requiring more than two years for recovery. More recently, the 2022-2023 winter resulted in nearly 500,000 animal losses by March 2023, with dzuds accounting for 87% of livestock loss in 2022 (UNDP, 2023). Drought conditions also pose significant challenges, leading to soil moisture shortages and a temporal lack of feed for animals, impacting the viability of nomadic pastoralism (Sugita et al., 2015). Despite these climatic influences, recent empirical studies suggest that the direct impact of livestock grazing often outweighs climate change as a primary driver of vegetation decline, particularly when assessing specific degradation indicators (Hilker et al., 2014c; Jamsranjav et al., 2018). While precipitation changes explained about 30% of degradation nationwide, and up to 50% in denser vegetation areas, temperature changes played only a minor role. Most rangelands are assessed as slightly (33–53%) or moderately (25–40%) degraded, with very severe and irreversible degradation being rare (1–18% of land area), yet the cumulative effect of overgrazing is a primary contributor to widespread degradation.

Effectively addressing rangeland degradation in Mongolia necessitates a nuanced approach that acknowledges both anthropogenic and climatic drivers, emphasizing sustainable management strategies. The concept of carrying capacity (CC) and relative stocking density (RSD) is paramount for maintaining ecological balance, yet significant regional variations exist, with some southern regions exhibiting extremely fragile carrying capacities as low as 0.3 Sheep Units (SU) per hectare (Q. Wang et al., 2024). Mitigation efforts include legislative reforms to secure land user rights and tenure over grazing lands, as well as the implementation of community-based grassland management programs that have shown success in improving household incomes. Adopting management practices such as rest-and-rotation grazing systems offers a common and cost-effective approach to allow pastures to recover (Tuvshintogtokh, 2014). Beyond grazing management, improving livelihood resilience for herder households involves investing in animal feed and adapting to unpredictable seasonal changes, as well as rehabilitating wells and protecting local environments to secure water for livestock and pastures (UNDP, 2023; World Bank, 2024). While the precise interplay between climate and grazing remains a subject of ongoing scientific inquiry, the overwhelming evidence points to the urgent need for targeted rangeland restoration, adaptive management, and strengthened governance to prevent further irreversible degradation across Mongolia's invaluable steppe ecosystems (Jamsranjav et al., 2018). The resilience of this coupled human-nature system hinges on integrated strategies that balance the socio-economic needs of herders with the ecological limits of the grasslands, fostering a shift from quantity to quality in livestock production (UNDP, 2023).

1.3.2 Grassland degradation on eastern Mongolia steppe

This section provides an overview of past and current research on land degradation monitoring in eastern Mongolia since the 1990s. A particular focus is placed on vegetation dynamics in the region, including temporal patterns and spatial variability across the steppe landscape. The primary drivers of grassland degradation are discussed, encompassing both anthropogenic pressures—such as overgrazing, increasing livestock numbers, and land-use changes—and environmental factors like climate variability and drought events. In addition, the section explores ongoing challenges in the sustainable use and management of grassland resources, especially concerning the complex ecological interactions between human activities, wildlife movement, and vegetation responses. Finally, an overview of commonly used methods for detecting vegetation dynamics, including field surveys, remote sensing approaches, and time-series analyses, is briefly presented to provide a methodological context for the subsequent chapters.

The extensive grazing pressures in Mongolia's rangelands have profoundly altered vegetation dynamics, leading to discernible patterns of vegetation succession in degraded grasslands. This phenomenon, driven primarily by anthropogenic factors and, to a lesser extent, by climatic shifts, involves shifts in species composition, cover, and overall plant community structure (Davaanyam et al., 2024; Munkhzul et al., 2021; Tuvshintogtokh, 2014). Long-term monitoring studies in dry steppe zones have observed a clear, albeit not always statistically significant, downward trend in species richness and a gradual decrease in average species diversity (Davaanyam et al., 2024). This reduction in species diversity and plant cover serves as a key indicator of vegetation degradation (Davaanyam et al., 2024; Herrero-Jáuregui & Oesterheld, 2018; Y. Wang & Wesche, 2016).

The intensified grazing pressure, marked by a substantial increase in livestock numbers (from 25.8 million in 1990 to over 71 million by 2022), is a primary driver of these changes ("National Report on the Rangeland Health of Mongolia - Second Assessment | Land Portal", 2018; Tuvshintogtokh, 2014). This overgrazing can lead to a progressive succession where weed and unpalatable species increase in coverage and abundance (Tuvshintogtokh, 2014). For instance, species such as *Cleistogenes squarrosa*, *Allium polyrrhizum*, and *Ephedra sp.* have shown vigorous spread and expanding ranges in degraded areas (Bazha et al., 2015; Tuvshintogtokh, 2014). In mountain-meadow and meadow steppes, overgrazing tends to result in the dominance of *Artemisia frigida* and *Caragana pygmaea*. In true and dry steppes, *Caragana microphylla* and *Artemisia frigida* become more prevalent, while desertified and desert steppes see an increase in *Caragana stenophylla* and *C. korshinskii* (Bazha et al., 2012). This shift often leads to strongly monodominant communities, where subdominants like *Artemisia adamsii*, *Carex duriuscula*, and *Potentilla acaulis* may also increase depending on the subzonal steppe type (Bazha et al., 2012; Lkhagvajav et al., 2022). Research also highlights that while edible plants are generally dominant, the fraction of grazing- and trampling-tolerant plants increases with livestock pressure, with species like *Artemisia adamsii* flourishing in degraded areas (Koyama et al., 2016; Narantsetseg et al., 2018). The degradation process observed in Fescue-forbs rangelands, a main type in the mountain steppe, shows significant declines in dominant species like *Festuca lenensis*, replaced by increaser and tolerant species such as *Arenaria capillaris* and *Chamaerodos erecta* (Lkhagvajav et al., 2022).

The interaction between grazing intensity and climatic conditions is crucial in shaping these successional patterns. While the effects of grazing on plant species diversity and composition are well-documented, their influence on plant functional traits and genetic structures is less understood (Oyundelger et al., 2023; Wesche et al., 2016). Long-term studies employing grazing exclusion along climatic gradients in the Palearctic steppe biome reveal that grazing can have a significant positive effect on genetic diversity, as seen in *Artemisia frigida*, suggesting that moderate grazing might even be beneficial for certain species and ecosystem functioning (Oyundelger et al., 2023). Conversely, intensive grazing has been linked to decreased genetic diversity in common grassland species (Peng et al., 2015). This complex relationship means that grazing effects can differ between relatively moist equilibrium and dry non-equilibrium rangeland systems, with environmental filtering dominating vegetation composition in drier areas, and grazing-tolerant species becoming more prominent in wetter regions (Ahlborn, 2020; Milchunas & Lauenroth, 1993). Beyond affecting plant community composition and genetic diversity, nomadic livestock also play an instrumental role in shaping vegetation patterns through seed dispersal. The attachment of seeds to the fur of sheep (epizoochory) is the primary mechanism for long-distance dispersal, which is particularly crucial for key fodder grasses such as Agropyron cristatum and Stipa krylovii. As herds of sheep and goats can travel up to 15 km per day and undertake long-range migrations during drought years, they act as key vectors for maintaining the genetic connectivity and species distribution of the grassland ecosystem. Research has found that while goats are relatively poor vectors for seed dispersal, their proportion in Mongolian livestock herds has increased significantly in recent years—a trend that warrants concern for the long-term ecological dynamics of these grasslands (Bläß et al., 2010). The observed changes in vegetation, such as the transformation of typical steppe into dry steppe and desert steppe, coupled with the relative stability of desert steppe and desert vegetation, highlight the vulnerability of different ecological zones (Gunin et al., 2019; Tuvshintogtokh, 2014). Satellite remote sensing, through the analysis of Fractional Vegetation Cover (FVC) and AGB, along with Normalized Difference Vegetation Index (NDVI) trends, provides critical tools for monitoring these changes. Studies using Sentinel-2 and Landsat data show significant declines in NDVI across large areas of the eastern Mongolian steppe, indicating widespread vegetation cover changes consistent with landscape degradation (Dashpurev et al., 2023; Gunin et al., 2019). These tools also allow for a more accurate estimation of degradation levels, which, while substantial (with 58% of pastureland degraded by 2016), may not be as universally severe and irreversible as sometimes perceived (Jamsranjav et al., 2018; “National Report on the Rangeland Health of Mongolia - Second Assessment | Land Portal”, 2018).

The multifaceted nature of vegetation succession in Mongolia’s degraded grasslands underscores the urgent need for effective management. Given that overgrazing is considered a primary driver of degradation, even potentially outweighing climate change in some contexts, the adoption of sustainable grazing practices is crucial (Tuvshintogtokh, 2014). Implementing rest-and-rotation systems for pastures offers a common and cost-effective approach to allow vegetation recovery (Tuvshintogtokh, 2014). Furthermore, understanding the distinct impacts of grazing versus trampling, particularly near water sources where heavy animal traffic compacts soil and alters plant communities, is essential for targeted interventions (Narantsetseg et al., 2018). While some studies explore the use of prescribed burning and mowing for controlling undesirable subshrubs, their long-term effectiveness in the context of climate variability and grazing impact requires further evaluation (Koyama et al., 2016).

1.3.3 Drivers leading to grassland degradation

Natural drivers

Climate change. Mongolia's semi-arid continental climate, characterized by low precipitation and significant temperature fluctuations, is a primary driver of its ongoing land and grassland degradation. Climate data reveals a significant warming and drying trend over recent decades. Between 1940 and 2015, the country's annual mean air temperature increased by 2.24 ℃, while annual precipitation decreased by 7%, leading to a higher aridity across the country (Lkhaakhuu et al., 2023). This combination of factors, coupled with a positive feedback loop between soil moisture deficits and surface warming, has led to a hotter and drier regional climate. The effects are evident in the landscape, with more than three quarters of the country's land affected by drought and desertification (Han et al., 2021b). The dramatic impact is further underscored by the fact that over a quarter of lakes larger than 1.0 km^2 on the Mongolian Plateau dried up between 1987 and 2010 (Han et al., 2021a). This climate-driven environmental stress also affects herder livelihoods by altering the timing of rainfall, which in turn interferes with plant growth and reduces pastureland quality (Tugjamba et al., 2021b). This persistent drying trend is a major factor in recurring droughts (Han et al., 2021b) and has culminated in severe atmospheric events like the 2021 East Asia sandstorms, which were triggered by a combination of unusually warm temperatures and low precipitation (X. Xu et al., 2022). While human activities like overgrazing and mining are significant contributors to land degradation, climate change provides the overarching natural framework that exacerbates these issues (Dorj et al., 2013; Han et al., 2021b). However, some research suggests a more complex dynamic; a study of the Mongolian Plateau from 2000 to 2019 found that a period of increasing precipitation and temperature was the main driver behind a documented decline in desert extent, which highlights the role of climate as a primary, though not uniform, factor in shaping vegetation trends (X. Guo et al., 2021).

Natural hazards. Grasslands in Mongolia spanning the steppe and semi-arid zones of the Mongolian Plateau, are a critical biome shaped by a continental climate with extreme temperature swings and low precipitation (200–400 mm annually). Natural hazards—wildfires, snowstorms ("Dzud"), droughts, and sand storms—disrupt vegetation dynamics, influencing net primary productivity (NPP), species diversity, and ecosystem stability.

Natural hazards alter grassland vegetation ecologically by reshaping community structure and function. Wildfires, common during the dry season, deplete aboveground biomass, reducing the survival, resprouting and reproductive capacity of species with faster regeneration rates, such as *Stipa krylovii* (Schellenberg et al., 2020). In eastern Mongolia's Dornod Province, the increase in fire frequency and the expansion of fire-affected areas led to a 7.2-fold increase in the proportion of Artemisia and Artemisia frigida, indicator species of grassland degradation, while the proportion of Carex duriuscula and *Stipa krylovii* decreased by about 86% (Munkhbat et al., 2023). Droughts and dust storms compound these effects, lowering moisture and stripping soils, respectively, driving vegetation toward drought-tolerant states, especially in northcentral and northeast Mongolia (B. Nandintsetseg et al., 2021). Dzuds are characterized by heavy snow or ice cover that limits access to forage and delays spring greening. Due to a lack of adequate preparation, the 2010 dzud in the central steppes killed an estimated 8.4 to 10 million livestock, representing approximately 20% to 22% of the country's total herd (Girvetz et al., 2012). The spatial distribution of disasters determines the response of vegetation in Mongolia's diverse terrain. Although there is no statistically significant data showing that the spatial distribution of shrubs after fire is related to fire occurrence, the distribution of shrubs represented by Caragana microphylla was affected to varying degrees in the central and eastern steppes of Mongolia after being mixed with the impact of drought, especially for A. adamsii, fire caused the loss of its woody branches, thereby reducing biomass and the number of flowering branches (Koyama et al., 2016; Narantsetseg et al., 2014).

Soil degradation. Soil degradation in the eastern Mongolian steppes significantly inhibit the primary productivity of vegetation by reducing soil organic matter content and destroying surface structure. Studies have shown that soil compaction caused by overgrazing reduces water infiltration, enhances drought stress, and stunts the root growth of perennial grasses such as Stipa grass and Leymus chinensis (Kinugasa et al., 2015). At the same time, soil nutrient loss (such as nitrogen and phosphorus) due to vegetation succession to barren-tolerant annual herbs (such as Salsola salsa) further reduces community instability (Venter et al., 2021). This process is extremely significant in drought, and the accelerated decomposition of soil carbon pools forms a positive feedback loop with the recovery of vegetation cover (Sodnomdarjaa et al., 2022).

Soil degradation can lead to changes in plant community composition, which in turn affects species diversity. In general, soil degradation can lead to a decrease in species diversity, especially for species that are sensitive to environmental changes (Sundev et al., 2018). For example, studies have shown that in the eastern Mongolian grasslands, as grazing intensity increases, soil degradation worsens, and both plant species richness and diversity indices show a downward trend (Hannam, 2017). Soil degradation can affect plant growth and reproduction, which in turn affects biomass and productivity. For example, soil nutrient loss can limit plant growth, thereby reducing biomass and productivity (Lkhagvajav et al., 2022). Studies have shown that in the eastern Mongolian grasslands, soil degradation has led to a significant decrease in both aboveground and belowground biomass of plants (Q. Wang, 2014).

Anthropogenic drivers

Overgrazing. Livestock husbandry stands as a cornerstone of Mongolia's economy, playing a role as significant as its burgeoning mining sector. However, the rapid growth in livestock numbers, particularly in key provinces, presents a severe and escalating challenge to the carrying capacity of the nation's vast grasslands. In 2024, Mongolia's total livestock population surged to 57,649.7 thousand heads (Figure 1.4). A substantial portion of this increase is concentrated in the eastern provinces of Dornod, Sukhbaatar, and Khentii, alongside Tuv province, which collectively accounted for 11,003.2 thousand heads. This represents over one-fifth of the national total across just four out of 22 provinces. This marks a dramatic increase from 1970, when the national total was 22,574.9 thousand heads, and these same four provinces collectively held 4,632.82 thousand heads Figure 1.5. Over 54 years, the livestock population in these pivotal regions has more than doubled, intensifying pressure on an already fragile ecosystem. While grasslands, covering approximately 75% of Mongolia, have historically supported nomadic herding sustainably for millennia, recent decades have witnessed a profound transformation in social systems and nomadic practices, contributing to widespread pasture degradation (Koda & Fujita, 2014).

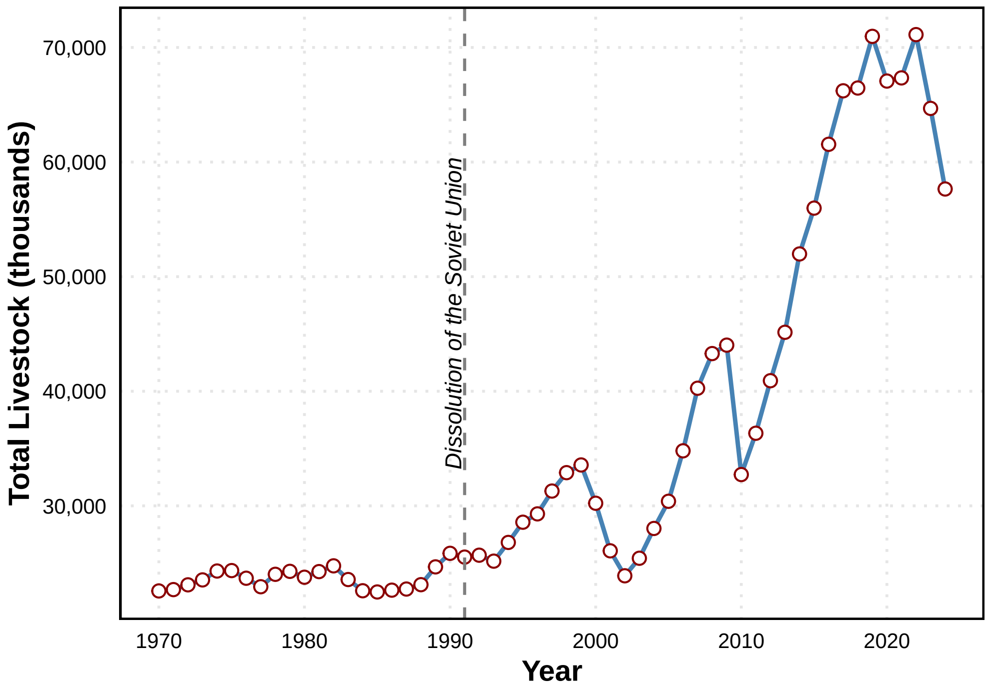


Figure 1.4: Number of livestock in Mongolia from 1970 to 2024 (NSO2003,NSO2024c).

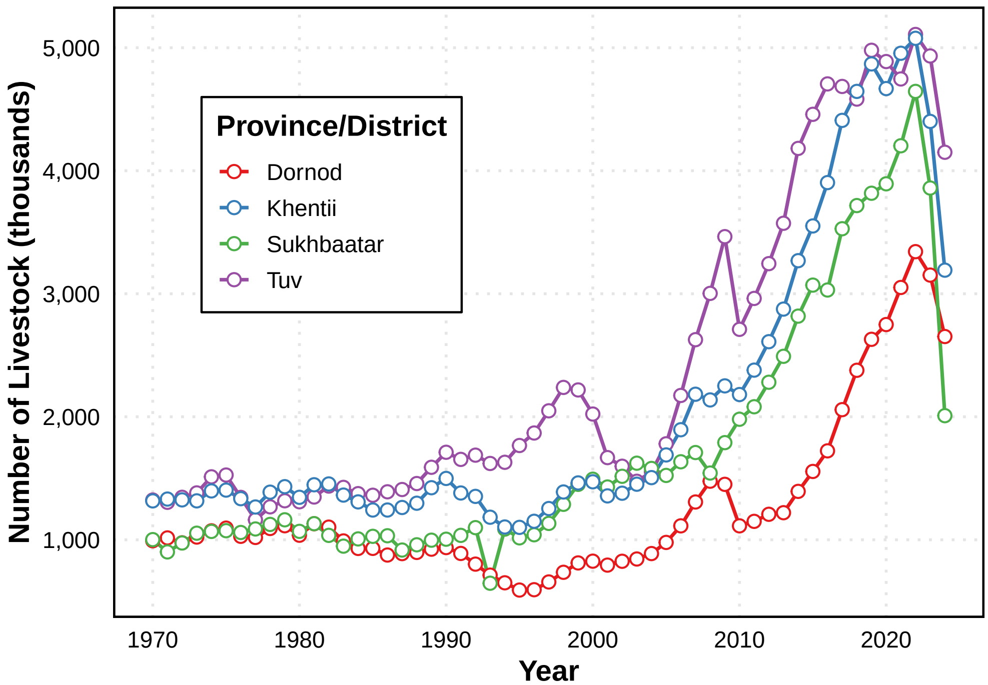


Figure 1.5: Number of livestock in eastern Mongolia from 1970 to 2024 (NSO2003,NSO2024c).

The escalating livestock numbers, largely fueled by a market-driven demand for cashmere, have led to increasingly concentrated grazing patterns. Herders, influenced by the market economy shift post-1992, often gravitate towards urban centers and main roads for better access to markets, education, and healthcare (Yoshihara et al., 2008). This transition from traditional, highly mobile nomadic patterns to more sedentary grazing practices directly impacts vegetation, causing a significant reduction in palatable plant biomass and altering natural plant communities and structures (Sasaki et al., 2005). Intensive continuous grazing has been shown to rapidly decrease overall plant species richness and aboveground annual production, potentially leading to irreversible changes, such as the dominance of unpalatable, grazing-tolerant species like certain rhizomatous plants over valuable tussock grasses (Fujita & Ariunbold, 2014; Koda & Fujita, 2014; Van Staalduinen et al., 2007). This ecological imbalance creates a detrimental feedback loop: as pasture quality declines, livestock productivity (e.g., weight gain, milk yield) and survival rates decrease due to insufficient forage, often compelling impoverished herders to further increase herd size for short-term economic survival, thereby exacerbating degradation (Lise et al., 2006).

Beyond the direct removal of vegetation, overgrazing profoundly contributes to soil degradation, manifesting as increased soil erosion (Onda et al., 2007) and accelerated soil alkalization (Fujita & Ariunbold, 2014). This soil alteration can significantly delay the natural recovery of degraded pasture vegetation, impacting long-term ecosystem health. Furthermore, the combined environmental pressures from intensive grazing and mining activities, which contaminate soils with heavy metals and dust, collectively inhibit natural plant regrowth and promote the proliferation of invasive species over native flora (Oyuntsetseg et al., 2012; Shabanova et al., 2019). The cascading ecological consequences extend to other biodiversity; for instance, studies indicate that moth species diversity, recognized as an indicator of pasture health, is significantly lower in heavily grazed areas compared to lightly grazed ones (Enkhtur et al., 2017). Moreover, the production of crucial plant biomass in drylands becomes notably more vulnerable to intensified grazing and shifts in precipitation patterns, especially in comparatively moister and more productive rangelands. This highlights the intricate and fragile interactions between species richness, herbivory, and climatic variability (Ahlborn et al., 2021). These multifaceted and interconnected impacts collectively compromise the biodiversity, ecological resilience, and long-term sustainability of Mongolia's iconic steppe ecosystems.

Given the array of problems arising from overgrazing, sustainable livestock management is not merely an option but a critical necessity for Mongolia's future. Traditional nomadic pastoralism, a millennia-old cultural practice, offers a compelling solution by intrinsically balancing livestock numbers with pasture regeneration. This system relies on seasonal migrations across vast territories, ensuring the dispersal of grazing pressure and allowing pastures sufficient time to recover and regenerate. Research consistently demonstrates the effectiveness of this mobility: studies comparing traditional nomadic grazing to sedentary practices reveal that nomadic animals exhibit better body weight gains and improved mineral balance due to access to a more diverse range of plant species across varied landscapes (Morinaga et al., 2016; Yoshihara et al., 2013). This inherent flexibility in movement is especially vital in arid and semi-arid regions where forage supply and quality vary unpredictably with precipitation (Michler et al., 2023). Therefore, promoting and supporting such traditional mobile strategies are crucial for maintaining adequate forage intake for livestock and effectively dispersing grazing pressure across the expansive rangelands.

However, the efficacy of traditional nomadic practices faces formidable contemporary challenges. The allure of urban centers, driven by desires for improved education, healthcare, and market access, has notably reduced the frequency of herder camp migrations and shortened livestock walking distances (Michler et al., 2023; Teickner et al., 2020). This trend towards increased sedentarization inevitably leads to intensified, concentrated grazing pressure around permanent or semi-permanent settlements, creating what are often termed "sacrifice zones"—areas characterized by severe trampling, concentrated waste deposition, and a stark reduction in plant diversity (Michler et al., 2022). To counteract this, a holistic approach is required, one that integrates the invaluable insights from traditional ecological knowledge with modern monitoring tools like GPS tracking, which can quantitatively analyze livestock movement patterns and inform adaptive management strategies (Teickner et al., 2020). Maintaining the inherent flexibility of grazing mobility, adapting to variations in biomass availability across the landscape, and leveraging altitudinal migrations are likely the most robust strategies for achieving sustainable pasture use amidst increasing livestock populations, complex socio-economic transformations, and an unpredictable climate (Michler et al., 2023). Ultimately, effective rangeland management policies must embrace and support these dynamic approaches to ensure both the long-term health of Mongolia's natural ecosystems and the continued viability of its herding communities. A review of research on rangeland management policies will be presented by following.

Management policies. Grassland management policies in eastern Mongolia have played a pivotal role in shaping the region's grassland vegetation dynamics, often with mixed outcomes due to the interplay between traditional practices, post-socialist reforms, and modern environmental challenges (Sneath, 2003; Upton, 2010). Historically, Mongolia's steppe ecosystems, including those in the eastern provinces like Dornod and Sukhbaatar, were managed through nomadic pastoralism, a system that relied on seasonal mobility to prevent overgrazing and maintain vegetation balance (Dorj et al., 2013; Neupert, 1999). However, the transition from a centrally planned economy to a market-based system in the 1990s dismantled collective herding structures and led to a privatization of livestock, resulting in a dramatic increase in herd sizes—from 25.8 million in 1990 to over 60 million by the mid-2010s (Jamsranjav et al., 2018; Kowal et al., 2021). Without corresponding policies to regulate grazing intensity, this shift has driven widespread overgrazing in eastern Mongolia, reducing plant diversity and biomass while favoring unpalatable species like Artemisia frigida over nutritious grasses such as Stipa krylovii (Akhmadi et al., 2022; Davaanyam et al., 2024).

In response to growing degradation, the Mongolian government introduced policies aimed at sustainable grassland management, though their implementation in eastern Mongolia has faced significant hurdles (Endicott, 2012; Undargaa, 2023). The 2002 Law on Land and subsequent amendments sought to formalize pastureland use by assigning usufruct rights to herder groups, intending to encourage rotational grazing and reduce pressure on specific areas . However, studies indicate that in eastern Mongolia, where population density is relatively low but livestock numbers are high, enforcement has been weak, and many herders lack the resources or coordination to adhere to these guidelines (M. E. Fernandez-Gimenez & Batbuyan, 2004). As a result, vegetation dynamics have shifted, with research showing a 20-30% decline in aboveground biomass in heavily grazed zones, alongside a decrease in species richness as grazing-sensitive plants are outcompeted (Nakano et al., 2020). The lack of clear boundaries and monitoring has thus undermined the policy's effectiveness, exacerbating degradation rather than mitigating it.

More recent initiatives, such as the Green Gold Project and the National Livestock Program launched in the 2010s, have aimed to integrate scientific management practices with traditional knowledge to improve grassland health in eastern Mongolia. These programs promote community-based management, providing training on sustainable stocking rates and pasture rotation, and have shown some success in pilot areas, with restored vegetation cover increasing by up to 15% in managed plots (Jamsranjav et al., 2018). However, their reach remains limited, and in eastern Mongolia, where mining and agricultural expansion compete for land, policy priorities often favor economic development over ecological restoration (Kasymov et al., 2023). Remote sensing data highlights that areas under effective management exhibit higher NDVI values compared to unmanaged regions, underscoring the potential of well-executed policies to positively influence grass dynamics (Fujita & Ariunbold, 2014; Jamsranjav et al., 2019).

Mining. Mining plays a pivotal role in Mongolia's national economy, and its rapid expansion has significantly impacted the country's steppe ecosystems. As a resource-rich economy, Mongolia's development strategy has long centered on mineral resources. Between 1999 and 2024, Mongolia's total exports surged from 454.2 million to 15.7834 billion, with exports to China escalating from 208.2 million to 14.4207 billion. Within export categories, coal exports alone dramatically increased from 0.435 million tons in 2003 to 28.7 million tons in 2024. The share of mineral products in the national export composition also rose sharply from 32.3% in 1999 to 87.2% in 2024 (NSO2003,NSO2024c). While this heavy reliance on the mining sector has substantially contributed to economic growth and improved local livelihoods, it has also introduced economic vulnerabilities, such as susceptibility to commodity price fluctuations and diminished competitiveness in other traditional sectors (Dagys et al., 2023; Taguchi & Ganzorig, 2018).

Mining activities have profoundly influenced vegetation dynamics in Eastern Mongolia's grasslands, a region facing increasing pressure from resource extraction driven by economic development (Enkhjargal, 2021; Jarsjö et al., 2017). Since the early 2000s, Mongolia's mining sector has expanded rapidly, with Eastern Mongolia hosting deposits of coal, gold, and other minerals that attract both large-scale operations and artisanal mining (Sodnomdarjaa et al., 2023). These activities directly destroy vegetation cover and disrupt soil integrity through processes such as open-pit excavation, overburden removal, and tailings disposal (Timofeev & Kosheleva, 2017). Studies estimate that mining-related land disturbance in Mongolia affects over 40,000 hectares annually, with eastern provinces like Dornod and Sukhbaatar experiencing significant ecological impacts due to their proximity to mineral-rich zones 2019(. The resulting loss of native grassland species and alteration of plant communities threaten both biodiversity and the traditional pastoral livelihoods dependent on these ecosystems (Krtz et al., 2010). The direct impact of mining on Eastern Mongolia's grasslands is profound, as it replaces diverse vegetation with barren landscapes or degraded patches. Excavation removes topsoil and perennial grasses like *Stipa krylovii* and *Leymus chinensis*, which are critical for maintaining steppe stability, leaving behind exposed surfaces prone to erosion and desertification (Hartwig et al., 2016; Kasimov et al., 2016). Remote sensing analyses reveal that the area of grassland disturbed by dirt roads and oil extraction infrastructure has increased by 88% since 2005, with the fastest increase of 47% between 2005 and 2010 (Dashpurev, Bendix, & Lehnert, 2020). Furthermore, the deposition of dust and heavy metals from mining operations—such as arsenic, lead, and mercury—contaminates soils and inhibits plant regrowth, favoring ruderal or invasive species over native flora (Oyuntsetseg et al., 2012; Shabanova et al., 2019). These changes not only reduce grassland productivity but also compromise the ecosystem's capacity to recover naturally. Despite the economic importance of metallic mineral resources in Mongolia, improper mining management can lead to the pollution of stream waters, posing a threat to aquatic ecosystems and human health. For instance, after passing through the Zaamar gold mining area, the Tuul River's water becomes highly turbid (up to 742 Nephelometric Turbidity Units (NTU)) due to the disturbance of sediments and soils by placer gold mining (Batsaikhan et al., 2017). The Zaamar area also serves as a contamination source for the Tuul and Orkhon rivers, particularly with aluminum (Al), iron (Fe), and manganese (Mn) during the mining season. The hydrochemistry of the Khangal River is influenced by heavy metal-loaded mine drainage (especially Mn, Al, cadmium (Cd), and arsenic (As)) originating from a large tailings dam of the Erdenet porphyry copper-molybdenum (Cu-Mo) mine. These two contaminated rivers, the Tuul and Khangal, merge into the Orkhon River, which then flows into the Selenge River near the border between Mongolia and Russia, eventually reaching Lake Baikal, a UNESCO World Heritage site. Given the critical water quality problems arising from mining, activities in central northern Mongolia require careful management to minimize the transboundary movement of aquatic contaminants (particularly turbidity, dissolved organic carbon, Fe, and Al) (Batsaikhan et al., 2017; Myangan et al., 2017).

Land use change. Overgrazing has emerged as a significant driver of grassland vegetation dynamics in eastern Mongolia, a region characterized by vast steppe ecosystems that have supported nomadic pastoralism for centuries (Han et al., 2021b; Jamsranjav et al., 2018; Y. Y. Liu et al., 2013). The Mongolian Plateau, including eastern Mongolia, hosts one of the world's largest remaining grassland ecosystems, but it has faced increasing degradation, with studies estimating that approximately 70% of this ecosystem is now compromised (Hilker et al., 2014b; Miao et al., 2021). Overgrazing, primarily due to a sharp rise in livestock numbers following the shift from a centrally planned to a market-based economy in the early 1990s, has been identified as a key contributor to this decline. For instance, livestock numbers in Mongolia surged from 25.8 million in 1990 to 43 million by 2009, intensifying grazing pressure and altering vegetation composition and productivity (Tuvshintogtokh & Ariungerel, 2013). This increase has led to a progressive succession where palatable species are replaced by unpalatable or grazing-resistant plants, such as Cleistogenes squarrosa and Allium polyrrhizum, signaling degradation rather than resilience to climatic stressors alone (Sasaki et al., 2008; Tuvshintogtokh & Ariungerel, 2013). Grazing has a significant impact on the Artemisia frigida biome, with plant height and specific leaf area significantly different compared to ungrazed areas (Oyundelger et al., 2023). In addition, the growing market demand for meat has led to an increase in the number of farmed livestock, which has also increased the consumption of water resources. In the hydrological simulation of 29 rivers across the country, livestock water use is even comparable to mining and urban water use. In local hotspots, groundwater degradation caused by human activities and grazing has further promoted grassland degradation (Nakayama, 2025).

Agricultural expansion has had an increasing impact on grassland vegetation dynamics in eastern Mongolia. An experiment on wheat production efficiency in Hentii in 2017 found that limited water and low soil fertility intensified interspecific competition among plants. The study highlighted that competition for productive water in spring was a major factor, which increased the competition between agricultural crops and native grasslands (Litvinova et al., 2020). As Mongolia transitioned from a socialist economy to a market-driven system in the 1990s, pressures to increase food production and economic diversification led to the conversion of grasslands into croplands, particularly in areas with relatively fertile soils and adequate moisture. This shift has been notable in eastern Mongolia, where the steppe's flat terrain and proximity to water sources make it suitable for cultivation. However, this expansion has come at the cost of reducing native grassland cover, altering plant community composition, and disrupting the ecological balance that sustains both biodiversity and traditional herding practices (Gantumur et al., 2018; Sankey et al., 2018). Studies estimate that agricultural land use in Mongolia increased by approximately 6% between 1990 and 2021, with significant implications for vegetation dynamics in the eastern provinces (Hao et al., 2023).

The indirect effects of agricultural expansion on eastern Mongolia's grasslands are equally significant, as it intensifies land-use competition and alters grazing patterns (Barcus, 2018). As arable land encroaches on traditional pastures, herders are often forced to concentrate livestock on smaller, remaining grassland patches, exacerbating overgrazing pressures and accelerating degradation in those areas (Galvin, 2009; Sheehy & Damiran, 2013). Additionally, agricultural activities introduce chemical fertilizers and pesticides, which can alter soil nutrient cycles and affect non-target plant species, further shifting the composition of remnant grasslands toward less palatable or invasive species (Hofmann et al., 2011; Merbold et al., 2021). These changes threaten the resilience of the steppe ecosystem, particularly in a region where climate variability already poses challenges to vegetation stability.

Urbanization and infrastructure development, including road construction, have increasingly shaped grassland vegetation dynamics in eastern Mongolia, a region traditionally defined by its vast, unbroken steppe landscapes (Hao et al., 2023; J. Wang, Cheng, Liu, Zhu, Ochir, Davaasuren, Li, Wei, Chonokhuu, Namsrai, & Bat-Erdene, 2019). As Mongolia's economy has grown since the post-socialist transition in the 1990s, urban centers like Ulaanbaatar have expanded, and the demand for improved transportation networks has surged. This has led to the conversion of grasslands into built environments and the fragmentation of ecosystems through roads and associated infrastructure (Myagmartseren et al., 2020; Tsutsumida, 2014). Studies estimate that urban land cover in Mongolia increased by over 50% between 1990 and 2015, with eastern Mongolia experiencing notable impacts due to its strategic location near borders and resource-rich areas (Y. Zhang, Wang, et al., 2022). These changes disrupt the continuity of grassland vegetation, reduce habitat availability, and alter the ecological processes that sustain the steppe's biodiversity and productivity (Deng et al., 2011). Roads, in particular, act as linear barriers, fragmenting plant communities and limiting seed dispersal, which can shift species composition toward ruderal or invasive plants better suited to disturbed environments, Vehicle activity can remove the top 1 cm of seeds, making population recovery more difficult (Kinugasa & Oda, 2014).

Indirectly, urbanization and infrastructure development exacerbate grassland degradation by altering hydrological patterns and facilitating human activity. Roads and urban sprawl disrupt surface water flow, reducing soil moisture availability critical for grassland recovery in eastern Mongolia's semi-arid climate (Y. Ren et al., 2022). Additionally, improved road access often accelerates resource extraction, such as mining, and increases vehicular traffic, both of which contribute to dust deposition and soil compaction—factors that inhibit plant growth (Kinugasa et al., 2015; Sodnomdarjaa et al., 2024). Studies have noted that The vegetation coverage, biomass, species composition and richness within one kilometer around the paved road are lower than those of the unpaved road (Amarsanaa et al., 2022).

Demographic Changes

Demographic changes and settlement patterns, particularly the migration of herders from eastern Mongolia to urban centers like Ulaanbaatar, have significantly influenced grassland vegetation dynamics in the region. Since the collapse of the Soviet-supported socialist system in the 1990s, Mongolia has experienced rapid urbanization, with the population of Ulaanbaatar swelling from approximately 540,000 in 1990 to over 1.5 million by 2020, representing nearly half of the country's total population (M. E. Fernández-Giménez et al., 2017). This shift has been driven by economic pressures, harsh winters (known as dzuds), and the allure of urban opportunities, pulling herders away from rural eastern provinces like Dornod and Sukhbaatar (J. Chen et al., 2018; Fan et al., 2016). As herders abandon traditional nomadic pastoralism, the resulting changes in land use and grazing pressure have led to uneven impacts on grassland ecosystems, ranging from vegetation recovery in some areas to intensified degradation in others (M. Fernandez-Gimenez, 2001).

Conversely, the concentration of remaining herders and livestock in areas closer to settlements or transportation hubs in eastern Mongolia has intensified pressure on nearby grasslands, accelerating degradation (Jamsranjav et al., 2018). As herders migrate to Ulaanbaatar, those who stay behind often consolidate their herds near rural towns or roads for easier access to markets and services, leading to localized overgrazing. Research shows that within 5-10 kilometers of such settlements, aboveground biomass can decline by up to 30%, with palatable grasses replaced by grazing-resistant or unpalatable plants (Otgontuya et al., 2019). This spatial redistribution of grazing pressure disrupts the traditional mobility that once balanced vegetation dynamics across the steppe, creating hotspots of degradation that contrast with underused, recovering areas further afield (Upton, 2009). The resulting patchwork of grassland conditions reflects how demographic shifts indirectly reshape ecological outcomes.

While both natural and anthropogenic factors contribute to grassland degradation in the Eastern Mongolian steppe, anthropogenic influences have emerged as the dominant driver in recent decades. Natural factors such as climatic variability and episodic droughts exert long-term pressure on ecosystem stability; however, human activities—particularly those related to intensive grazing and land-use changes—often induce rapid and profound impacts on the landscape. These impacts include the disruption of soil structure, alterations in vegetation composition, and the fragmentation of habitats, which collectively accelerate ecosystem degradation. Compared to gradual natural changes, anthropogenic disturbances tend to cause abrupt and sometimes irreversible shifts in grassland function and resilience. Given this context, this PhD thesis places particular emphasis on grazing-induced vegetation dynamics, aiming to better understand how pastoral practices shape grassland condition and to identify measurable indicators of degradation using remote sensing techniques.

1.3.4 Problem statement

Monitoring Grazing Dynamics and Herding Movements in Eastern Mongolia

The transition to a market economy in Mongolia since the 1990s has profoundly reshaped the mobility patterns of pastoralists, driven by socioeconomic changes, environmental pressures, and evolving livelihood strategies. Traditionally, Mongolian herders practiced seasonal migrations, moving between distinct summer, autumn, winter, and spring camps to optimize pasture use and livestock health. For instance, in the Dayan high valley of the Mongolian Altai, herders historically moved four times annually, covering distances of 10–170 km between camps to access suitable forage and water (Lkhagvadorj et al., 2013a). However, post-decollectivization, many herders have reduced migration frequency and distance, often moving only two or three times per year or remaining stationary, as observed in Dayan, where two-thirds of households have curtailed migrations to cut transportation costs, reduce labor, or adapt to changing climate conditions like earlier snowmelt (Lkhagvadorj et al., 2013a). In Altanbulag soum, herders select summer camps based on ecological factors (abundant grass and water), territorial bonding, and social accessibility to markets or schools, reflecting a blend of traditional ecological knowledge and modern economic considerations (Ono & Ishikawa, 2020). Similarly, in the Great Gobi Strictly Protected Area, herders shift camps approximately nine times yearly, prioritizing biomass availability in summer and shelter from wind in winter, with *Stipa* spp. communities preferred for their nutritional value (Michler et al., 2022). These shifts in mobility are influenced by rising livestock numbers, particularly goats for cashmere production, which accounts for 70% of cash income in some regions, intensifying grazing pressure (Lkhagvadorj et al., 2013a).

The impacts of these mobility choices are significant, contributing to pasture degradation and socioeconomic challenges. Reduced mobility and increased herd sizes, as seen in Ugtaal and Gurvansaikhan, have led to overgrazing, with pasture surveys in Gurvansaikhan showing a 28.2% increase in overgrazed land between 1992 and 2002 (Lise et al., 2006). Overgrazing alters vegetation composition, replacing nutritious species with less desirable ones like Chenopodium and *artemisia*, diminishing pasture carrying capacity (Lise et al., 2006). In Dayan, intensified forest grazing due to reduced migrations has further strained ecosystems, with herders resorting to forest edges for early spring forage, exacerbating degradation (Lkhagvadorj et al., 2013a). Socioeconomically, herders face a reverse assurance game where maximizing herd size yields the highest payoff but risks long-term environmental degradation, potentially reducing income by 30% in Gurvansaikhan and up to 60% in Ugtaal if sustainable practices are adopted (Lise et al., 2006). Additional factors influencing mobility include access to education, as seen in Khangai, where semi-nomadic families overwinter in towns to support children's schooling, and harsh winters (dzuds), which force emergency moves or lead to livestock losses, prompting investments in education for urban migration (Ahearn, 2018; Lkhagvadorj et al., 2013b). Herders' perceptions of environmental conditions, as highlighted by Fernández-Giménez, further guide these decisions, often prioritizing short-term economic gains over long-term sustainability (M. Fernández-Giménez, 1993). Thus, while mobility remains a cornerstone of Mongolian pastoralism, its adaptation to modern pressures underscores the tension between economic survival and ecological sustainability.

Building on the insights into Mongolian pastoralists' mobility choices and their ecological and socioeconomic impacts, a critical research gap exists in systematically tracking the spatial and temporal dynamics of herders' seasonal movements to inform sustainable pasture management. While studies have documented reduced migration frequencies and overgrazing in regions like Ugtaal, Gurvansaikhan, and the Mongolian Altai (Lise et al., 2006; Lkhagvadorj et al., 2013a), there is limited research on using advanced spatial tools, such as GPS tracking or remote sensing, to monitor herder routes and guide scientifically informed grazing strategies that optimize pasture use across Mongolia's diverse landscapes. Moreover, the interaction between human activities and ecological dynamics is often spatially complex and poorly understood. In Mongolia, nomadic pastoralism, wildlife movements (e.g., gazelle grazing), and environmental constraints co-exist and shape vegetation patterns in intricate ways. There is a growing need to develop integrated approaches that combine spatially explicit data—such as GPS tracking of herder routes and wildlife distributions—with remote sensing indicators to quantify and disentangle the ecological footprints of humans and wildlife across the steppe.

Grazing Impacts on Vegetation Dynamics in Eastern Mongolia

The grasslands of Eastern Mongolia, a cornerstone of nomadic pastoralism and regional biodiversity, have faced increasing ecological pressure since Mongolia's transition from a planned to a market economy. These grasslands are critical for sustaining livestock-based livelihoods and carbon sequestration, yet their productivity and stability are influenced by grazing activities from both livestock and wildlife, such as gazelles. While nomadic pastoralists depend on these ecosystems for socio-economic well-being, the ecological impacts of intensified grazing on vegetation dynamics, particularly aboveground biomass, remain insufficiently quantified.

Despite growing research on Mongolian grasslands, significant gaps persist in understanding the combined effects of livestock and wildlife grazing on vegetation dynamics. Previous studies have often focused on livestock grazing in isolation, documenting its role in grassland degradation (Hilker et al., 2014d), or examined wildlife impacts without integrating human-driven pressures (Olson, Fuller, Schaller, et al., 2010). Few studies have employed process-based ecosystem models, such as LPJ-GUESS, to simulate AGB and validate these predictions against field surveys and remote sensing data at fine spatial resolutions (e.g., 0.1°). Moreover, there is a lack of research addressing the interplay between human population dynamics, livestock numbers, and wildlife populations as drivers of ecological change in eastern Mongolia, particularly over short-term temporal scales (2019–2021). Existing work often relies on coarse-scale remote sensing or localized field studies, limiting the ability to capture spatially explicit vegetation responses to grazing (M. E. Fernández-Giménez, 2000; Wesche et al., 2010). Additionally, the differential impacts of livestock versus wildlife grazing on grassland ecosystems remain underexplored, as most studies fail to explore their respective contributions to vegetation dynamics (Sankey et al., 2009). This fragmented approach hampers the development of sustainable land management strategies tailored to the region's unique socio-ecological context.

1.4 Methods and proxies to monitor grassland vegetation changes

The eastern Mongolian Steppe represents a vast and ecologically critical grassland ecosystem, supporting both biodiversity and traditional pastoral livelihoods. However, this ecosystem is increasingly threatened by the compounded effects of climate variability and intensifying anthropogenic pressures, particularly from extensive grazing practices. These pressures contribute to shifts in vegetation productivity, degradation processes, and ultimately to the loss of ecosystem services. Understanding and monitoring these dynamics at broad spatial and temporal scales is essential for sustainable rangeland management and ecological conservation. This section reviews the commonly used methods for studying grassland vegetation dynamics, encompassing both traditional field-based approaches and modern remote sensing techniques.

1.4.1 Field measurements

AGB is one of the most important measures of ecosystem health and function (Naidoo et al., 2019; Shen et al., 2008). It is widely used in ecosystem research. Traditionally, AGB is measured by a destructive method, which involves cutting and weighing the vegetation. However, this is time-consuming, expensive, and often not possible in places like nature reserves or long-term study sites. For this reason, non-destructive methods for estimating biomass have become an important tool. To get around these problems, researchers have developed several non-destructive techniques. These methods work by finding a relationship between certain measurable features of the vegetation and its actual biomass. The most common of these methods in grassland research are **visual cover estimation**, **the point intercept method**, and **field spectroscopy**.

Each of these non-destructive methods has its own way of being used:

Visual Cover Estimation is a subjective but efficient method. It involves an observer visually estimating the plant cover for a specific species or for the entire plant community in a plot. While this method is often questioned because of its subjective nature, studies show a positive link between cover and biomass (Y. Jiang et al., 2017; Röttgermann et al., 2000). For example, a study on a semi-arid grassland found that visual cover estimation was just as accurate as the other two methods, and sometimes even more so (Ónodi et al., 2017). However, the results can vary depending on the plot size and the experience of the observer (Klimeš, 2003). Therefore, it is often suggested that several observers work together to ensure more consistent results.

The Point Intercept Method is an objective and common non-destructive method. It uses a frame with evenly spaced points (for example, a 62 × 80cm frame with 50 points). Researchers insert a pin vertically through each point and record what it hits, such as live vegetation, dead plants, or bare ground (Jonasson, 1988). The number of times the pin hits green vegetation gives a "canopy intercept" value, which is used to represent biomass. Studies show that adding canopy height to this method can significantly improve its accuracy (Frank & McNaughton, 1990). While this method can explain a large amount of biomass variation ($R^2 = 0.98$), some research suggests its accuracy might be lower than other methods in certain situations (Byrne et al., 2011; Ónodi et al., 2017).

Field Spectroscopy uses handheld devices like spectral radiometers to measure the light reflectance from the plant canopy. This method is based on the idea that plants reflect light differently in various light bands, like red and near-infrared. For example, healthy green plants absorb a lot of red light and reflect a lot of near-infrared light. The ratio of this reflectance is highly related to biomass. A study by (Pearson et al., 1976) found a very strong correlation of 0.98 between the reflectance ratio from a handheld radiometer and the biomass of short grass. Although this method might be less accurate than the point intercept method in some cases, a cost-benefit analysis showed that it can achieve a good level of accuracy with much less labor (Byrne et al., 2011), making it a very practical and efficient tool.

Field surveys are indispensable for obtaining firsthand data and gaining a clear understanding of research objectives, particularly when assessing local-scale phenomena. They are the most direct method for collecting subjective opinions from herders on specific indicators and for monitoring nuanced vegetation dynamics within a smaller spatial range (M. E. Fernandez-Gimenez, 1999; Ulambayar, 2017). This detailed, on-the-ground research provides the "ground-truthed" data necessary to understand and quantify the scale and speed of environmental changes, thereby establishing a scientific basis for ecological protection and sustainable development policies (Tumur et al., 2020). However, no matter how efficient these field-based methods are, they are still limited to small, isolated areas. For a vast and continuous landscape like the Eastern Mongolian Steppe, it is simply impossible to cover the entire area with ground surveys alone due to the sheer scale and human resource limitations. To solve this problem and monitor large-scale ecological dynamics, we must use a broader, more comprehensive approach. In this context, remote sensing technology becomes a vital tool. It offers a powerful and cost-effective way to overcome these spatial limitations, providing wide-ranging, repeated, and consistent observations of the landscape that field crews cannot achieve. Crucially, the detailed data from field surveys is not replaced by remote sensing, but rather becomes essential for calibrating and validating the models used to interpret the large-scale remote sensing imagery. By combining the detailed data from field surveys with the broad spatial coverage of remote sensing, we can more comprehensively and accurately portray the current status of grassland ecosystems and the multifaceted challenges they face (Kim et al., 2020; Z. Xie et al., 2024). In the following section, we will therefore investigate the critical role of remote sensing in retrieving AGB and its importance for sustainable rangeland management.

1.4.2 Remote Sensing

Accurately estimating AGB is a central challenge in grassland ecosystem research (Bazzo et al., 2023). As a key indicator of vegetation productivity and land degradation, AGB is crucial for understanding the health of these ecosystems (Vundla et al., 2020). However, with Mongolia's grassland area spanning nearly 1.1 million square kilometers, traditional manual survey methods are simply not practical. They are time-consuming, expensive, and logistically difficult, especially for reaching remote areas and capturing rapid vegetation changes. Furthermore, conventional field measurements provide limited spatial coverage, while remote sensing methods based on single data sources often have their own limitations, such as low spatial resolution or sensitivity issues. To effectively monitor such a vast and dynamic landscape, a more powerful approach is needed. Remote sensing technology provides a promising solution with its advantages of wide coverage, short revisit cycles, and high data volume, allowing for efficient, large-scale, and long-term vegetation monitoring.

Over the past decades, numerous methods have been developed to retrieve aboveground biomass (AGB) from remote sensing data, each with distinct assumptions, input requirements, and spatial–temporal applicability (Galeana-Pizaña et al., 2016; Tian et al., 2023). To establish effective links between remote sensing imagery and field plot data, researchers have applied a variety of algorithms within specific regions to conduct extensive biomass estimation and biomass mapping efforts. These studies aim to develop remote sensing indices with enhanced "penetration" capabilities or to integrate multiple indices in order to improve the accuracy of grassland biomass estimation (Table 1.1).These approaches can be broadly classified into empirical statistical models, physically based radiative transfer models, and, more recently, machine learning techniques (Ali et al., 2016).

Empirical / Statistical Models. In numerous studies, vegetation indices (VI) derived from optical sensors are frequently used as proxies to investigate the spatial and temporal dynamics of grassland productivity (Huete et al., 2002; Tucker, 1979). These indices, which typically leverage the near-infrared and red bands, are calculated and analyzed based on their sensitivity to chlorophyll content (Datt, 1999; Gitelson & Merzlyak, 1998; Hunt Jr. et al., 2011). Statistical models then utilize these vegetation indices and other spectral features from different bands within multiple linear or non-linear regression algorithm. This allows researchers to establish a mathematical relationship with ground-based measurement data, thereby achieving the goal of retrieving and monitoring surface characteristics over large areas. These studies used optical sensor-based vegetation indices as proxy indicators to investigate spatiotemporal patterns of grassland production, revealing varied performance across different indices and ecosystems. The Normalized Difference Vegetation Index (NDVI) has been widely employed to assess primary productivity and vegetation dynamics. For instance, in Sonora, Mexico, NDVI revealed reduced primary productivity in buffelgrass pastures compared to native vegetation, alongside a 50% reduction in species richness, highlighting the impact of land conversion (K. Franklin & Molina-Freaner, 2010). Globally, NDVI trends from 1982 to 2011 showed significant increases in grassland productivity in regions like the Arctic and central Africa, driven by temperature and precipitation changes, while declines were noted in areas like the Mongolian Plateau (Q. Gao et al., 2016). In central Nebraska, a 30-m resolution NDVI-based grassland productivity map, derived from MODIS and Landsat data, captured detailed ecological patterns, outperforming coarser 250-m maps for local management (Gu & Wylie, 2015). The Enhanced Vegetation Index (EVI) was used in eastern Australia to monitor grassland responses to extreme drought and rainfall, showing sensitivity to hydro-climatic and land-use factors, with soil moisture and C3:C4 ratios influencing decline and recovery patterns (Kath et al., 2019). In the Hindu Kush Karakoram, MODIS-based NDVI indicated higher productivity in subalpine zones but a negative trend suggesting degradation (Qamer et al., 2016). A remote sensing protocol using annual maximum NDVI identified degradation status in 16% of the northern and 9% of the southern Great Plains, with minimal net primary production loss (Reeves & Baggett, 2014). Time-integrated NDVI (TI NDVI) highlighted the role of C3 and C4 grass dominance in the U.S. Great Plains, with C4-dominated southern plains showing higher interannual variability (Ricotta et al., 2003; L. Yang et al., 1998). Early studies in the Sahel using NDVI from AVHRR data demonstrated its utility for regional drought monitoring by comparing primary production between years (TUCKER et al., 1986). Collectively, these studies underscore NDVI and EVI as robust tools for monitoring grassland dynamics, with their effectiveness varying by scale, resolution, and ecological context. A comprehensive review of 253 studies found that in investigations of grassland productivity using biomass samples and remote sensing data, the Normalized Difference Vegetation Index (NDVI) was tested as a model input in 62% of cases, underscoring its dominance as a reliable proxy for primary productivity (Reinermann et al., 2020). Other indices, such as the Enhanced Vegetation Index (EVI) (15%), Soil-Adjusted Vegetation Index (SAVI) (9%), and Leaf Area Index (LAI) (8%), were also frequently utilized, particularly in satellite-based biomass models, reflecting their complementary roles in capturing vegetation characteristics (Reinermann et al., 2020). Empirical relationships between these indices and biomass were predominantly established using simple linear or multivariate linear regression, with 60% of studies employing such methods (Reinermann et al., 2020). For example, in Australian grazing systems, NDVI derived from high-resolution satellite imagery showed a strong linear relationship ($R^2 = 0.84$) with field-measured pasture biomass, enabling reliable predictions across a range of 500–4000 kg DM ha^1 with a standard error of 315 kg DM ha^1 (Edirisinghe et al., 2011). Similarly, NDVI from SPOT-4 and SPOT-5 imagery in New Zealand dairy pastures exhibited an 81% correlation with biomass, achieving a paddock-scale prediction accuracy with a standard error of 260 kg DM ha^1 for biomass ranges of 1500–3500 kg DM ha^1 (Edirisinghe et al., 2012). In southwestern Australia, NDVI from MODIS data was used to estimate Feed On Offer (FOO) for early-season grazing management, with an exponential relationship (R^2 = 0.71–0.75) for FOO up to 2000 kg ha^1, though accuracy diminished at higher biomass or during senescence (R. C. G. Smith et al., 2011). These findings highlight NDVI's robustness in grassland monitoring, with EVI, SAVI, and LAI providing additional insights, particularly in diverse ecological contexts, while regression-based models enhance predictive accuracy for practical applications.

Radiative transfer models. Radiative transfer models (RTMs), such as the PROSAIL model, which integrates the PROSPECT leaf optical properties model and the SAIL canopy bidirectional reflectance model, are pivotal in estimating AGB from remote sensing data by simulating the spectral reflectance of vegetation canopies based on physical principles of electromagnetic radiation interactions (Jacquemoud et al., 2009; Vohland & Jarmer, 2008). Through model inversion, RTMs convert observed reflectance into biophysical parameters like leaf area index (LAI) and leaf dry matter content (Cm), enabling AGB estimation via the relationship AGB = Cm × LAI (L. He et al., 2019). In the Zoige Plateau, China, PROSAIL inversion with MODIS imagery produced AGB estimates with an RMSE of 60.06 $g \cdot m^2$ and R-RMSE of 18.1%, accurately reproducing reference AGB maps without field measurements, highlighting its potential for operational monitoring at regional scales (L. He et al., 2019). Similarly, PROSAIL with Landsat 8 OLI data outperformed exponential regression and artificial neural networks (R^2 = 0.64, RMSE = 42.67 g·m²) in estimating grassland AGB in China (Quan et al., 2017). On the Tibetan Plateau, PROSAIL inversion implemented on Google Earth Engine generated spatiotemporally continuous AGB products (2000–2021) with an R^2 of 0.87 and RMSE of 14.29 g·m², capturing grazing-induced biomass dynamics (J. Xie et al., 2022). In Southern England, Sentinel-2A data combined with PROSAIL inversion yielded reliable LAI estimates for diverse pastures, surpassing NDVI-based methods and supporting biomass mapping with moderate agreement to field data (Punalekar et al., 2018). To address heterogeneous landscapes, PROSAIL was paired with multiple endmember spectral mixture analysis (MESMA) in the Cantabrian Mountains, achieving accurate AGB estimation (R^2 = 0.67, RMSE = 43.44 g·m²) by accounting for subpixel variability (Fernández-Guisuraga et al., 2024). RTM applications have evolved through integration with advanced techniques. Data assimilation, such as incorporating PROSAIL-retrieved LAI into the SWAP crop growth model using 4D-VAR, improved AGB estimation in Ruoergai, China (R^2 = 0.76, RMSE = 542.52 kg·ha¹) (B. He et al., 2015). Hybrid approaches combining RTMs with machine learning, such as support vector regression (SVR), mitigated the ill-posed inversion problem, enhancing AGB accuracy in the Zoige Plateau (R^2 = 0.69, RMSE = 44.07 g·m²) (Z. Wang et al., 2024). In Tianzhu County, hybrid models using PROSAIL with deep neural networks (DNN) and SVR showed superior LAI retrieval performance, with SVR offering high computational efficiency for near-real-time applications (Qin et al., 2024). In Mediterranean grasslands, PROSAIL inversion with hyperspectral imagery achieved LAI estimates (R^2 = 0.91, nRMSE = 0.18) comparable to statistical methods (Darvishzadeh et al., 2011). Constraints, such as a 4:1 water-to-dry-matter ratio, further improved LAI accuracy in Central European grasslands (RMSE = 0.74) (Vohland & Jarmer, 2008). RTMs provide a robust, scalable, and physically-based approach for AGB estimation, reducing reliance on field data compared to empirical methods, and their integration with machine learning and spectral mixture analysis enhances versatility in complex landscapes (Atzberger, 2010; Baret & Buis, 2008). These advancements position RTMs as a promising methodology for operational, large-scale grassland AGB monitoring, despite challenges like the ill-posed inversion problem, which can be addressed through ecological constraints or hybrid techniques.

Machine learning method. Machine learning (ML) methods have revolutionized grassland aboveground biomass (AGB) estimation by leveraging advanced computational techniques to model complex relationships between remote sensing data and ground observations, offering enhanced accuracy and spatial generalization over traditional empirical/statistical approaches (Al-Jarrah et al., 2015). ML can be viewed as a subset of empirical models, as it relies on ground sample data to train algorithms that optimize performance metrics by searching through large parameter spaces (Al-Jarrah et al., 2015). In the context of the Mongolian steppe and other grassland ecosystems, ML methods, including regression and classification approaches, have been widely applied to estimate AGB, detect grazing land, and monitor vegetation health, providing critical data for sustainable land management (Ali et al., 2015; Rumpf et al., 2010). Regression-based ML techniques, such as random forests (RF), support vector regression (SVR), artificial neural networks (ANN), and Gaussian process regression (GPR), have proven particularly effective for AGB estimation due to their ability to capture non-linear relationships and handle multispectral and multitemporal remote sensing data.Random forest (RF) regression has been extensively used for AGB estimation due to its robustness and ability to integrate diverse predictors, such as vegetation indices (e.g., NDVI), topographic variables, and meteorological data. In the Kazbegi region of the Greater Caucasus, RF modeling, incorporating species composition maps, achieved an R^2 of 0.64 for AGB prediction, outperforming models without species composition ($R^2 = 0.42$) by mitigating saturation issues in high-yield grasslands (Magiera et al., 2017). Similarly, on the Loess Plateau, China, RF explained 65.01% of AGB variance, outperforming bagging, mboost, and SVM models, with NDVI from TM data identified as a key predictor (Y. Wang et al., 2017). On the Tibetan Plateau, RF estimated AGB with an R^2 of 0.86, revealing significant correlations with temperature and precipitation, thus enhancing understanding of climatic influences on grassland productivity (Zeng et al., 2019). In South Africa, RF combined with WorldView-2 data predicted AGB with over 84% variance explained, leveraging red-edge bands to improve accuracy during both wet and dry seasons (Ramoelo et al., 2015).Support vector regression (SVR) has also shown promise, particularly for high-resolution and near-real-time AGB monitoring. In Xilinhot, Inner Mongolia, SVR integrated with synthetic NDVI from a data-fusion approach (STARFM) using MODIS and Landsat data achieved an R^2 of 0.77 and RMSE of 17.22 $g \cdot m^2$, surpassing MODIS-only models ($R^2 = 0.73$, RMSE = 30.61 $g \cdot m^2$) and providing 30-m resolution biomass maps with 8-day intervals (B. Zhang et al., 2016). When coupled with the PROSAIL radiative transfer model (RTM) on the Zoige Plateau, SVR mitigated the ill-posed inversion problem, yielding AGB estimates with an R^2 of 0.69 and RMSE of 44.07 $g \cdot m^2$, demonstrating improved universality and reduced dependence on field data (Z. Wang et al., 2024). In Tianzhu County, SVR exhibited superior computational efficiency among hybrid RTM-ML models, making it ideal for operational AGB products (Qin et al., 2024).Artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) have been effective in capturing complex AGB patterns, particularly in intensively managed grasslands. In Ireland's pasture-based dairy farms, ANFIS achieved an R^2 of 0.85 (RMSE = 11.07 $kg \cdot ha^1 \cdot day^1$) at Moorepark and R^2 of 0.76 (RMSE = 15.35 $kg \cdot ha^1 \cdot day^1$) at Grange, outperforming multiple linear regression (MLR) and ANN when using MODIS-derived vegetation indices (Ali et al., 2017). In the West Songnen Plain, China, ANN with multitemporal MODIS data provided higher AGB estimation accuracy than statistical models, mapping spatial variability critical for grazing management (F. Li, Jiang, et al., 2013). However, ANN was outperformed by RTM-based methods in some cases, such as PROSAILH inversion with Landsat 8 OLI data ($R^2 = 0.64$ vs. ANN's $R^2 = 0.43$) (Quan et al., 2017).Gaussian process regression (GPR) has addressed challenges like spatial gaps in remote sensing data. In the Zoige Plateau, GPR combined with gap-filled Landsat 8 OLI reflectance via the CACAO method produced AGB maps with an R^2 of 0.64 and RMSE of 48.13 $g \cdot m^2$, accompanied by pixel-wise uncertainty estimates, enhancing reliability for carbon cycle modeling (G. Yin et al., 2018). Generalized linear models (GLMs), while simpler, have been less effective in some contexts; in NE-Iran's semi-arid rangelands, GLMs with transformed NDVI achieved an R^2 of 0.47, outperforming soil-adjusted indices like SAVI and EVI, which performed worse than a null model (Gholami Baghi & Oldeland, 2019).ML methods excel in integrating multi-source data, improving spatial and temporal resolution, and capturing ecological nuances, such as species composition or grazing impacts, compared to traditional statistical models (Ali et al., 2015). Hybrid approaches combining ML with RTMs, like PROSAIL with SVR or DNN, further enhance accuracy and scalability by blending physical principles with data-driven flexibility (Qin et al., 2024; Z. Wang et al., 2024). Despite challenges like computational complexity and data requirements, ML's ability to handle non-linear relationships and diverse predictors positions it as a powerful tool for operational AGB monitoring in the Mongolian steppe and beyond, supporting sustainable grassland management and carbon cycle studies.

In Mongolian grasslands, remote sensing has played a crucial role in enabling researchers to more effectively monitor vegetation dynamics, with early efforts dating back to the 1980s when images from the Soviet Soyuz-22 spacecraft were used to create the first 1:1,000,000 scale map for soil and landscape analysis (Vasil'yev, 1988). Since then, numerous studies have utilized satellite-based observations to estimate AGB and assess degradation. Researchers have successfully linked field observation data with various remote sensing indices to monitor large-scale vegetation dynamics (Kogan et al., 2004). This synergy between remote sensing and ground-based data has been particularly effective, with studies tracking desertification on the Mongolian steppe by establishing a significant correlation between field surveys and NDVI data, which revealed historical land cover changes and a decrease in plant density from 1998 to 2006 (Sternberg et al., 2011). Indeed, the use of satellite data for AGB estimation dates even earlier, with one of the first studies dating to 1989 exploring the relationship between ground biomass measurements and NOAA AVHRR reflectivity values (Adyasuren, 1989). This pioneering work laid the foundation for subsequent research that thoroughly explored the use of vegetation indices (VIs), such as a 2004 study that compared AVHRR-based vegetation health (VH) indices with biomass measurements to accurately estimate pasture biomass anomaly in a semi-dry steppe ecosystem (Kogan Corresponding author et al., 2004). Over the past two decades, different authors have developed and tested numerous satellite-based VIs for different test sites, with one study from 2005 comparing NDVI, MSAVI2, and EVI from SPOT-4 data to estimate biomass and monitor degradation in arid and semi-arid areas. The study found that MSAVI2 performed best in the desert steppe and Gobi zones, while EVI was superior in mountain steppe zones (Javzandulam et al., 2005). These techniques have been used to determine the spatial and temporal variability of vegetation cover, revealing that stable areas like the taiga and forest steppe zones are largely dependent on precipitation, while the more vulnerable steppe and desert steppe zones show high inter-annual fluctuations in vegetation dependent on the amount and distribution of rainfall (Vandandorj et al., 2015). The use of multi-source data has been particularly effective. For instance, multi-temporal optical and microwave data have been used to develop AGB prediction models that provide large-scale insights into grassland productivity. These efforts have produced valuable regional AGB maps: MODIS data were used to retrieve and generate maps for Dornod and Sukhbaatar provinces in 2016 (Damdinsuren et al., 2023). Remote sensing has also enabled broader land cover analyses, with Landsat images revealing that between 1990 and 2010, Mongolia experienced a decline in forest and steppe areas alongside an increase in desert steppe and bare land, indicating a severe trend toward desertification (J. Wang, Cheng, Liu, Zhu, Ochir, Davaasuren, Li, Wei, Chonokhuu, Namsrai, & Ariunsanaa, 2019; J. Wang et al., 2020). These changes are attributed to a combination of climate change and socio-economic factors, highlighting the complex drivers of land degradation (J. Wang et al., 2020). More recent research has continued to refine these methods. For instance, a 2022 study in the forest-steppe zone compared seven different vegetation indices and found that the atmospherically resistant vegetation index (ARVI) had the highest correlation (R^2 = 0.62) with above-ground biomass, making it a suitable candidate for pasture monitoring in north-central Mongolia (Bayaraa et al., 2022). Remote sensing has also been crucial for understanding other forms of human-induced land change, revealing that almost 88% of the grassland in Menengyn Tal was disturbed by dirt roads and oil infrastructure between 2005 and 2018 (Dashpurev, Bendix, & Lehnert, 2020). Studies have also monitored the ecological impact of other infrastructure like roads and railways, and the effects of wildfires on vegetation cover and plant functional groups (Dashpurev et al., 2021). Beyond broad-scale monitoring, remote sensing has become a predictive tool, used to create habitat preference models for plant species based on variables from Landsat data and digital elevation models (von Wehrden et al., 2009). This predictive capability extends to key pastoral challenges, with multi-sensor satellite data and machine learning models being successfully applied to identify the key natural factors driving annual livestock changes and devastating winter livestock disasters, known as dzud (Kang et al., 2024). A 2023 study further advanced this by comparing machine learning methods—random forest (RF), support vector machine (SVM), and partial least squares regression (PLSR)—to estimate and map pasture biomass in a forest-steppe area. Using spectral indices from Sentinel-2B imagery and field-measured data, the research found that the PLSR model was the most accurate, achieving a coefficient of determination of R^2 = 0.899 and a root mean square error of RMSE = 10.560 g/m^2. The study concluded that while all models showed high accuracy (R^2 = 0.82), PLSR provided the best results for pasture biomass estimation and mapping in the specific test site (Amarsaikhan et al., 2023).

While remote sensing applications have provided a wealth of information, previous research indicates that AGB estimation is a complex process influenced by multiple driving variables. Due to its capacity to model high-dimensional and multicollinear variables, machine learning has become increasingly popular for AGB estimation. However, the accuracy of these models can be impacted by several factors, including a lack of representative variables, discontinuous and highly variable ground conditions, and the presence of mixed grassland types. These issues can lead to models that are either unstable or overfitted. In this context, a **critical issue** remains largely overlooked: to what extent can we trust AGB maps derived from models trained on limited ground sampling data? Given the sparse and often uneven distribution of field observations in remote steppe regions, the reliability and generalizability of model predictions warrant a closer examination. Machine learning algorithms in spatio-temporal applications learn from observations to predict a certain variable for unknown locations and times within a defined model domain (Meyer et al., 2018). It is important to note that the term "prediction" here should not be confused with "forecasting," as most models focus on predicting in past or present times as well as in space. Therefore, addressing the research gap, the first study of this thesis aims to evaluate the accuracy of these AGB prediction maps through independent validation approaches, ultimately assessing their applicability for regional-scale grassland monitoring.

Table 1.1: Summary of pioneering studies on grassland AGB modeling for various grassland biomes using different algorithms, satellite data, explanatory variables, and R^2 values (H. Li et al., 2024).

Region	**Grassland type**	**Sample size**	**Models**	**Data source**	**Spatial resolution (m)**	**Explanatory variables**	R^2	**Reference**
Andean	Water-saturated grassland	100	Nonlinear	ERS	12.5	Backscattering coefficient	0.78	Moreau and Le Toan (2003)
Colombia	Savanna	42	Linear, nonlinear	MODIS	500	EVI	0.82	Anaya et al. (2009)
Swiss Plateau	Grassland along dry-mesic gradient	155	Multiple linear	EO-1	30	NDVI, RNDVI, SAVI, TSAVI, SR, OSAVI, MTVI1, NDWI, SRWI, PWI, WDVI, RESP, GMI, MCARI, TRVI, PRI, CAI, CAI_ATSAVI, TVI	0.86	Psomas et al. (2011)
Netherlands	Temperate grassland	30	Multiple linear	MERIS	300	BDR, BNA, NBDI	0.73	Ullah et al. (2012)
Western France	Grassland	37	Linear	SPOT	20	NDVI, LAI	0.73	Dusseux et al. (2015)
Iberian Peninsula	Meadow	17–39	Multiple linear	Landsat 5	30	NDVI, EVI, TCG, TCW, NDWI	0.76	Barrachina et al. (2015)

Region	**Grassland type**	**Sample size**	**Models**	**Data source**	**Spatial resolution (m)**	**Explanatory variables**	R^2	**Reference**
Inner Mongolia	Meadow steppe, typical steppe, desert steppe	288	Linear	MODIS, Landsat 8	250, 30	PVI	0.88	Li et al. (2016)
U.S. Great Plains	Grassland	30	Random forest	MODIS	250	NDVI	0.82	Wylie et al. (2016)
Three-River Headwaters	Alpine meadow, alpine steppe	287	Linear, nonlinear, multiple linear	MODIS	500	NDVI, EVI, SAVI, MSAVI, OSAVI, SATVI, RVI, climatic factors, topographic elements	0.70	Liang et al. (2016)
Ireland	–	936	Adaptive neuro-fuzzy inference system	MODIS	250, 500	NDVI, EVI2, SAVI, MSAVI, OSAVI	0.85, 0.76	Ali et al. (2017)
England	Mixed pasture	10	Radiative transfer	Sentinel-2	10, 20	NDVI, Radiative transfer parameters	0.87	Punalekar et al. (2018)
Mongolian Plateau	Meadow steppe, typical steppe, desert steppe	1188	Regression tree	MODIS	500	LSWI, NDVI, NDWI	0.68	John et al. (2018)
Sénégal	Savanna	63	Nonlinear	ENVISAT, ALOS, SSM/I	150, 100, 12500	V, H, VV, HH	0.52	Braun et al. (2018)

Region	Grassland type	Sample size	Models	Data source	Spatial resolution (m)	Explanatory variables	R^2	Reference
Mongolia	Meadow steppe, typical steppe, desert steppe	553	Random forest	Landsat 8	30	GNDVI, SR, GCL, NDVI, EVI, EVI2, WDRVI, GWDRVI, MSAVI2, CI, HI, BI, RI, GSI, NDWI, MSI, SOC	0.76	Otgonbayar et al. (2019)
South Africa	Wetlands grassland, marsh	62	Random forest	Sentinel-1/2, Worldview	20, 10, 1	NDRE, GNDVI, RVI	0.63	Naidoo et al. (2019)
Brazilian Pampa	Subtropical grassland	60	Multiple linear	Sentinel-2	20	EVI, NDRE, NDVI, PSRI	0.65	Guerini Filho et al. (2020)
Eastern Eurasia	Meadow steppe, typical steppe, desert steppe, meadow	546	Random forest	MODIS	500	NDVI, EVI, CI, NDWI, NDPI, climatic factors, topographical elements	0.47, 0.44	Ding et al. (2022)
Germany	Temperate grassland	150	Random forest	Sentinel-1/2	10	EVI, NDVI, MNDVI, GNDVI, NDII, MIRNIR, SAVI, ARVI, CHLRE, MCARI, LAI, topographical elements	0.42	Muro et al. (2022)

Region	Grassland type	Sample size	Models	Data source	Spatial resolution (m)	Explanatory variables	R^2	Reference
China	18 grassland types	10	Multiple linear regression, Support vector machine, Multilayer perceptron, Elastic net regression, Hist gradient boosting regressor, Random forest	Sentinel-1/2	10	31 variables	0.29 - 0.68	(H. Li et al., 2024)

1.5 Research questions and objectives

The overall aim of this thesis is to improve the understanding of human-induced impacts on vegetation dynamics and land degradation in the eastern Mongolian Steppe. By integrating remote sensing, machine learning, and ecosystem modeling, this study seeks to assess and map the current status of grassland conditions. To achieve this goal, several key research questions have been investigated, forming essential components of this final thesis. These questions address the spatial and temporal patterns of vegetation change, the role of grazing activities, and the broader ecological implications of human interventions on the steppe ecosystem:

Research question 1: How can different combinations of ground sampling data and multi-source satellite observations (e.g., Sentinel-2 optical and Sentinel-1 SAR) be used to generate a reliable and spatially consistent aboveground biomass product for the eastern Mongolian grassland?

To answer this question, the following three research objectives were settled:

Objective (1): Improve the large-scale grassland AGB estimation method - combine multi-source remote sensing data (including multi-scale and multi-temporal optical images and synthetic aperture radar (SAR) data) and more than 600 field sample data points to optimize the accuracy and applicability of AGB estimation.

Objective (2): Build a ML-based AGB prediction model - use machine learning combined with multi-source satellite data and more than 600 field data points to improve the accuracy of AGB prediction.

Objective (3): Evaluate the scope of model applicability - use a novel dissimilarity index (DI) method to calculate the model's area of applicability (AOA) and analyze the spatial applicability of AGB prediction in central and eastern Mongolian grasslands.

Research question 2: How did vegetation breakpoints in the Eastern Mongolian rangeland manifest temporally and spatially between 2019 and 2021, and can InSAR coherence time series data effectively differentiate those caused by herder and livestock mobility from natural events?

In order to achieve the research goal of monitoring the spatial-temporal dynamics of herders' grazing activities in Mongolian grasslands based on remote sensing data, this study set the following specific research objectives:

Objective (1): Develop grazing activity monitoring methods - Combine synthetic aperture radar interferometry (InSAR), optical imagery and meteorological time series data to monitor spatio-temporal grazing patterns.

Objective (2): Establish a grazing activity detection model based on machine learning - Develop a machine learning (ML)-based method to identify mutation points in vegetation conditions and compare them with the widely used Breaks For Additive Season and Trend (BFAST) algorithm to evaluate its performance.

Research question 3: How do livestock grazing and wildlife foraging influence vegetation dynamics in the eastern Mongolian Steppe?

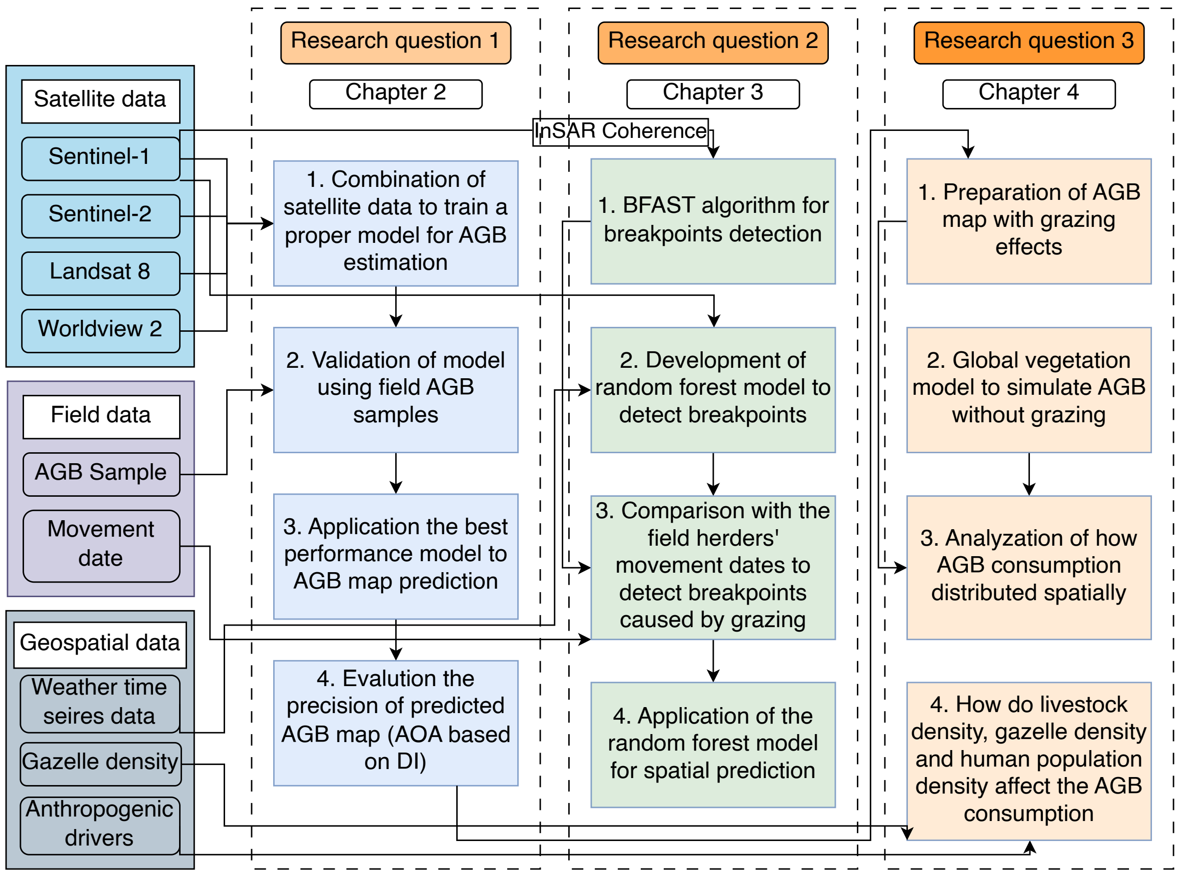
To address this question, I established two research objectives:

Objective (1): Quantify vegetation dynamics: Compare aboveground biomass predictions from the LPJ-GUESS ecosystem model with field survey and remote sensing data to analyze spatial and temporal vegetation changes.

Objective (2): Assess human and wildlife influence: Investigate the relationships between population, livestock, and wildlife numbers with model consistency to determine their respective impacts on vegetation.

1.6 Structural framework

1.6.1 Framework



***Research Progression**: Basic Data Acquisition → Herder Movements Monitoring → Ecological Impact Analysis*

Key Findings: S1+S2 with RF provides best AGB estimation (Chapter 2) →
ML outperforms BFAST for monitoring herders' movements (Chapter 3) →
Livestock has greater impact than wildlife on vegetation (Chapter 4)

Figure 1.6: Outline of thesis

This thesis is organized as a cumulative dissertation comprising three peer-reviewed papers, each contributing to the overarching objective of assessing human impacts on vegetation dynamics in the eastern Mongolian Steppe. Rather than aligning each manuscript directly with a single research question, the structure reflects a logical progression from data development to process analysis and impact assessment. The overall structure of this thesis is shown in Figure 1.6:

The first study establishes a spatially continuous baseline of AGB estimation using multi-source satellite data and machine learning, forming the critical input layer for the analyses that follow. The second study investigates spatiotemporal dynamics of grazing activity, using InSAR time series and change detection algorithms to trace the role of nomadic land use in driving vegetation changes. The third study synthesizes previous findings by directly quantifying the ecological effects of grazing using a dynamic vegetation model and AGB data from the first paper. This structured data, drivers, and impacts—ensures that each manuscript contributes to a deeper, integrated understanding of how anthropogenic pressure shapes ecosystem patterns over time.

1.6.2 Scientific publications

List of publications

Paper 1

Ji, S., Dashpurev, B., Phan, T. N., Dorj, M., Jäschke, Y., Lehnert, L. (2024). Above-ground biomass retrieval with multi-source data: Prediction and applicability analysis in E astern M ongolia. Land Degradation Development, ldr.5109. https://doi.org/10.1002/ldr.5109

Paper 2

Ji, S., Gonchigsumlaa, G., Damdindorj, S., Tseren, T., Sharavjamts, D., Otgondemberel, A., . . . Lehnert, L. (2025). Can vegetation breakpoints in Eastern Mongolia rangeland be detected using Sentinel-1 coherence time series data? GIScience Remote Sensing, 62(1). https://doi.org/10.1080/15481603.2025.2540222

Paper 3

Shuxin Ji, Jonas Van Laere, Bayarbaatar Buuveibaatar, Samantha Strindberg, Thomas Müller, Nandintsetseg Dejid, Thomas Hickler, Lukas W. Lehnert. Tracking the ecological footprint of humans and wildlife in Eastern Mongolia. This paper is under review at *Ecosphere*.

Above-ground biomass retrieval with multi-source data: prediction and applicability analysis in Eastern Mongolia

CHAPTER 2

ABOVE-GROUND BIOMASS RETRIEVAL WITH MULTI-SOURCE DATA: PREDICTION AND APPLICABILITY ANALYSIS IN EASTERN MONGOLIA

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This study developed the first remotely sensed AGB product for Eastern Mongolia, combining Sentinel 1 and 2 data with ML models, validated by over 600 field samples. It applied a dissimilarity index to assess model applicability across the steppe. The model, with high accuracy, is applicable to over 72% of the steppe area, demonstrating the potential of combining remote sensing and machine learning for large-scale grassland AGB estimation.

2.1 Abstract

Grassland aboveground biomass (AGB) is a key variable to measure grassland productivity, and accurate assessment of AGB is important for optimizing grassland resource management and understanding carbon, water, and energy fluxes. Current approaches on large scales such as the Mongolian Steppe Ecosystem often combine field measurements with optical and/or Synthetic Aperture Radar (SAR) data. Meanwhile, especially the representativeness of the field measurements for large scale analysis have seldom been accounted for. Therefore, we provide the first remotely sensed AGB product for central and eastern Mongolia which (1) uses random forest (RF), (2) is fully validated against over 600 field samples and which (3) applies a novel method, the dissimilarity index (DI), to derive area of applicability (AOA) of the model with respect to the training data. Therefore, different remote sensing data sources such as multi-scale and multi-temporal optical images – Worldview 2 (WV2), Sentinel 2 (S2) and Landsat 8 (L8) in combination with SAR data are tested for their suitability to provide area-wide estimation on large scale. The results showed that, the AGB prediction by combining Sentinel 1 (S1) and S2 using RF had the highest accuracy. Furthermore, the model was applicable on at least 72.61% of the steppe area. Areas, where the model was not applicable are mostly distributed along the edges of grassland. This study demonstrates the potential of combining Sentinel derived indices and machine learning (ML) to provide a reliable AGB prediction for grassland for extremely large ecosystems with strong climatic gradients.

Key words: AGB – prediction – machine learning – AOA – DI – spectral and SAR

2.2 Introduction

The Eurasian steppe, the largest continuous temperate grassland in the world, provides vital ecosystem services for humans. These include regulating global climate through significant organic carbon storage, sustaining biodiversity, and supporting livelihoods through agricultural and pastoral production (Bengtsson, Bullock, et al., 2019). However, the steppe is facing severe environmental pressure, climate change and overexploitation of resources which contributes to the presumed grassland degradation and desertification, threatening the integrity of this vast ecosystem (Darbalaeva et al., 2020; Dashpurev, Bendix, & Lehnert, 2020). Unsustainable use of grassland resources has also forced local communities to change land use, preventing improvements in their living standards in pastoral areas in the long run (Khishigbayar et al., 2015; Reid et al., 2014). The increase in numbers of grazing, mining activities, as well as the effect of grassland reclamation for food production and development, have been the main cause of grassland degradation on the Mongolian Plateau (Leisher et al., 2012; Sainnemekh et al., 2022a). *In situ* measurements showed that these human disturbances, coupled with climate warming, have reduced biodiversity and ecosystem functions within the region (Kauffman et al., 2021; ZHANG et al., 2010). Therefore, timely and accurate monitoring of vegetation dynamics is key to assess potential grazing capacities and to protect the vast ecosystems (J. Wang et al., 2013). Since presumed drivers of vegetation condition are changing over time, stable and validated time series products are required for Mongolia.

AGB is a key biophysical indicator characterizing grassland growth and conditions. Traditionally, data collected in situ within the enclosure in the undisturbed, natural plant communities is representative of aboveground net primary production. However, sampling with destructive methods is labour and cost-intensive and has limiting spatial and temporal representativeness. Satellite remote sensing has been established as a low-cost and widely used tool to monitor vegetation across large areas and to provide accurate data for management of vast ecosystems. Several previous studies reported the capability of optical data to be used for estimating AGB (Guerini Filho et al., 2020; F. Li, Jiang, et al., 2013; Mundava et al., 2014; Otgonbayar et al., 2019; H. Ren & Zhou, 2019), however several limitations remain, including (1) spaceborne optical remote sensing is limited by clouds; (2) saturation of the relationship between AGB and surface reflectance at moderate to dense grassland vegetation; and (3) the spectral information is mainly from the top of canopy and ignores vertical vegetation structure. As a result, uncertainties of AGB estimates may vary in space and time according to the quality of the optical satellite data and the vegetation type.

One option to include information on vertical structure of grassland vegetation is to use synthetic aperture radar (SAR data) which provide observations at a high spatial resolution in the order of tens of meters. In addition, the data are independent from clouds and solar illumination (Torres et al., 2012; Veloso et al., 2017). Microwaves are sensitive to the water content of vegetation and soil, consequently, SAR data has been proven to be a good supplement, especially to estimate AGB of forests and crops (Blickensdörfer et al., 2022; Forkuor et al., 2020). In contrast, only few studies used SAR data to estimate AGB of grasslands (J. Wang, Xiao, et al., 2019), which is noticeable because a free data source of SAR data became available with Sentinel-1 (S1) since 2014.

To estimate ABG based on any satellite data, a transfer function is necessary. Most commonly, such transfer functions are established using statistical approaches which can be divided into parametric and non-parametric methods (Güneralp et al., 2014). ML methods fall into the latter category. In a simplified perspective, ML can be seen as searching for parameter values through a large option space, guided by training data, to find a solution that optimizes a performance metric. Among the 26 articles published before the end of 2019 on the use of ML/deep learning to estimate AGB in grassland, random forest (RF), support vector machines (SVM), artificial neural network (ANN) are the three most used (Morais et al., 2021). Popular advanced methods used to retrieve biomass via multivariable satellite data are RF (Jansen et al., 2019; Meyer et al., 2017; Ramoelo et al., 2015) and SVM (J. Wang, Xiao, et al., 2019; C. Wu et al., 2016) that have been evaluated as valuable tool to be independent from multicollinearity among predictor variables.

In most of the existing studies, one ML method is used to train a model based on sampled data, which is then applied to a larger study area without paying, attention to whether the prediction is equally valid across the study area also beyond the training points used for training. For instance, a recent study on salinity intrusion mapping in Vietnam's Mekong

Delta, lacked training points at two cities in the north (Nguyen et al., 2021). Another example is a recent study on mapping rainfall in Eastern Asian, where no training data are included from outside of China (Yushan Zhang et al., 2021), but predictions are still made for these areas. In this case, how reliable is the accuracy of prediction in such areas without training points?

Thus, the objectives of this paper were to: (1) develop a fully validated time series of AGB for Eastern Mongolia, (2) investigate the importance contribution of different indices and bands to AGB mapping, and (3) evaluate in which area model predictions are reliable.

2.3 Materials and methods

2.3.1 Study area

The largest area of mostly intact steppe ecosystem in the world is found in Eastern Mongolia which is characterized by a close integration of social and natural processes at an altitude of 500 - 1300 m Figure 2.1. Average temperatures range between around -4℃ and -8° and varies strongly among years (Harris et al., 2020). Annual precipitation rarely exceeds 400 mm and is typically much lower in the south and central desert and steppe regions. The vegetation in Eastern Mongolia is mainly grouped as steppe zone, and a limited area belongs to the forest steppe belt (in the north and east), and a small area in the south is covered by desert steppe. Dry steppe is the most dominant steppe type in Eastern Mongolia (Tuvshintogtokh, 2014), while meadow steppe, mountain steppe, and desertified steppe occur in the area of the forest steppe belt and transitional area to desert steppe. Our study region covers mainly dry steppe, and the most dominant grass communities are *Stipa krylovii* + *Leymus chinensis* + forbs and *Stipa grandis* + *Caragana spp*. + forbs. Most frequent common species include grass species such as *Stipa krylovii*, *S. grandis*, *Leymus chinensis*, and *Cleistogenes squarrosa*; sedge species like *Carex duriuscula*; shrub species like *Caragana microphylla*, *C. stenophylla*; subshrubs such as *Artemisia frigida*, *A. adamsii*; and forb species including *Allium polyrhizum*, *Convolvulus ammannii*, *Chenopodium spp*. and *Astragalus spp*.

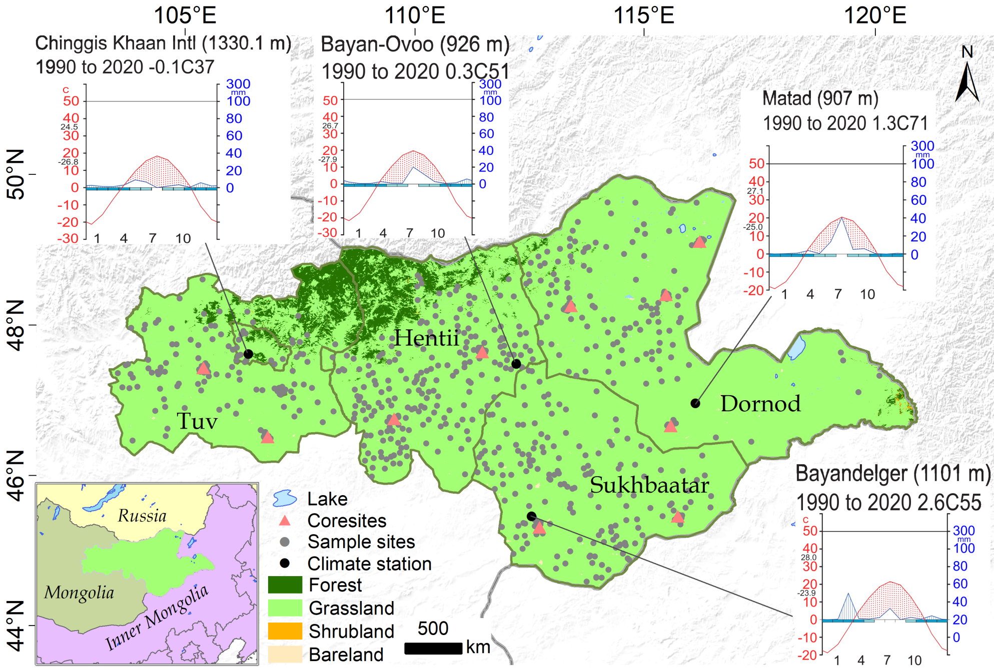

Figure 2.1: Overview of the location of study area and land cover types (Phan et al., 2022). Climate diagrams for the period 1990 to 2020 are calculated using data from the Global Historical Climatology Network (Menne et al., 2012)

2.3.2 Data acquisition and pre-processing

In this section, we will first summarize the acquisition of field data used as reference in the analysis. Then, we will describe the satellite data and the pre-processing used in this study. For a general overview of the methods applied, please refer to Figure 2.2. The major methodological steps include (1) data collection and preprocessing of different data sources (e.g., optical images from WV2, S2 and L8 and SAR data from S1); (2) creation of feature spaces (indices used as predictors derived from optical and radar sensor) to be used for AGB prediction; (3) comparing the performance of the two popular ML methods RF and SVM to retrieve the grassland biomass; (4) evaluation of AGB estimation results. In this study, a total of 603 samples were systematically allocated on the grassland, of which 216 were from 10 core sites. Core sites differed from other sampling area that WV2 data was available.

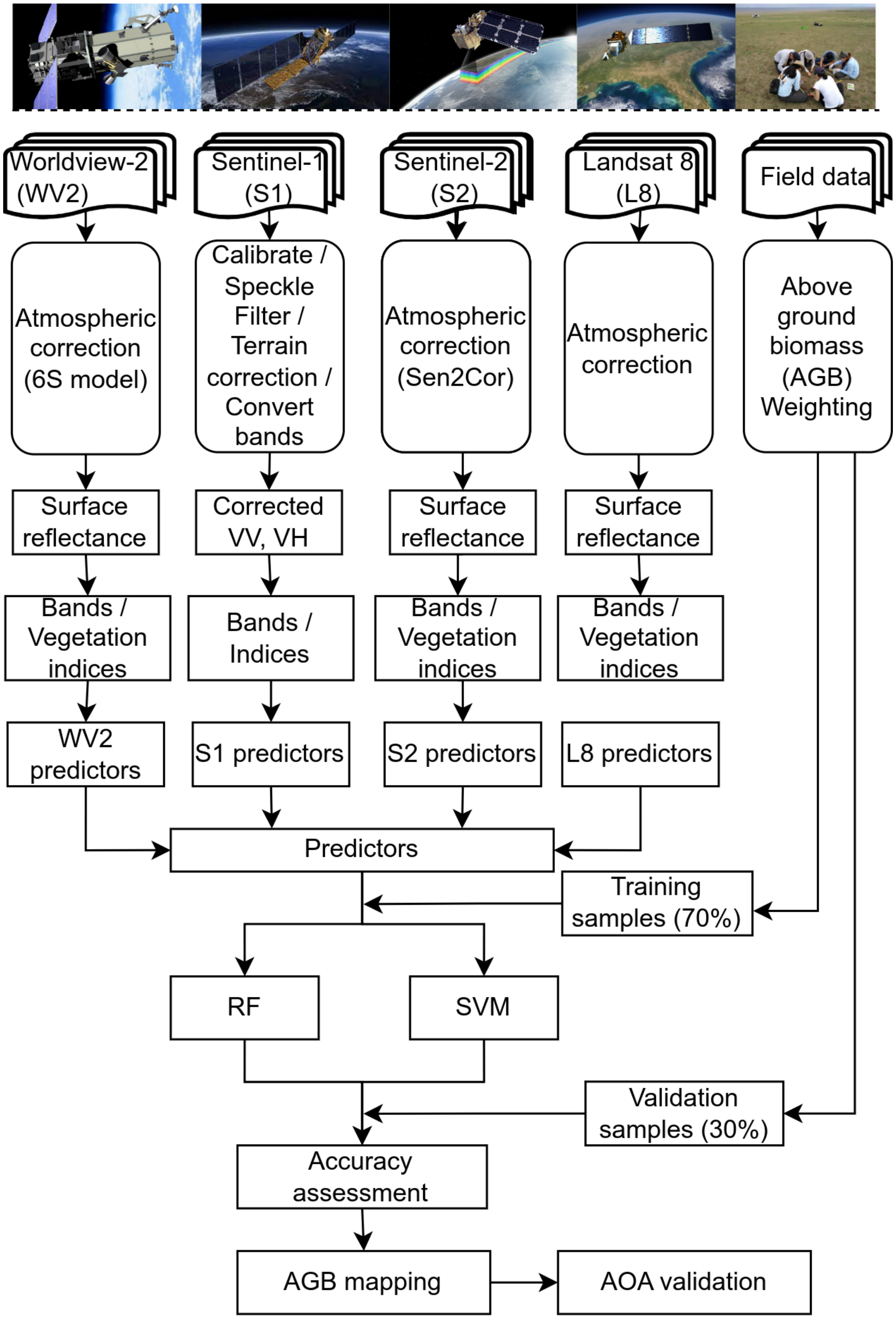

Figure 2.2: Schematic overview of AGB mapping with multi-source satellite data.

In-situ data collection

Field data on core sites were collected during the growing season of 2019 and 2021 by members from MORE STEP project (https://www.morestep.org), a stratified semi random sampling method was conducted at different geographical scales to support the multiscale modeling and to ensure that only plots were considered which were representative for the surrounding vegetation. Semi random in our context means that plots have been selected based on the constraint that surrounding vegetation must be homogeneous in order to reduce spatial scale effects. At 216 plots within the 10 core sites (Core sites differed from other sampling areas that WV2 data was available), AGB has been removed within a rectangle of 1 x 1 m marked with rulers (for statistics descriptive of field data see Table 2.1). Biomass samples have been dried and weighted in the laboratory. Field data outside of core sites were downloaded from the Agency for Land Administration and Management, Geodesy and Cartography in Mongolia (https://egazar.gov.mn). Location of sampling plots were recorded with a GPS.

Table 2.1: Descriptive statistics of the AGB (g/m^2) collected from core sites during field campaign.

Year	N	Minimum	Mean	Median	Maximum	SD (%)	SE
2019	153	7.27	75.99	72.72	211.03	57.71	3.56
2021	63	17.85	96.18	94.17	200.16	39.95	4.88

Sentinel-1 data and pre-processing

S1 images were selected based on acquisition dates to minimize the time lapse between field campaigns and satellite overpasses and downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu). The data were acquired in the Interferometric Wide Swath (IW) mode with dual polarization (VV, VH). Pre-processing includes four steps: radiometric calibration, speckle filtering, terrain correction and conversion of the backscatter values to backscattering coefficients using the following equation:

$$\sigma_0\,(\text{dB}) = 10\log_{10}\sigma_0$$

where $\sigma_0\,(\text{dB})$ is the normalized radar cross section and σ_0 is the backscatter for a specific polarization, and the unit of backscattering coefficient is dB. Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM) at 30m resolution was used for the terrain correction. To reduce speckle noise, Refined Lee speckle filtering algorithm (which adapting the window size to the local texture and edge information) was applied to the backscatter data which was selected due to its reported superior performance in SNAP (Lukin et al., 2018). In order to co-registrate of S1 and S2 datasets at a spatial resolution of 10 m, the S1 dataset was chosen as the reference layer and bilinear interpolation method was utilized (De Luca, M. N. Silva, et al., 2022).

S2 data and pre-processing

S2 images acquired during June to August of 2019 2020 and 2021 were downloaded from the ESA Sentinel Scientific Data Hub (http://scihub.copernicus.eu) according to the closest dates for field samplings from June to August. The Level-1C was atmospherically corrected with Sen2Cor processor plugin. S2 has 13 spectral bands with different spatial resolution from visible to short-wave infrared. Except bands 1, 9 and 10, all bands were pre-processed and included in the further analysis. The desired pixel size for the S2 image was selected to be 10m. For the bands with a lower pixel resolution, the nearest neighbor resampling method was used.

WV 2 data and pre-processing

WV2 images covered 10 core sites and were acquired in 2019 and 2021, scheduled in correspondence with the field campaigns. Radiance images were atmospherically corrected and transformed from top-of-atmosphere to bottom of the atmosphere reflectance via 6S model (Vermote et al., 1997) adopted for large scales and altitudinal gradients (Curatola Fernández et al., 2015).

L8 data and pre-processing

With extensive data archive and wide range of wavelengths in the visible, near-infrared, and shortwave-infrared band, Landsat images have been proved to be capable to predict grass biomass with 30 m spatial resolution (Otgonbayar et al., 2019). L8 images were downloaded from the United States Geological Survey's Earth Explorer website (https://earthexplorer.usgs.gov), radiometric calibration and FLASSH atmospheric correction were conducted in ENVI 5.3. Only band 1 to band 7 were extracted in this study. For the summary of all satellite images used in this paper please see Table 2.4 in the supplementary material.

2.3.3 Predictor selection and experiment design

For the variables from S1, in addition to the backscatter values, the difference (VV-VH), sum (VH+VV) (Vaglio Laurin et al., 2018) and ratio (VH/VV) (Veloso et al., 2017) were computed as predictors. Besides that, depending on the number of bands available in each optical sensor (S2, WV2 and L8), 12 common vegetation indices (CIre, mNDVIre, MSRre, MTCI, NDVIre, SRre, CIgreen, OSAVI, EVI2, mNDVI, MSR, NDVI) (supplementary material Table 2.5) and all NDVI-like normalized differences indices (Thenkabail et al., 2000) (45 NDIs from S2, 32 from WV2 and 20 from L8) were calculated and used as additional - predictors. This resulted in feature spaces consisting of up to 72 predictor variables for S2 and S1 (for number of predictors in other data sets see Table 2.2). In accordance with the objectives of the study, performances of five different feature spaces were compared to understand the applicability of indices from different datasets and their combinations in mapping and predicting the AGB in Eastern Mongolia. R package 'caret' (Kuhn, 2008) was employed to conduct two ML methods. Using the NDIs derived from two different spectral bands causes that variable importance values are difficult to interpret because one spectral band contributes to several predictors in the feature space. Consequently, the variable importance values were summed up by spectral bands contributing to each feature.

Table 2.2: Feature spaces in the ML regression models

Predictors	Abbreviation	Description	Number
A: All optical data of S2	S2all	Spectral and indices	67
B: All SAR	S1all	VV, VH and derivatives	5
C: Optical and SAR	S1S2all	All available predictors	72
D: All optical data WV2	WV2all	Spectral and indices	48
E: All optical data of L8	L8all	Spectral and indices	35

2.3.4 Assessing the accuracy of model performance

To evaluate the accuracy of grass biomass prediction models in this study and reduce the error caused by the accidental division of training samples, 10-fold cross validation was used. Each method in the model training was validated by a test dataset that was not used in the model training process in the same resolution (70% for training and 30% for testing), using the coefficient of determination R^2, the cross-validation correlation coefficient (rcv), RMSE, relative RMSE (RMSEr) and bias for evaluating the accuracy of predicted values.

Then AOA was calculated to evaluate the representativeness of the model for areas not covered by the field sample locations (Meyer & Pebesma, 2021). Since the model has no knowledge about such area, predictions on such areas must be considered more uncertain compared to areas covered by sufficient training data. We calculated the recently proposed DI (based on the minimum distance to the training data in the multidimensional predictor space) which can be used to automatically derive the AOA of ML models. The basic idea of the calculation is based on the minimum distance between each pixel to the training data in the multidimensional predictor space, with predictors being weighted by their respective importance in the model. Then, AOA was derived by applying a threshold which was the maximum DI of the training data derived via cross-validation (Meyer & Pebesma, 2021).

2.4 Results

2.4.1 Establishing model of AGB prediction

We used data from three satellite sensors to build models to predict AGB. In total, 6 AGB models (A, B, C) have been developed based on variables from S1, S2 and their integration, and 4 models from WV2 (D) and L8 (E) with two ML methods Table 2.3. The results showed that accuracies in predicting AGB differed among the models and ranged from moderate to high (r_c between 0.46 and 0.75, RMSE between 935.83 kg/ha and 532.12 kg/ha). Among the models, RF based on S1 and S2 (RF_S1+S2) performed best with $r = 0.87$ and RMSE of 532.12 kg/ha. When compared only optical sensor-based models, S2 showed better performance than WV2 and L8 Figure 2.3. Irrespective of which ML method has been used, adding S1 data as an additional predictor improved the accuracy.

The comparison of two ML methods showed that RF outperformed SVM in all cases except when only S1 data was used. The performance of RF showed high quality when backscatter from S1 was introduced as additional predictors in the models. Models based on S1 and S2 ($r = 0.87$) still showed higher fits than models based on Landsat ($r = 0.80$).

Table 2.3: Summary of biomass (kg/ha) prediction model results in 2019 and 2021.

Method	Predictors	RMSE (kg/ha)	r_{cv}	R^2	Bias	RMSEr
RF	A	535.12	0.86	0.74	14.16	40.56
RF	B	935.83	0.46	0.22	32.75	68.92
RF	C	532.12	0.87	0.75	16.75	40.79
RF	D	586.25	0.71	0.51	69.46	29.31
RF	E	610.49	0.80	0.65	18.89	66.93
SVM	A	582.71	0.82	0.67	39.21	44.41
SVM	B	929.78	0.45	0.20	115.96	69.87
SVM	C	604.03	0.82	0.67	33.73	46.04
SVM	D	652.15	0.63	0.39	37.9	27.18
SVM	E	638.53	0.79	0.62	62.11	76.78

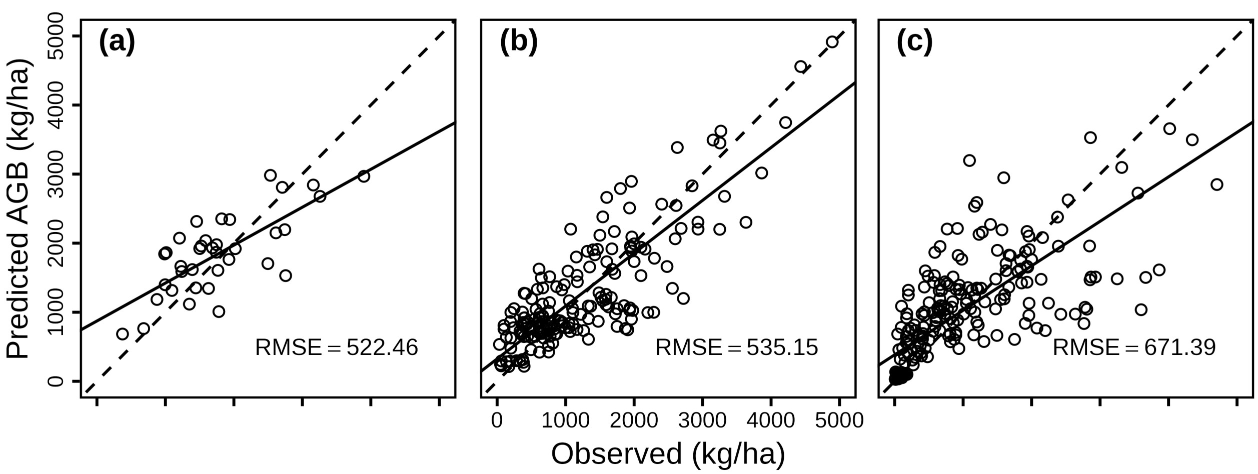

Figure 2.3: Scatterplot of predicted against observed AGB based on datasets of three optical sensors (see Table 2.2 for definitions of datasets), (a) WV2, (b) S2 and (c) L8. The dash lines are the 1:1 line, and solid lines are linear regressions. Note that there were only limited sample sites on the Worldview scale caused by the spatial extent of the available WV2 data.

2.4.2 Variable importance

Sum of variable importance values per spectral bands were highest in the red-edge part of the electromagnetic radiation for S2 and WV2 Figure 2.4. For Landsat, the red band had the highest contribution to the model. Variable importance of the blue bands was lowest irrespective of the sensor used for AGB-prediction. Intermediate importance values have been observed for NIR and SWIR parts of the electromagnetic radiation.

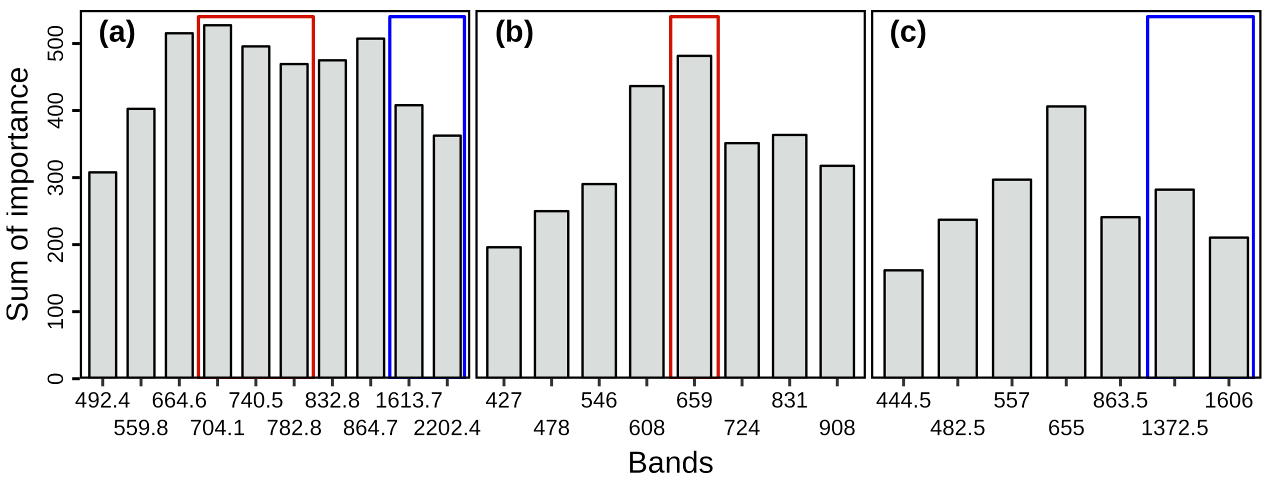

Figure 2.4: Sum of variable importance in three trained models, (a) S2, (b) WV2, (c) L8. Red rectangles show the red edge bands of S2 and WV2, blue rectangles indicate the SWIR bands of S2 and L8.

2.4.3 AGB prediction and validation

Figure 2.5 shows the average AGB estimation of Eastern Mongolia in June, July and August (summer period), in 2021 as calculated by the best performing method (RF regression) on 10m pixel resolution based on S1 and S2 data. In the north of Tuv, Khentii and Dornod, AGB more than 4000kg/ha were observed. This area is the transition zone between mountain steppes and forest steppes. Biomass is highest in the area of the most eastern part of Dornod. The histograms indicate the distribution of the AGB estimation in four provinces in study area. The proportion of pixels with 1000-3000 kg/ha AGB in Dornod is more than 50%, mainly distributed in the eastern region. Around 40% of the grassland area in Sukhbaatar had less than 1000 kg/ha. In the north of Khentii and Tuv, models are not applicable to some areas because the distribution of meadow steppe even forest steppe, AGB below 500 kg/ha is predicted in far south region, which is the area most closely to the Gobi desert in Mongolia.

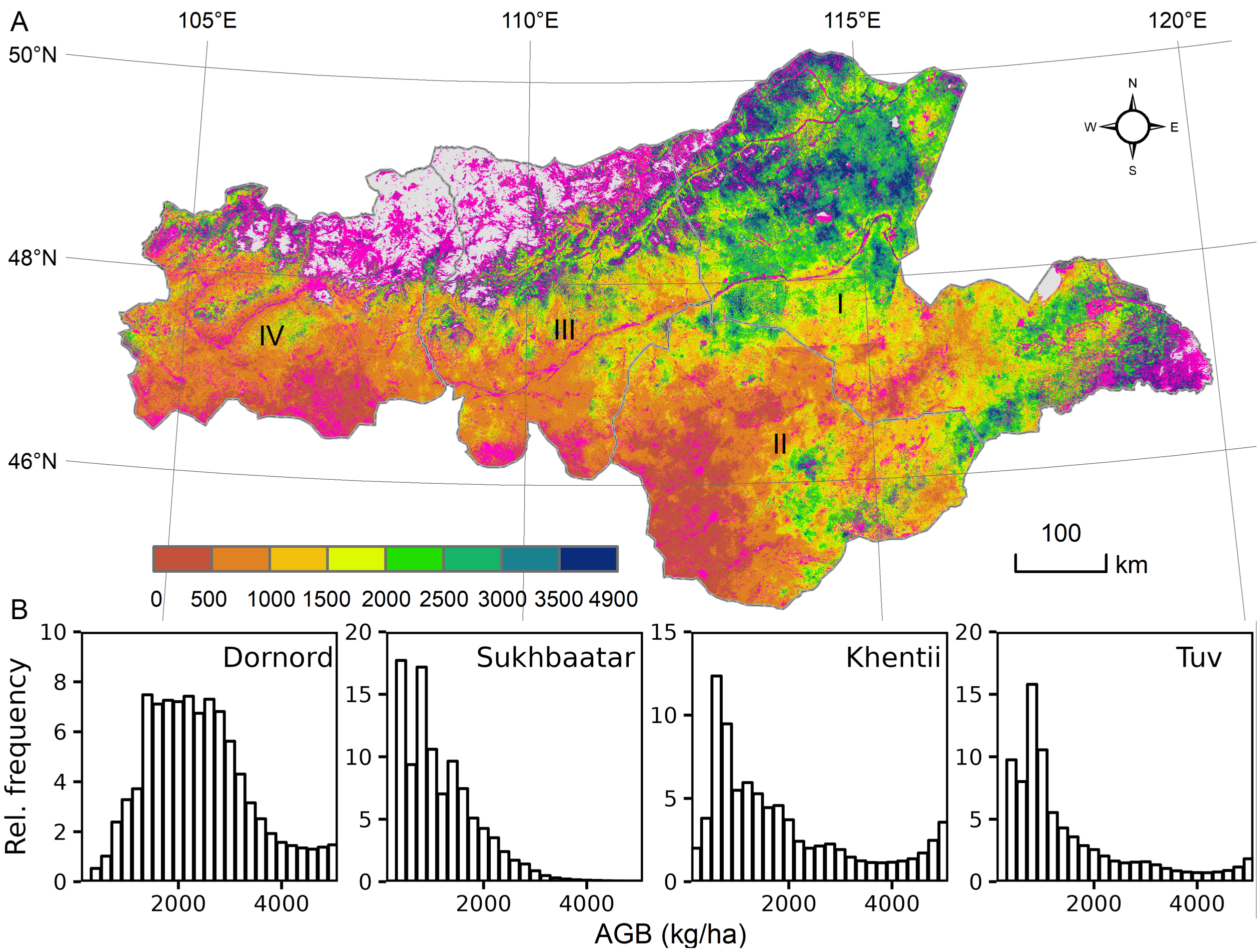

Figure 2.5: Application of the best performing model to estimate biomass (kg/ha) across Eastern Mongolia (A) in 2021 (for 2019 and 2020, see Figure 2.8 and Figure 2.9 in supplement). Areas not fulfilling AOA criteria are in pink, forest in grey has been excluded before prediction. Histograms in (B) show the distribution of AGB with in different provinces (I, Dornod; II, Sukhbaatar; III, Khentii; IV, Tuv, locations are marked in A).

Except the area covered with forest steppe in the north part of Tuv and Khentii, the area outside of AOA is mostly having AGB under 500 kg/ha or above 3500 kg/ha, especially the south part of study area near to the Gobi desert and north of Dornord where distributed mainly with mountain steppe (marked with red circles in Figure 2.6). Among the study periods, the spatial accuracy of the selected model remains above 72.61% (Figure 2.7), which means the model is trustworthy in the spatial prediction of grassland AGB in this region.

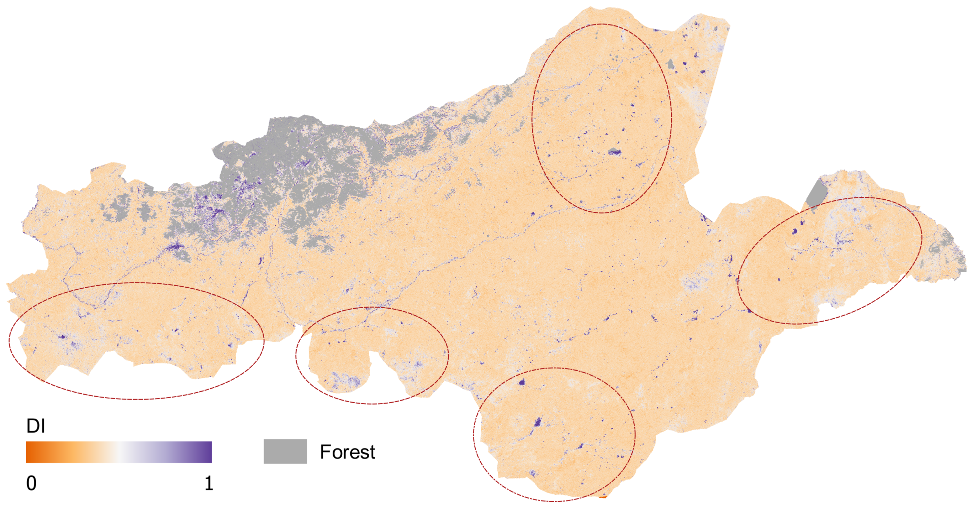

Figure 2.6: Dissimilarity index (DI) of 2021 biomass prediction map, darker colours symbolize areas outside of AOA (For 2019 and 2020, see Figure 2.10 and Figure 2.11 in supplement). Red ellipses mark regions with low AOAs discussed in the text.

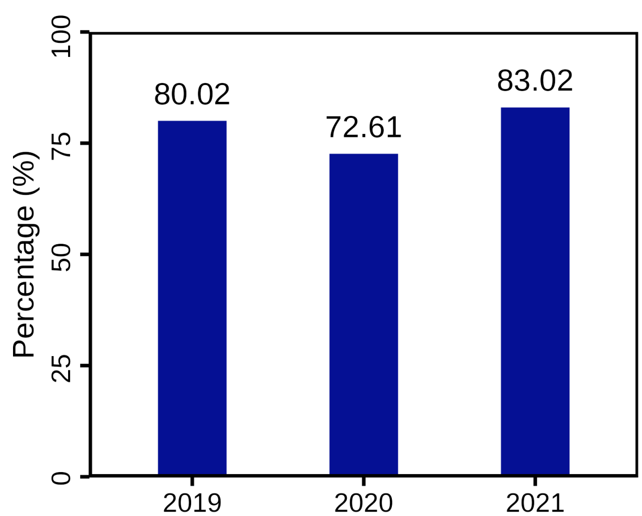

Figure 2.7: Percentage of pixels full-filling area of applicability (AOA) criteria for each year

2.5 Discussion

Grassland AGB monitoring provides a valuable data source for management and decisions by local governments prohibiting degradation and, thus, maintaining biodiversity and ecosystem functioning. In this paper, we used different source of satellite images for biomass estimation and found that the estimation accuracy under combination of SAR and optical data with RF was promising.

2.5.1 Accuracy of models

Integrating SAR data with optical data has been found to improve the accuracy of biomass estimates (De Luca, M. N. Silva, et al., 2022; De Luca, Silva, & Modica, 2022). However, our study found that integrating S1 and S2 only slightly improved the accuracy of grassland AGB prediction. This could be due to high percentages of bare soils in areas near desert steppe, leading to surface roughness and uncertainty of vegetation conditions, which can affect electromagnetic waves to some extent (Benninga et al., 2020). Additionally, the year 2019 was relatively wet in the study area, resulting in a high cloud cover (Javzmaa et al., 2019). As a result, there were no cloud-free optical remote sensing images available near the time of field sampling, and only images acquired earlier in the year could be used. This resulted in a larger discrepancy between the vegetation condition at field samplings and the time of satellite image acquisition compared to other years.
vspace0.28cm

Comparing different sensors, we found that integrating of S1 and S2 data outperformed WV2 and L8. These sensors differ in spectral and spatial resolution. Using sums of variable importances per spectral band, we could show that red-edge bands contributed most to the models if such bands are available. In contrast, NIR bands were only intermediately important. SWIR bands were also intermediate if present. The red edge band is particularly useful for estimating chlorophyll content because it is sensitive to the absorption and reflectance properties of the pigment and reflectance is correlated with the amount of chlorophyll in the vegetation, which is a key indicator of plant health and productivity (Tong & He, 2017). S2 has three red-edge bands (ranging from 689.1 to 802.8) which is different from WV2 (one band) and L8 (no bands in the red edge part). If SWIR bands are available, they contributed intermediately to the models. Here, the SWIR band at 1600 nm outperformed the bands at 2500 nm for S2 and L8 (WV2 does not have bands in the SWIR part of the electromagnetic radiation). From a physical perspective, bands in the SWIR region are particularly important for the discrimination of dead organic material from bare soils (Daughtry et al., 2005). Consequently, we conclude that S2 outperformed the other two sensors because of its spectral configuration encompassing three bands in the red edge and two bands in the SWIR part of the electromagnetic radiation. The higher spatial resolution of WV2 does not equalize the disadvantage of the lower spectral resolution of its sensor in homogeneous grasslands such as the Eastern Mongolian Steppe (Spagnuolo et al., 2020).

The integration of optical and radar sensors, along with the use of machine learning (ML) methods for biomass prediction, has become a popular practice due to its ability to produce more accurate results than traditional empirical models. However, spatial accuracy assessments are rarely performed, which is particularly important for large-scale analyses. In this study, we introduced a new approach to evaluate the model's ability to predict biomass at each pixel, and we found a minimal AOA of 72.61%, indicating that the training data used in this study is representative of most parts of the study area. Nevertheless, areas not represented by training data were mainly observed near the forest steppe in the north and the Gobi-desert in the south, suggesting that future fieldwork should pay more attention to collecting samples from the ecological transition areas at the edges of the pristine steppe.

2.5.2 Limitations and future work

AGB prediction through vegetation indices generated by optical sensors will cause ‘saturation’, because these indices are constructed based on healthy vegetation absorbing radiation in a certain wavelength range and reflecting radiation in another, such as NDVI is based on the principle that healthy vegetation reflects more near-infrared (NIR) radiation and absorbs more red radiation than non-vegetation surfaces, such as soil or water. Limited by the spectral radiation range of sensors, ‘saturation” is difficult to be completely eliminated. In the southwest of Eastern Mongolia, where desert grassland dominates and the surface is more exposed, the prediction may be ignored or decreased, which have been proved optical indices to be sensitive to soil optical properties under conditions of in complete vegetation cover (H. Ren et al., 2018; G. Wang et al., 2019a). While in the eastern Dornod province, where meadow steppe dominates, relying solely on the indices may lead to a lower estimated biomass. And previous studies have utilized hyperspectral sensors, which can better capture the canopy reflection signal and mitigate the influence of bare soil (Cooper et al., 2021; Zandler et al., 2015). Therefore, our direction is to develop a new machine learning model for biomass inversion and correction, using data from the upcoming CHIME hyperspectral satellite data.

2.6 Conclusion

The objectives of this study were three - fold: First, we aimed to develop the first fully validated time series of AGB for Eastern Mongolian Steppes. Therefore, we used over 600 in situ samples to train powerful machine learning models. In addition, we compared the suitability of four different sensors to estimate AGB of Mongolian grasslands and found that combining S1 and S2 outperformed models solely based on L8 data or the high spatial resolution data of WV2. Second, the importance of different spectral regions for AGB mapping was evaluated. Here, we found the red edge band is particularly useful for estimating chlorophyll content, the high spatial resolution of WV2 seems not advantageous compared to the additional spectral bands of S2 especially in the red edge and SWIR. Third, we aimed to evaluate, in which spatial areas model predictions are reliable based on the configuration of in situ samples. We found that that the prediction accuracy of the model is higher when the sampling point is in a more homogeneous grassland. This means that uncertainties of AGB estimates are low in the north near to forest steppe and south covered by Gobi desert, while they are increasing in the typical steppe.

Sampling data acquisition often has accessibility limitations, resulting in a limited number of ground sampling points. Therefore, it is crucial to ensure the accuracy of these points to facilitate machine learning-based regional predicting. To achieve this, accurate decision-making using AOA and DI is essential. As we strive for continuity in future sampling work, it’s important not to overlook sample collection in diverse environments.

2.7 Acknowledgements

This study was funded by German Federal Ministry of Education and Research (01LC1820B), German Academic Exchange Service and Chinese Scholarship Council. Thanks go to the MORE STEP project for supporting this study. We are grateful that the Sentinel-1 and Sentinel-2 data could be downloaded without charge from European Space Agency and Landsat 8 data can be downloaded from USGS. Special thanks go to Agency for Land Management in Mongolia for sharing field sample data. We are grateful for the open source application SNAP that developed by European Spatial Agency and two anonymous reviewers for their comments that improved our paper.

2.8 Conflicts of Interest

The authors declare no conflicts of interest.

2.9 Data available

The data that support the findings of this study are available from the corresponding author upon reasonable request.

2.10 Author contribution

Shuxin Ji carried out the research and wrote the first version of manuscript. Batnyambuu Dashpurev did experimental support and data acquisition. Munkhtsetseg Dorj helped collect and process the field data. Thanh Noi Phan conducted processing of big scenes dataset. Yun Jäschke provides vegetation type and species information. Lukas Lehnert provided the scientific guidance and code contribution.

2.11 Supplementary

Table 2.4: Summary of satellite image selected for core sites in this study.

Location	**Field work**		**Satellite image acquaintance date**			
	Start	**End**	**Worldview 2**	**Sentinel 1**	**Sentinel 2**	**Landsat 8**
Altanbulag	2019-07-16	2019-07-21	2019-08-31	2019-07-14	2019-07-12	2019-07-08
Bayantsagaan	2019-07-22	2019-07-27	2019-08-20	2019-07-21	2019-07-09	2019-07-08
Kherlen	2019-08-01	2019-08-04	2019-08-23	2019-07-28	2019-07-31	2019-06-24
Batnorov	2019-08-06	2019-08-08	2019-08-23	2019-08-04	2019-07-31	2019-08-04
Choibalsan	2019-08-09	2019-08-13	2019-08-21	2019-08-11	2019-08-02	2019-08-04
Tsagaan-Ovvo	2019-08-14	2019-08-16	2019-08-30	2019-08-11	2019-08-04	2019-07-14
Tsogt	2021-09-10	2021-09-12	2021-08-28	2021-09-01	2021-09-09	**2020-08-18**
Choibalsan	2021-08-28	2021-08-30	2021-08-28	2021-08-24	2021-09-10	**2020-07-07**
Matad	2021-09-01	2021-09-02	2021-08-17	2021-08-31	2021-08-23	**2020-08-24**
Erdenetsagaan	2021-09-05	2021-09-06	2021-08-19	2021-09-03	2021-08-23	**2020-08-01**
Bayandelger	2021-09-02	2021-09-03	2021-08-17	2021-08-24	2021-08-21	**2020-07-14**

Table 2.5: Indices selected in this study

Abbreviation	Spectral index	Equation / Definition	Citation
Red edge-based VIs			
CI_{re}	red-edge chlorophyll index	$\frac{\rho_{\text{NIR}}}{\rho_{\text{Red-edge}}} - 1$	(Gitelson et al., 2003)
mNDVI_{re}	modified red-edge NDVI	$\frac{(\rho_{\text{NIR}} - \rho_{\text{Red-edge}})}{(\rho_{\text{NIR}} + \rho_{\text{Red-edge}} - 2\rho_{\text{Blue}})}$	(Sims & Gamon, 2002)
MSR_{re}	Modified red-edge simple ratio	$\frac{\left(\frac{\rho_{\text{NIR}}}{\rho_{\text{Red-edge}}} - 1\right)}{\sqrt{\frac{\rho_{\text{NIR}}}{\rho_{\text{Red-edge}}} + 1}}$	(C. Wu et al., 2008)
MTCI	Meris terrestrial chlorophyll index	$\frac{(\rho_{\text{NIR}} - rho_{\text{Red-edge}})}{(\rho_{\text{Red-edge}} - \rho_{\text{Red}})}$	(Dash & Curran, 2004)
NDVI_{re}	Red-edge NDVI	$\frac{(\rho_{\text{NIR}} - \rho_{\text{Red-edge}})}{(\rho_{\text{NIR}} + \rho_{\text{Red-edge}})}$	(Gitelson & Merzlyak, 1997)
SRre	Red-edge simple ratio	$\frac{\rho_{\text{NIR}}}{\rho_{\text{Red-edge}}}$	(Sims & Gamon, 2002)
Broad band-based VIs			
CI_{green}	Green chlorophyll index	$\frac{\rho_{\text{NIR}}}{\rho_{\text{Green}}} - 1$	(Gitelson et al., 2005)
OSAVI	Optimized soil adjusted vegetation index	$\frac{\rho_{\text{NIR}} - \rho_{\text{Red}}}{\rho_{\text{NIR}} + \rho_{\text{Red}} + 0.16}$	(Rondeaux et al., 1996)
EVI2	Enhanced vegetation index 2	$\frac{\rho_{\text{NIR}} - \rho_{\text{Red}}}{1 + \rho_{\text{NIR}} + 2.4 \times \rho_{\text{Red}}}$	(Z. Jiang et al., 2008)
mNDVI	Modified NDVI	$\frac{\rho_{\text{NIR}} - \rho_{\text{Red}}}{\rho_{\text{NIR}} + \rho_{\text{Red}} - 2\rho_{\text{Blue}}}$	(Sims & Gamon, 2002)
MSR	Modified simple ratio	$\frac{\left(\frac{\rho_{\text{NIR}}}{\rho_{\text{Red}}} - 1\right)}{\sqrt{\frac{\rho_{\text{NIR}}}{\rho_{\text{Red}}} + 1}}$	(J. M. Chen, 1996)
NDVI	Normalized difference vegetation index	$\frac{(\rho_{\text{NIR}} - \rho_{\text{Red}})}{(\rho_{\text{NIR}} + \rho_{\text{Red}})}$	(Rouse et al., 1974)
S1 based paramenters			

VH		
VV		
VH-VV		(Vaglio Laurin et al., 2018)
VH+VV		(Vaglio Laurin et al., 2018)
VH/VV		(Veloso et al., 2017)
S1 based paramenters		
Band2	Blue, 490nm	
Band3	Green, 560nm	
Band4	Red, 705nm	
Band5	Red edge, 705nm	
Band6	Red edge, 749nm	
Band7	Red edge, 749nm	
Band8	Near Infrared (NIR), 842nm	
Band8A	Near Infrared (NIR), 865nm	
Band11	SWIR-1, 1610nm	
Band12	SWIR-2, 2190nm	

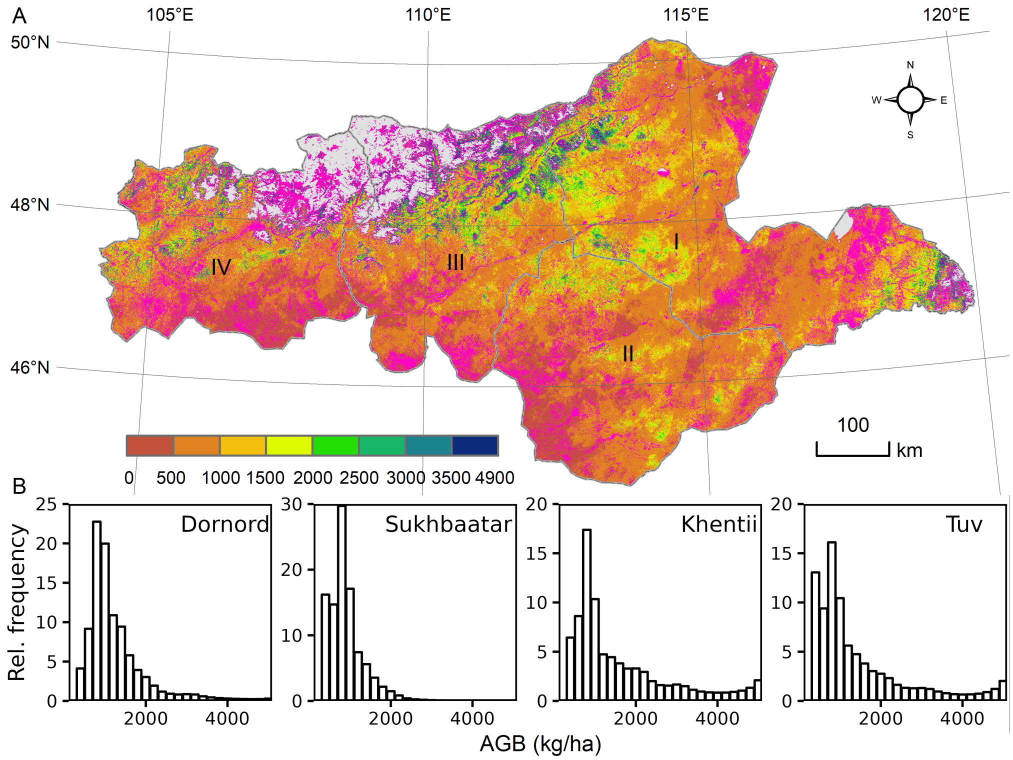

Figure 2.8: Colours represent the mean value of sentinel scenes during the growing season in 2019. Areas not fulfilling AOA criteria are in pink, forest in grey has already been excluded before prediction. Histograms in (B) show the distribution of AGB within different provinces (I. Dornod; II. Sükhbaatar; III. Khentii; IV. Töv, locations are marked in A).

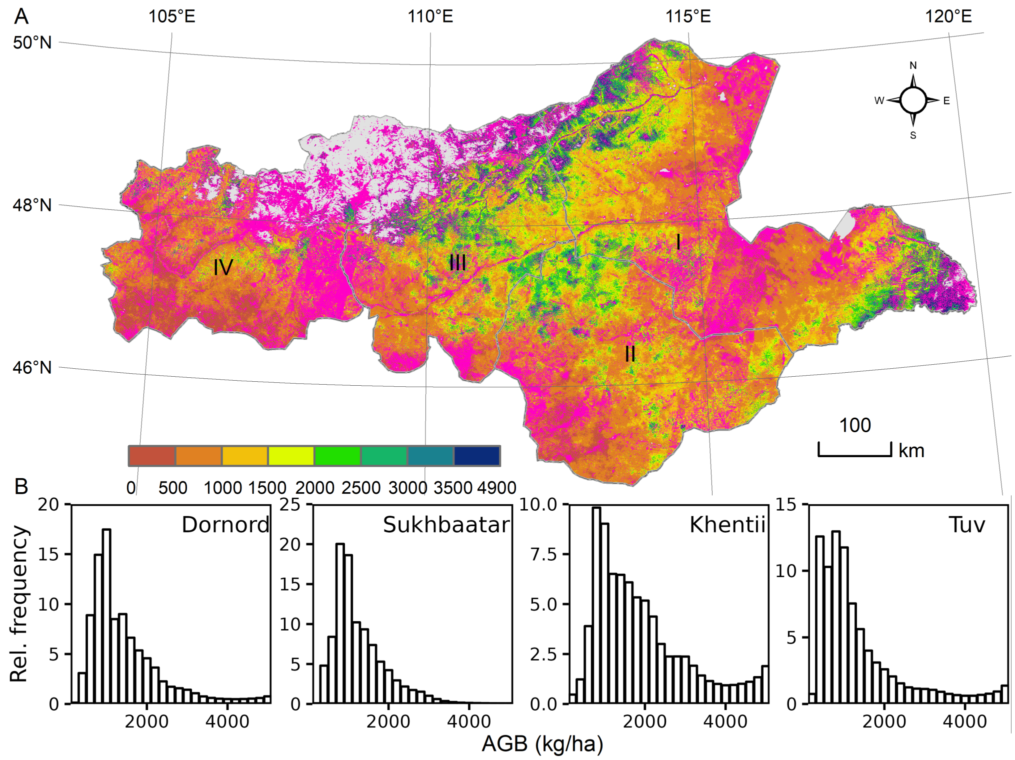

Figure 2.9: Colours represent the mean value of sentinel scenes during the growing season in 2020. Areas not fullfilling AOA criteria are in pink, forest in grey has already excluded before prediction. Histograms in (B) show the distribution of AGB with in different provinces (I. Dornod; II. Sükhbaatar; III. Khentii; IV. Töv, locations are marked in A).

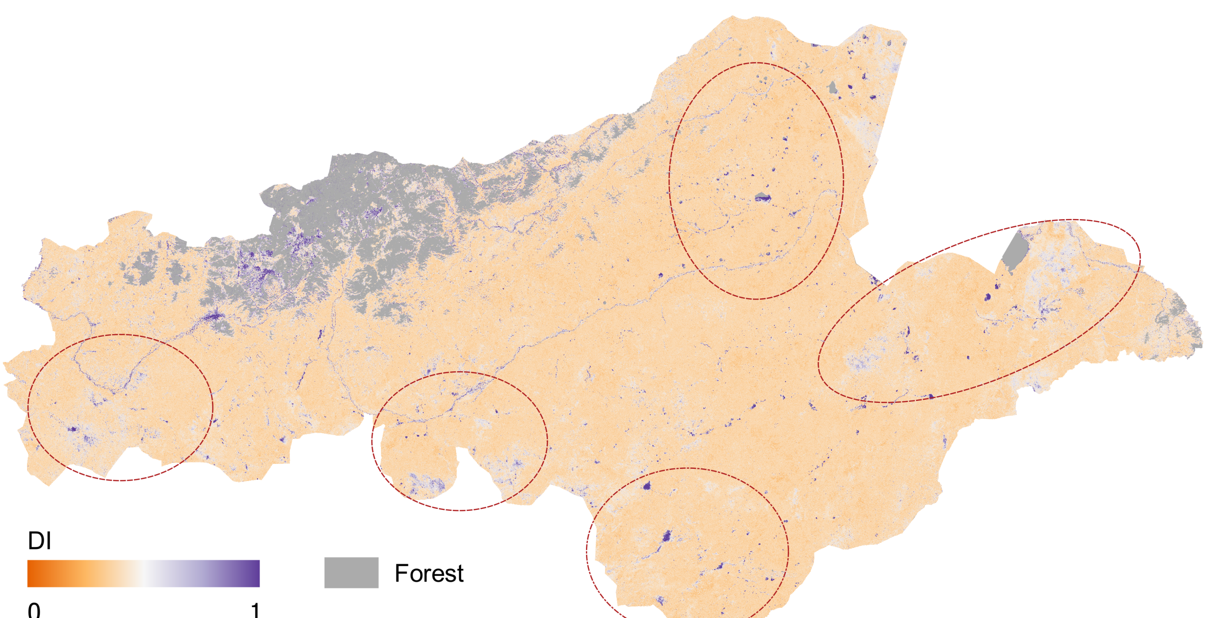

Figure 2.10: Dissimilarity index (DI) of 2019 biomass prediction map, darker colours symbolize areas outside of AOA. Red ellipses mark regions with low AOAs discussed in the text.

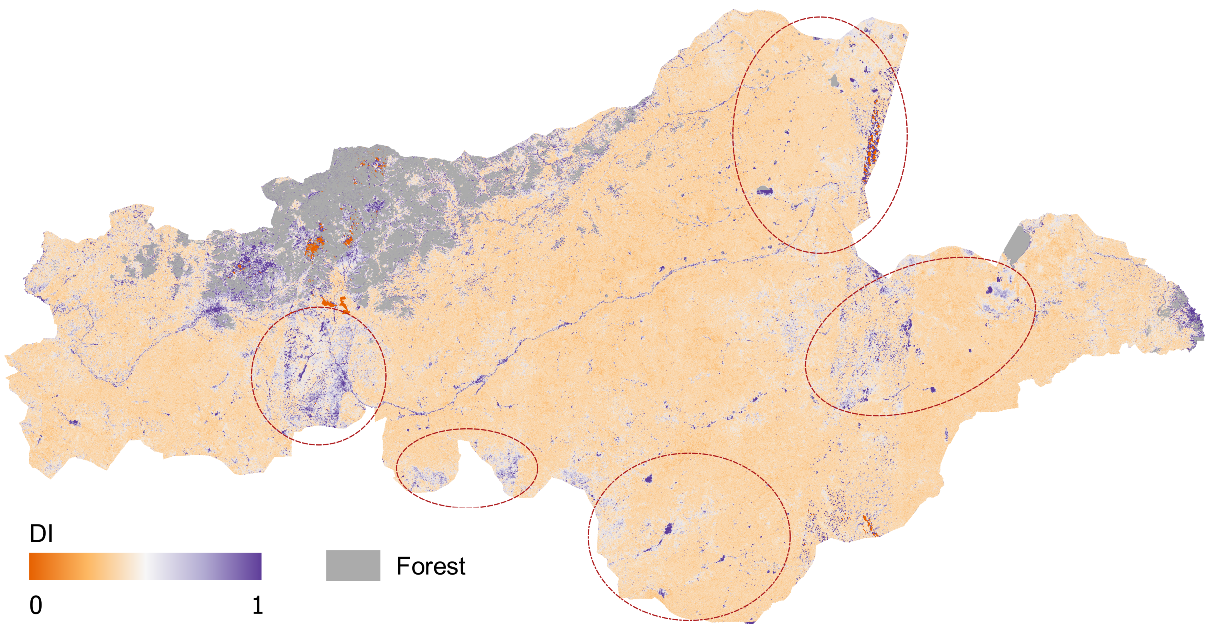

Figure 2.11: Dissimilarity index (DI) of 2020 biomass prediction map, darker colours symbolize areas outside of AOA. Red ellipses mark regions with low AOAs discussed in the text.

CAN VEGETATION BREAKPOINTS IN EASTERN MONGOLIA RANGELAND BE DETECTED USING SENTINEL-1 COHERENCE TIME SERIES DATA?

CHAPTER 3

CAN VEGETATION BREAKPOINTS IN EASTERN MONGOLIA RANGELAND BE DETECTED USING SENTINEL-1 COHERENCE TIME SERIES DATA?

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This study combined InSAR, optical, and weather time series data with machine learning for spatio-temporal grazing monitoring in Eastern Mongolia. A novel random forest method, outperforming BFAST, was developed to detect vegetation breakpoints, distinguishing grazing impacts from natural events. Validated across the steppe, the model effectively identified seasonal and spatial grazing patterns aligning with herder movements. However, definitively attributing all breakpoints solely to livestock activity remains challenging, especially in drier areas.

3.1 Abstract

Mongolian society and food production depends heavily on livestock farming, which is usually practiced through nomadic systems. Consequently, movement patterns of herders are crucial in respect of finding sufficient forage and sustainable use of pastures. Since vegetation presumably changes after livestock pasture use, this study hypothesize that changes in Interferometric Synthetic Aperture Radar (InSAR) data over time are linked to herder and livestock mobility. In this study, a combination of InSAR, optical and weather time series data has been explored as a tool for spatio-temporal grazing monitoring. To detect movement patterns, a new random forest based method to detect breakpoints in vegetation condition has been developed and compared to the widely-used Breaks For Additive Season and Trend (BFAST) algorithm. In contrast to BFAST, the new method accounts for vegetation changes caused by weather events such as snow and rainfall. The results have been validated using test sites spread across the entire eastern Mongolian steppe ecosystem, covering different rangeland use intensities. The results indicate that (1) random forest performed superior than BFAST indicating that random forest is able to separate vegetation changes caused by grazing from those caused by natural events. However, the detecting was challenging especially for winter movements (for summer camps, random forest and BFAST detected 44% and 28% of movements, respectively). (2) Breakpoints in summer pastures mainly occurred from April to June, while on winter pastures, they emerged in October, November, and the following February and March. The breakpoints in October and November can be explained by increasing grazing pressure as the herders moved to the winter camps while those occurring in spring are associated to enhanced vegetation growth after herders left for summer camps. (3) From a spatial perspective, the random forest model predicts summer and winter pastures with homogeneous patterns. In areas with higher productivity and higher grazing pressure, the summer pastures are located along the rivers while the winter pastures are in the surrounding mountainous areas. This is in agreement to the general movement patterns. In drier and less intensively used areas, the predicted pattern agrees less with the known movements. Consequently, there is insufficient evidence to definitively attribute the occurrence of pasture breakpoints solely to herder movements especially in the eastern and southern parts of the eastern Mongolian steppe ecosystem.

Key words: breakpoints; InSAR coherence; BFAST; random forest; grazing

3.2 Introduction

Rangeland are vital ecosystems that provide essential services such as biodiversity conservation, carbon sequestration, and support for pastoral livelihoods (Bengtsson, Bullock, et al., 2019; Y. Zhao et al., 2020b). Globally, extensive grazing remains the predominant form of rangeland management in many regions, including North America, South America, Australia, and Central Asia (D. Augustine et al., 2021; Bell et al., 2014; Bork et al., 2021; Jaurena et al., 2021; Mirzabaev et al., 2016). These systems are typically characterized by low-input practices and large-scale livestock mobility, which are shaped by environmental conditions, socio-economic factors, and historical land-use traditions. Among them, the nomadic grazing systems of Mongolia rangeland represent one of the few remaining examples of long-standing, large-scale mobile pastoralism (Drees et al., 2022; Teickner et al., 2020). It is characterized by seasonal mobility, where herders move livestock among spring, summer, autumn, and winter camps. This rotational grazing pattern is guided by climatic variability, local ecological knowledge, and customary tenure systems (M. E. Fernandez-Gimenez, 2000; Peter et al., 2024). Nomadic herding plays a crucial role in sustaining ecological functions by allowing grazed areas to recover seasonally, thus promoting vegetation resilience (Tugjamba et al., 2021a). Despite its ecological significance, the dynamics of nomadic land-use—particularly patterns of camp movement and their impacts on vegetation—remain poorly quantified at larger spatial scales.

Although optical satellite data such as NDVI are widely used to monitor vegetation productivity (Pettorelli et al., 2005; Reinermann et al., 2020), their effectiveness in semi-arid regions is limited by cloud cover and long revisit cycles. Synthetic aperture radar (SAR) has emerged as a robust alternative due to its ability to collect data regardless of weather or illumination. SAR backscatter and interferometric coherence have shown promise in detecting vegetation height and cover changes (Y. Gao et al., 2021; Tamm et al., 2016). In particular, InSAR data are sensitive to vegetation structure and elevation, making them suitable for identifying changes related to grazing pressure (Santoro et al., 2018).

Studies have also shown that grazing activity with high livestock density can cause jumps in SAR coherence, similar to those caused by mowing events, complicating classification tasks (De Vroey et al., 2021). Recent advances have explored combining optical and SAR data with machine learning techniques to improve change detection and classification accuracy (Holtgrave et al., 2023).

Breakpoints in remote sensing time series—points where vegetation dynamics change abruptly —can be caused by management events such as mowing or grazing. Algorithms such as LandTrendr (Kennedy et al., 2007) and BFAST (Verbesselt, Hyndman, Newnham, & Culvenor, 2010) have been widely used for detecting such disturbances. However, these methods do not distinguish between anthropogenic and natural causes of change, limiting their utility in complex systems like nomadic grazing.

Machine learning provide new avenues for ecological monitoring by offering flexibility in analyzing complex, nonlinear patterns in satellite data. Algorithms such as random forest (Breiman, 2001), Support Vector Machines (Mountrakis et al., 2011), and recurrent models like LSTM (Hochreiter & Schmidhuber, 1997; Noa-Yarasca et al., 2024) have shown high performance in detecting land use changes and temporal anomalies. These models can help isolate human-induced disturbances from natural variability, making them particularly well-suited for monitoring grazing patterns in dynamic, heterogeneous landscapes like the Mongolian steppe.

The primary objective of this study is to develop and evaluate a machine learning-based approach to detect grazing-induced changes in vegetation using InSAR coherence time series in the nomadic rangeland of Eastern Mongolia. Specifically, we aim to:

1. Train a Random Forest model to identify breakpoints in InSAR coherence data that

correspond to shifts in grazing intensity;
2. Compare the performance of the random forest model with the widely used BFAST algorithm in detecting grazing-related breakpoints;
3. Integrate field interviews with herders to validate detected breakpoints and provide socio-ecological interpretation;
4. Explore the feasibility of mapping seasonal pasture use (e.g., summer vs. winter camps) through breakpoint analysis.

3.3 Materials and methods

3.3.1 Study area

Approximately 83% of Mongolia's territory (1.3 million km2) is covered with rangeland (including grasslands, shrublands, forest steppes, and deserts where livestock graze) (Angerer et al., 2008), peaked in supporting 71 million heads of livestock in 2019 [National Statistical Office of Mongolia, 2021]. There is a long tradition of nomadic herding, which has been the main form of agricultural production for centuries. Livestock graze freely, centered around Gers (traditional Mongolian tents), and the livestock include cattle (*Bos taurus*), horses (*Equus*), camels (*Camelidae*), goats (*Capra*), and sheep (*Ovis aries*). In summer, herders commonly choose to set up their camps close to riverbanks, while in winter they stay on wind-sheltered slopes. We conducted field data collection in 10 study sites in Eastern Mongolia, which cover gradients in rainfall from 148mm to 447mm annually Figure 3.1. Consequently, the study sites represent different rangeland types that are characteristic of the Mongolian Steppe Ecosystem. In addition, the grazing intensities vary along the gradient from the west (higher grazing intensity by livestock) to the east (lower). The gradient in numbers of wildlife is reverse, with higher densities in the east.

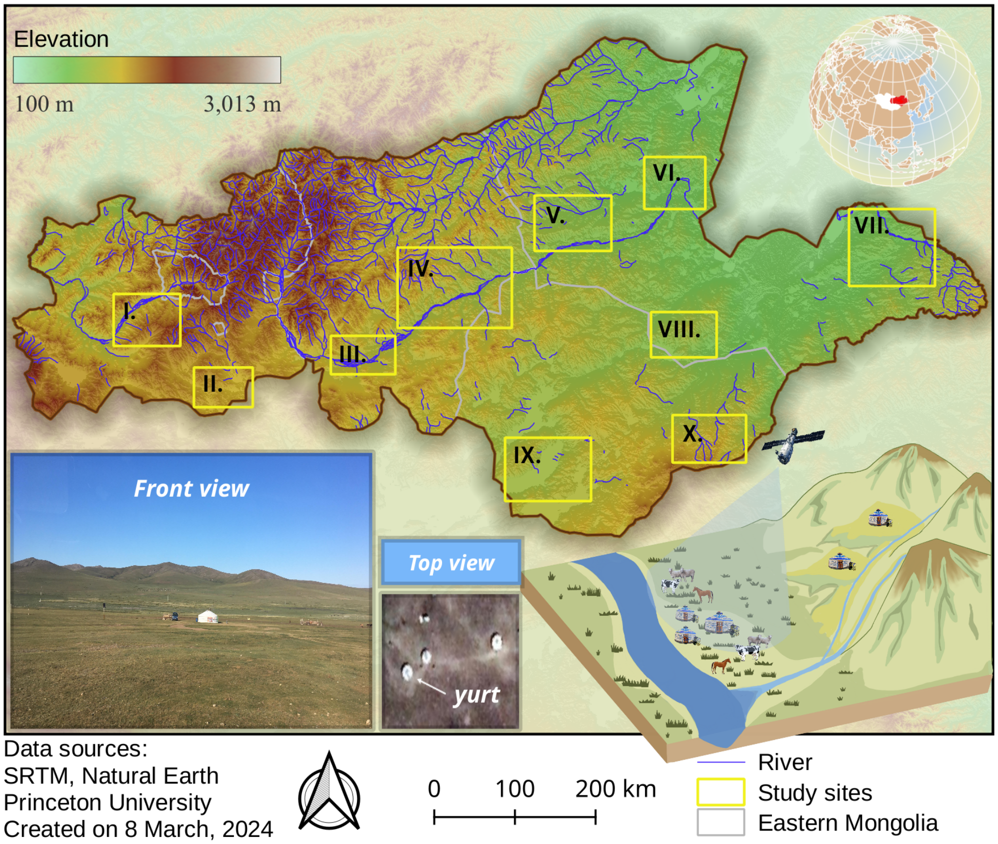

Figure 3.1: Location of the study area. Camps in the lower left corner are the residence place for local herders, and livestock graze around the camps. Number I to X: the core sites where we design the experiment and interview with herder families.

3.3.2 Data collection and pre-processing

This section begins by summarizing the field data collection process, which serves as a reference for our analysis. We then provide a detailed description of the satellite data and associated preprocessing steps including. An overview of the applied methods can be found in Figure 3.2. Following this, the build processes of the two algorithms employed in this study, BFAST and the random forest based machine learning method, are described in detail.

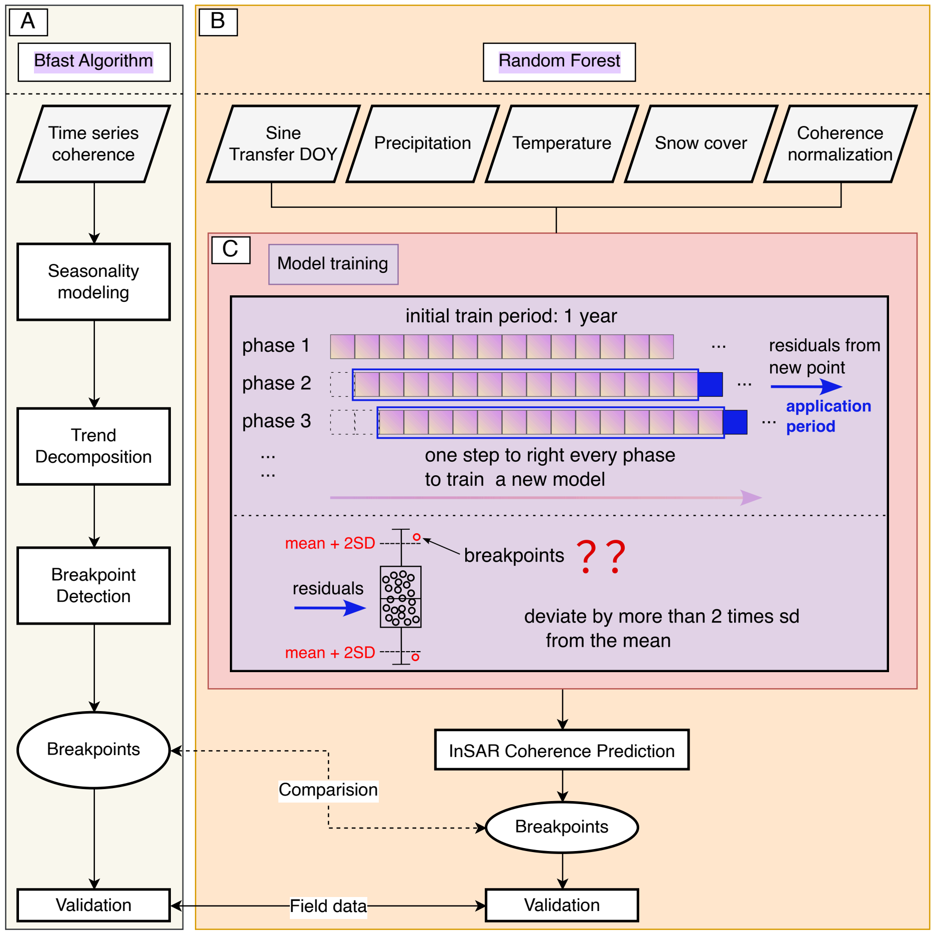

Figure 3.2: Overview of the study's workflow, (A) general steps of the BFAST algorithm, (B) parameters and workflow of the random forest model used in this study and (C) data processing and model building (for details, refer to Sect. 2.3.2).

In situ data collection

Field surveys were conducted in 2019, 2020, and 2022 in the summer camp sites using structured interviews as the primary data collection method Table 3.1. Over the course of the three years, a total of 862 households were interviewed, including some that were revisited in more than one survey year. Each household corresponds to a seasonal camp and is treated as one sample in the subsequent analysis. Household sizes ranged between 2 and 9 members, with interviews conducted with the male or female head of the household. On each camp sites, we crafted a comprehensive dataset covering various aspects of grazing management. This dataset serves as an invaluable reference, helping us to gain insight into important parameters such as arrival and departure dates at/from the camps, livestock numbers, and perceptions of rangeland degradation by local herders. It is important to note that these data were carefully collected by field staff and derived from interviews with the herders themselves, as documented in the original questionnaire.

Locations of the summer camp sites were collected using a GPS device. For detailed information regarding the survey questionnaires, please refer to Figure 3.8 in the Appendix.

Ultra-high resolution imagery obtained from Google Maps was utilized in the winter camp sites to identify point locations (Jawak et al., 2019). The distinctive feature of these camps is the presence of an artificial stone wall on the north side to shield against cold winds and snowstorms during winter. Together with the low vegetation cover due to long-term trampling effects of livestock, the stone wall creates a clearly visible feature in the aerial images (Houle, 2024a).

To delineate the effective area of grazing around the gers, we utilized GPS collar data from livestock. GPS tags were deployed on 89 individual livestock (30 goats, 31 horses, 26 cows, and 2 camels) across ten core sites in Figure 1, with data recorded every 30 minutes (Michler et al., 2022). The maximum range of livestock movement was up to 8 km from the camps. With increasing distance, grazing pressure decreases and intersection with grazing grounds of neighboring families increases. The direct vicinity of the camps is usually heavily disturbed especially at the winter camp locations. Consequently, we developed a ring around each camp, excluding the central 50-meter area to avoid the direct influence of human activities, and then extending outward from 50 meters to a 950-meter range resulting in a total area from 50 meters to 1 kilometer for further analysis. This ensures that the grazing pressure on the rangeland is assessed without the confounding effects of human disturbance near the camps.

Table 3.1: Movement characteristics of respondents

Year	Number of families (N)	Date move to				Days stay on				Distance to river avg [m]	No. of animal units
		spring camps avg [DOY]	summer camps avg [DOY]	autumn camps avg [DOY]	winter camps avg [DOY]	spring camps avg [DOY]	summer camps avg [DOY]	autumn camps avg [DOY]	winter camps avg [DOY]		
2019	320	58	149	247	305	114.89	109.45	64.84	153.31	970.6	191
2020	289	69	149	247	309	100.79	112.18	68.87	148.20	994.52	203
2022	253	76	148	248	308	76.95	102.34	63.69	144.01	1034.46	207

Note. DOY: day of year. Animal units were calculated based on conversion factors from Holechek (1988).

InSAR coherence

The two Sentinel-1 satellites (Sentinel-1A and Sentinel-1B, abbreviated with S1 in the following) are equipped with a C-band synthetic aperture radar (SAR) operating at a center frequency of 5.405 GHz (wavelength of approximately 5.54 cm). While S1 provides a 6-day revisit time in Europe, its temporal resolution for most of the rest of the world is 12 days (Potin et al., 2021). Since S1-B suffered technical problems on December 23, 2021 leading to its cessation of operations, we used a 12-days interval to derive S1 InSAR coherence.

The Hybrid Pluggable Processing Pipeline (HyP3) provided by the Alaska Satellite Facility was used for small baseline InSAR processing (Hogenson et al., 2025). Key steps included the selection of temporally close interferometric pairs, precise co-registration of master and slave images, interferogram generation, and coherence calculation. InSAR coherence, a dimensionless measure ranging from 0 to 1, quantifies the similarity between two complex SAR signals acquired at different times. Higher coherence values indicate temporal stability of surface scattering properties, while lower values reflect decorrelation caused by vegetation dynamics, soil moisture variation, or anthropogenic disturbances.

The use of HyP3 benefits from the tool's high level of integration and ultra-high arithmetic power relied on Amazon services (Hogenson et al., 2016). From 2018/01/01 to 2021/12/31, a total of 745 coherence images with a 40 m spatial resolution were processed for 10 study sites.

Weather data

The impact of precipitation on rangeland vegetation is significant, and the biomass will increase rapidly within 3-5 days after precipitation (Didiano et al., 2016). Precipitation data comes from Global Satellite Precipitation Programme (GPM) with a spatial resolution of 0.1° x 0.1°. Air temperature data from ERA5 - Land was monthly averaged and rescaled to the same resolution as precipitation products. We computed the mean air temperature (in ℃) and cumulative precipitation (in mm) for individual study sites on a daily basis. Subsequently, we determined left-aligned rolling sums spanning 3, 6, 9, and 12 days for precipitation and temperature data (Holtgrave et al., 2023). Employing these rolling sums for precipitation and temperature, we aimed to capture the aggregated meteorological conditions over preceding days, with the intent of reflecting plant growing conditions or management influences. The utilization of MODIS snow products (Hall et al., 2006), with a spatial resolution of 500 m, was additionally motivated by the potential impact of the frequency of winter storms, which may serve as a threshold in the assessment of environmental conditions. The weather data and MOD10A1 products were resampled to 40m to align with the InSAR coherence using bilinear interpolation (F. Gao et al., 2006; H. Wu & Li, 2009).

3.3.3 Experiment design and model building

Detection of breakpoints using random forest

This study proposes a novel methodology for breakpoints detection using random forest, based on the assumption that a random forest model learns the relationship between weather conditions (predictor variables) and the signal at the satellite (response variable, in our case coherence of S1 data). Consequently, if the model fails to predict the satellite signal correctly, this failure can be caused by changes in rangeland usage by livestock and/or wildlife. Therefore, breakpoints detected by the machine learning method are those points in time, where absolute values of residuals of the predicted coherence vs. the measured coherence are high. From a technical perspective, we used a sliding window of training and prediction periods for which separate random forest models are trained and validated. This encompassed the following steps which are conducted separately for each herder location (shown in Figure 3.2B):

(1) An initial random forest model was trained. To build this model, a subset of the available time series data was selected as the training period. This initial training period was set to 1 year, based on preliminary tests comparing the performance of longer/shorter periods. The predictor variables include snow cover, precipitation rolling sums, mean air temperatures rolling means and the sine of the day of the year. The latter has been introduced as predictor to capture seasonal fluctuations in time series data. As the response variable, coherence was chosen Figure 3.2C. To evaluate the model performance, a 5-fold 2-times repeated cross validation was used. Therefore, training data was split into training and validation folds before the model was trained.

(2) Model performance was evaluated in each fold, and the average performance across folds was recorded by calculating the RMSE (Root Mean Square Error). Once trained and validated, the model was applied to predict coherence for a time period following the training period (application period). The length of the application period was varied between 1 and 5 to test the ability of the random forest model to predict coherence values in future relative to the training data. A value of 1 means that the model was used to predict the coherence of the next available time step, which was 12 days after the last training data due to the 12-day temporal resolution of the coherence data. If the application period was set to 5 coherence data within the next 60 days were predicted. After testing the different values for the application period, 1 was selected for this study as it resulted in best model performance, with highest accuracy of breakpoints detection. After prediction of coherence in the application period, residuals between the predicted and observed coherence values were calculated and stored for further analysis.

(3) Model retraining occurs in a sliding window approach: the training period was subsequently shifted by the length of the application period and the random forest model was retrained. This updated model was then used to predict coherence of the next application period. Again, residuals between predicted and observed coherence values were stored. This step was repeated until the end of the time series was reached. This iterative process ensured that the model adapts to temporal changes in the input data and provided new residuals for each time step as the window progresses.

(4) Based on the assumption that the model will learn the relationship between weather conditions and coherence, we searched for high absolute values of residuals between predicted and observed coherence. These are points in time when the model was not capable of predicting changes in the vegetation conditions due to factors which none of the predictors contain such as grazing. Therefore, the distribution of residuals across the entire time series was analyzed in the final step. Finally, breakpoints were defined as those residuals which deviate by more than 2 times of standard deviations from the mean values of all residuals. Assuming a normal distribution in the residuals, this means that breakpoints are the 5% of less accurately predicted coherence values.

BFAST algorithm

BFAST is a data-based unsupervised statistical algorithm. Based on models of stable historical behavior, abnormal changes in newly acquired data can be detected (X. Fang et al., 2018; Watts & Laffan, 2014). Initially, regression coefficients are estimated from historical observations and used to predict the values of observations in the monitoring period. Subsequently, if the predicted values statistically differ from the observed values, it indicates the presence of abnormal changes (Browning et al., 2017; Ma et al., 2020). Parameters were set as follows: the historical period comprised one full year, followed by another year as the monitoring or detection period. The sbin parameter, which controls the number of seasonal dummies, was set to 3, and the h parameter, representing the minimum segment size, was set to 0.5, allowing the detection of significant breaks or changes within the monitoring period Figure 3.2A. The function used in this study comes from BFAST package for R statistical computing (Version: 1.6.1)(Verbesselt et al., 2012).

Assessing the model accuracy

Prediction accuracy of the model is estimated using a 5-fold cross-validation with 2 repetitions. Here, RMSE was calculated (Cherif et al., 2024). To understand the effect of the different predictor variables in the models, the variable importance has been analyzed.

In general, if breakpoints are detected in the time series, this does not necessarily mean that the models are capable of detecting those changes caused by grazing (Ersi et al., 2023). To ensure that the detected changes were indeed related to grazing activities, we compared them with the actual movement dates of herders (Lobert et al., 2021). Given the potential legacy effect between herder movements and vegetation responses observable by satellite, we considered breakpoints occurring within 50 days after camp relocation as grazing-related. To quantitatively evaluate the performance of the random forest method and the BFAST algorithm in detecting these grazing-induced breakpoints, we constructed confusion matrices for both summer and winter camps. These matrices allowed for a direct comparison of true and false detections between the two approaches (Y. Zhang, Wang, et al., 2022).

3.4 Results

3.4.1 Breakpoints prediction and validation

Observed coherence Figure 3.3a aligned well with predicted coherence Figure 3.3b in time series. Accuracies in coherence prediction among the models are ranged from moderate to high (RMSE between 0.28 and 0.08). Since the initial training phase is limited to the first year, values are always the same, then the RMSE remains 0 during this phase. (RMSE is always calcualated for each model from every new phase) Figure 3.3c. Most of the residuals are concentrated around 0, indicating that the overall prediction deviation is small Figure 3.3d. At the two points marked by the red dotted line, the residuals deviate significantly from 0 and are detected as breakpoints.

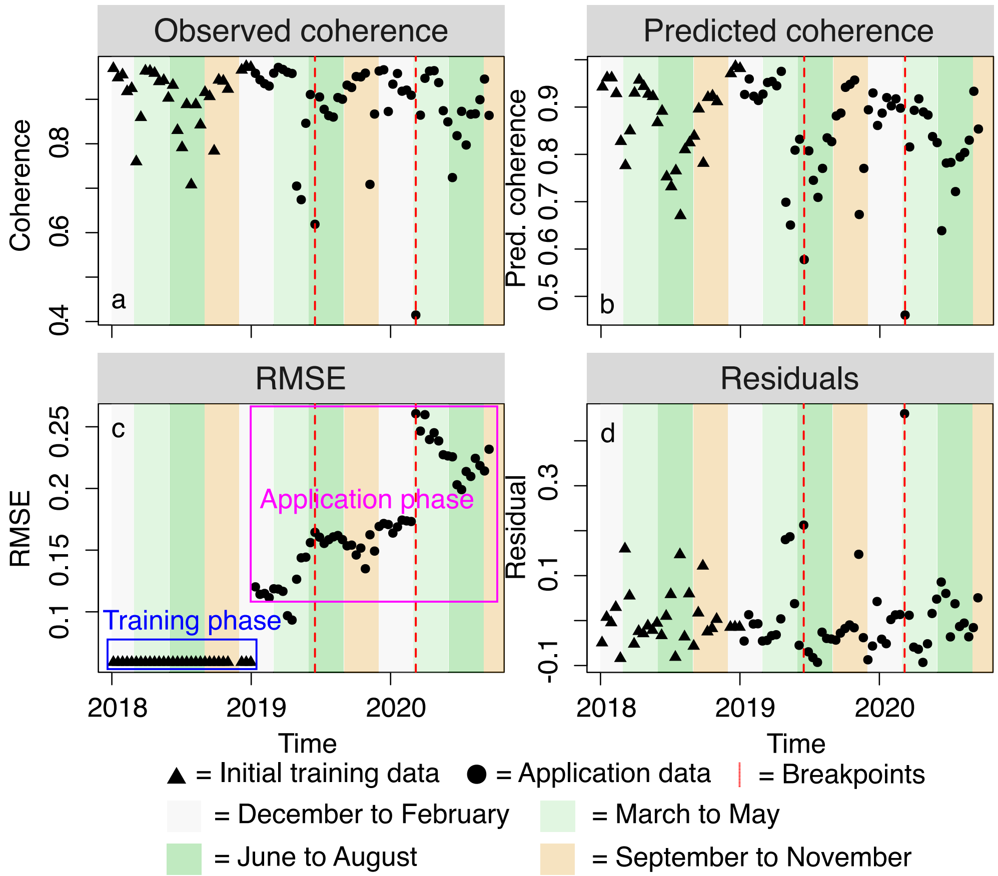

Figure 3.3: Breakpoints detection using random forest model for a sample point. (a) observed coherence from 2018 to 2020; (b) predicted coherence using the random forest model developed above; (c) RMSE of each model in successive moving windows, since the initial training phase encompasses the first year, RMSE values are constant over the first year and set to 0 during this phase. (d) residuals in the model training process. Triangles represent initial training data, circles represent application period data. Breakpoints are marked with red dashed lines, background colors indicate seasonal periods.
Note: This figure demonstrates the model training and prediction process for one of the sample points in the dataset comes from middle of Hentii province.

3.4.2 Variable importance

Among the variables in the model training process, the sine transformation of day of the year Figure 3.4b and the left-aligned rolling sum across 6 days of precipitation Figure 3.4d had the greatest variable importance in the model. The left-aligned rolling sum across 3 days Figure 3.4c, the left-aligned rolling sum across 12 days of precipitation Figure 3.4f and temperature Figure 3.4g had medium contribution to the model. While snow cover was partly important in single models Figure 3.4a and the left-aligned rolling sum across 9 days of precipitation Figure 3.4e had the lowest contribution to the model.

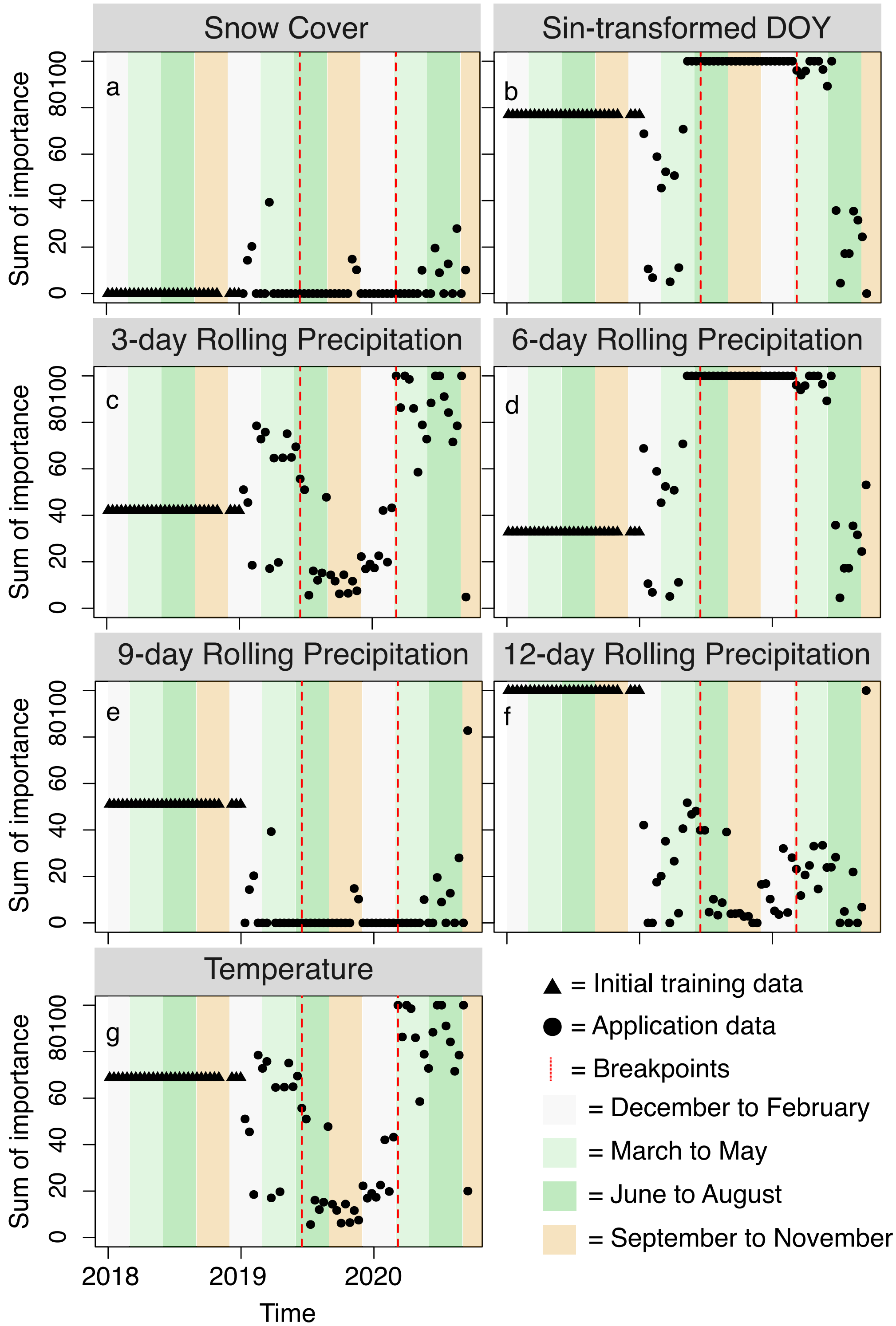

Figure 3.4: Sum of variable importance in random forest model, (a) snow cover, (b) sine transformation of day of the year, (c) precipitation 3 days rolling sum, (d) precipitation 6 days rolling sum, (e) precipitation 9 days rolling sum, (f) precipitation 12 days rolling sum and (g) temperature.

3.4.3 Application on temporal breakpoints detection

The random forest method successfully predicted 149 breakpoints at 200 summer camp sites Figure 3.5, with the majority of these breakpoints occurring between April and June Figure 3.6a. Notably, the random forest algorithm detected 44% of breakpoints occurring after herders moved to their summer pastures Figure 3.6e. To benchmark the performance of the random forest method, we applied the well-established BFAST algorithm to the coherence time series data. Breakpoints were detected for every month except January Figure 3.6c. Of the 200 camp sites, 115 breakpoints were detected throughout the year using BFAST, but only 28% of them occurred after herders arrived at the summer camp sites Figure 3.6f.

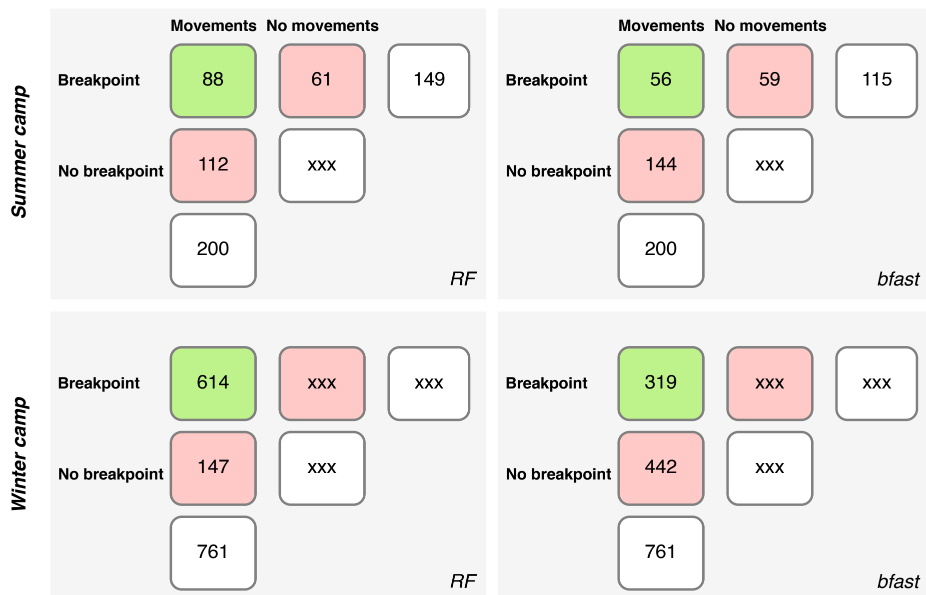

Figure 3.5: Confusion matrix of breakpoints detection using random forest and BFAST algorithm. No comparison is possible for winter camps because the movement dates cannot be aligned with the winter locations detected from high resolution satellite data.

At 761 winter camp sites, the random forest method detected 614 breakpoints Figure 3.5, primarily occurring in February, March, and October to November Figure 3.6b. In comparison, BFAST exhibited much lower performance at detecting breakpoints at winter camp sites, identifying only 319 breakpoints (FIgure 5). Moreover, the temporal distribution of breakpoints detected by BFAST was less concentrated during the winter months, with breakpoints detected in nearly every month except January Figure 3.6d.

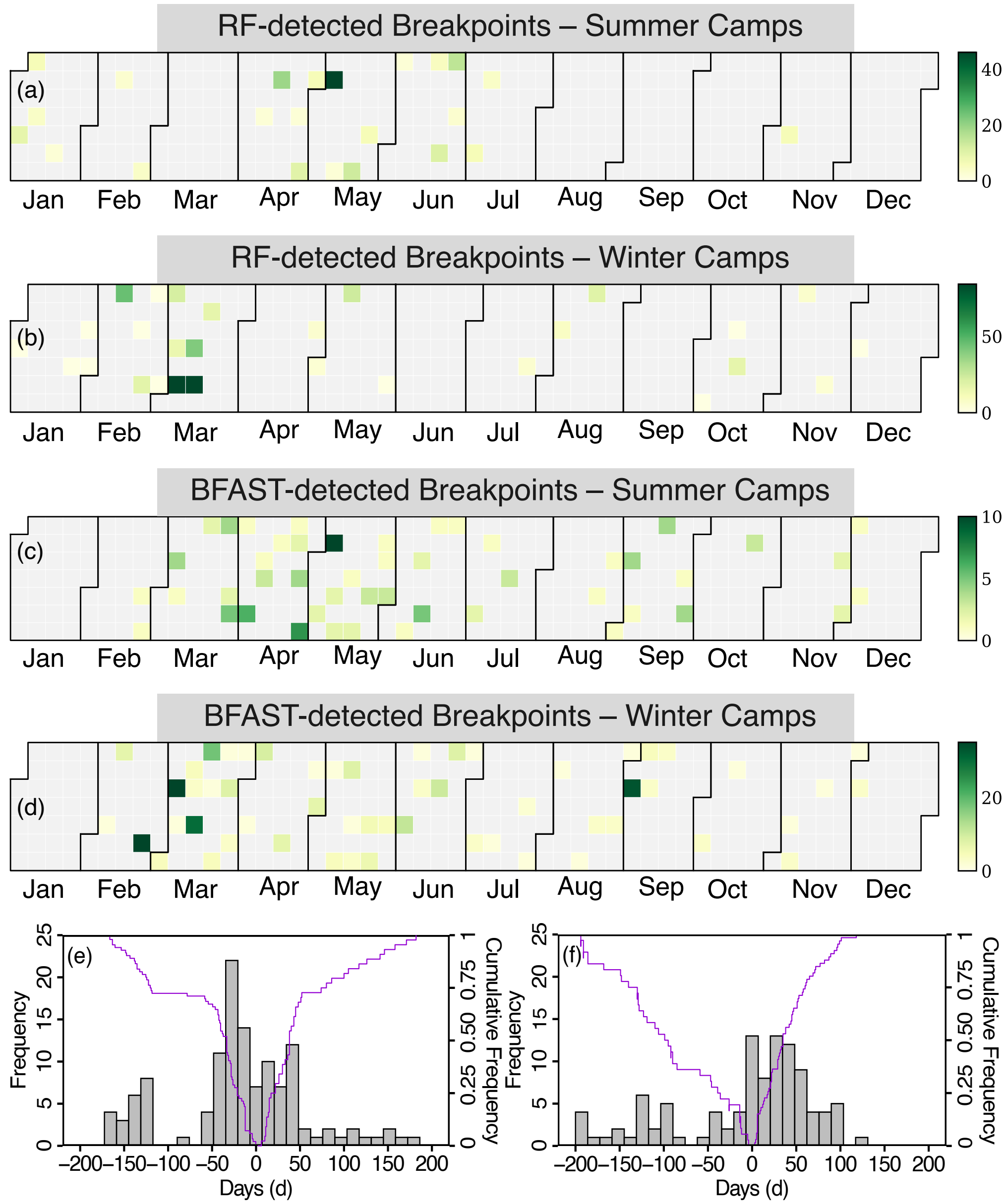

Figure 3.6: (a) and (b):Heatmaps of breakpoints detected by random forest method for summer and winter camp sites respectively. (c) and (d): Heatmaps of breakpoints detected by BFAST method for summer and winter camp sites respectively. Each heatmap shows the temporal distribution of breakpoints aggregated across all sites; colored blocks indicate frequency on specific day. (e): Difference in days between detected breakpoint and actual moving dates using the random forest method. (f): same as (e) but for BFAST (Bars indicate frequency distribution; the purple line indicates cumulative frequency).

3.4.4 Spatial prediction of breakpoints

Based on the method developed in Section 2.3.2, we performed spatial predictions for year 2019 for the four steppe sites in Eastern Mongolia marked by I, V, VII, and IX in Figure 3.7. The figure illustrates that summer breakpoints are primarily detected along riverbanks in regions I (UB) and V (Khentii), exhibiting a relatively clustered distribution. Correspondingly, winter breakpoints are distributed in adjacent areas. In Region VII, located in Dornod Province, summer breakpoints are rarely detected, with winter breakpoints dominating most of the region. In contrast, Region IX, situated in the southern part of Sukhbaatar Province, exhibits a prevalence of summer breakpoints, while winter breakpoints are less frequently observed.

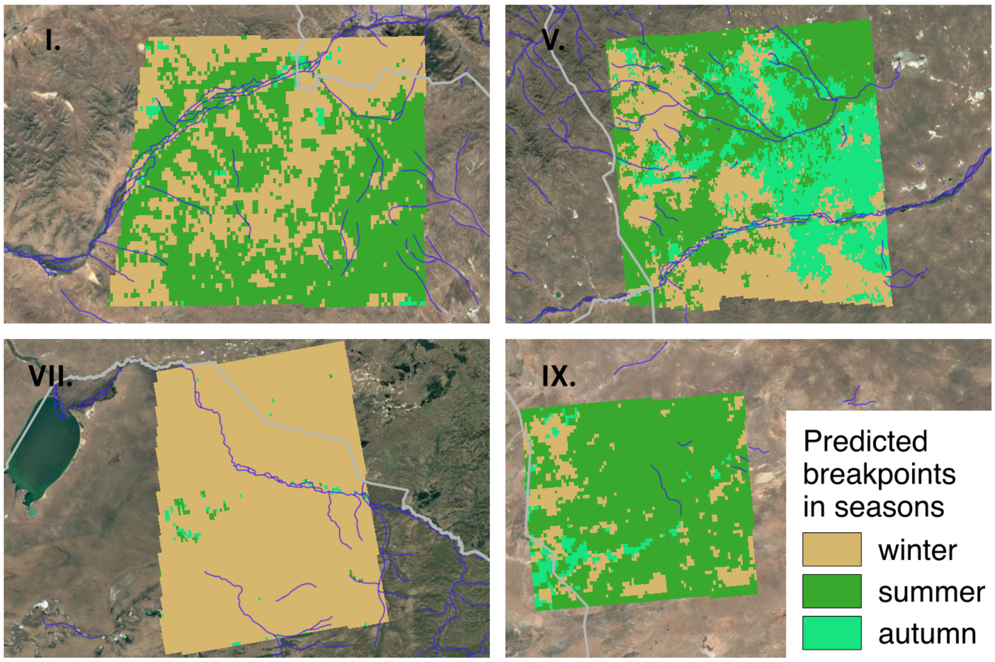

Figure 3.7: Seasons when breakpoints have been detected four different areas in Eastern Mongolia. (I, V, VII, and IX comes from Figure 1, winter is from December to March, summer is from June to August).

3.5 Discussion

3.5.1 Methodological Performance: random forest vs. BFAST in Breakpoint Detection

This study demonstrates the capability of machine learning, particularly random forest, in detecting grazing-induced breakpoints using InSAR coherence data. The random forest method accurately detected 44% of summer camp breakpoints—substantially outperforming BFAST, which achieved only 28%. Moreover, random forest derived breakpoints in summer pastures were temporally consistent, mainly clustering between April and June, a period that aligns well with the onset of the growing season in Eastern Mongolia. In contrast, BFAST showed irregular breakpoints patterns and lower temporal alignment In theory different reasons could be responsible for the lower accuracy of BFAST compared to the random forest method: BFAST is trained only on coherence data and calculates regression coefficients based on the specified historical period (Dutrieux et al., 2015). When a new value is introduced, it is predicted using the regression equation and compared with the observed value. If there is a statistical difference between the predicted and observed values, the introduced value is considered anomalous. If there are outliers in coherence values in the selected historical period caused e.g., by extreme weather events or heavy grazing, the regression equation and coefficients derived from that period will become "unstable" (Verbesselt, Hyndman, Zeileis, & Culvenor, 2010). This instability makes the subsequent evaluation of anomalies in the prediction period uncontrollable. Moreover, in rangeland ecosystems, vegetation growth is influenced by a multitude of natural and human factors. Simply addressing temporal changes statistically overlooks the broader impact of these factors on vegetation dynamics (Gaujour et al., 2012; Y. Liu et al., 2019). Consequently, the new random forest method provides a much more efficient approach to detect those vegetation changes which are caused by grazing in time series dominated by large scale effects of natural factors such as snow and rainfall.

3.5.2 Seasonal and Spatial Breakpoint Patterns

Breakpoint patterns differed markedly between seasons. In winter camp sites, most breakpoints occurred between February and March Figure 3.6b, when snow is the main natural driver of coherence. This is likely due to the impact of snow cover on InSAR signal quality, which can hinder the detection of displacement signals (Eppler & Rabus, 2022). Unlike summer camps sites, where grazing pressure necessitate careful management, herders often designate specific areas as winter pastures during the growing season (Ono & Ishikawa, 2020). These areas are monitored and protected to prevent unauthorized grazing during summer, allowing forage to accumulate for livestock use in winter. Hay feeding also plays a critical role, our interview data indicate that in 2019, herders reported spending an average of 105,000 Mongolian Tugrik on hay for livestock feeding. Thus, the main energy source for livestock is hay fed by herders, rather than relying heavily on free grazing (Tsevegemed et al., 2019).

From a spatial perspective, random forest successfully predicted seasonal breakpoints across all four study sites Figure 3.7. At sites near river systems, such as site I (near Ulaanbaatar) and site V (northern Khentii), summer breakpoints predominantly aligned along river systems, exhibiting pronounced clustering effects. The proximity of summer camps to rivers is plausible, as herders typically avoid valley bottoms during winter due to lower nighttime temperatures and the lack of natural wind shelters compared to locations at slope feet. Since the 1990s, water resources, particularly river flow and depth, have steadily declined in Eastern Mongolia, increasingly constraining herders' ability to graze livestock along riverbanks, which are critical for ensuring adequate water intake (Tugjamba et al., 2021a).

In contrast, breakpoints patterns at sites VII and IX were less related to topography because summer pastures have been predicted both in mountainous and flat areas around the rivers. This may be a consequence of extensive grazing in the eastern study sites, where low population densities and low livestock numbers reduce the grazing signal within coherence time series (Hilker et al., 2014a). Moreover, the eastern region hosts higher numbers of wildlife, such as Mongolian gazelles, whose roaming contributes to a general grazing signals without seasonal cycles. This overlap with livestock grazing activities complicates the identification of breakpoints caused solely by livestock (D. Nandintsetseg et al., 2019; Yoshihara et al., 2008). In the southern study sites, located at the grassland-desert boundary, shorter vegetation further complicates the detection of grazing signals, because the signal of vegetation in the InSAR-data is generally low (Michler et al., 2022; Pan et al., 2022). Even biomass estimation in this region demonstrates lower accuracy compared to other areas (Ji et al., 2024). Additionally, the uncertain spatial distribution of grazing activities contributes to monitoring challenges, as some areas are heavily grazed by livestock from multiple households, while others are rarely utilized.

3.5.3 Drivers of Grazing Patterns

The results presented in Figure 5 indicate that detection of breakpoints in summer and winter camps remains challenging for both the random forest and BFAST methods, irrespective of whether they pertain to winter or summer camps. Precipitation variability directly impacts forage availability and quality (Munkhtsetseg et al., 2007), serving as a critical driver in determining herders' movements time and destination. Additionally, the depletion of water resources and the decline in river flow compel herders to adapt their traditional movements routes and schedules (Gantuya et al., 2021). Based on a study in northeastern Mongolia (Tugjamba et al., 2021a), resource constraints, economic pressures and policy changes have further contributed to a reduction in the frequency of seasonal movements, with the customary four seasonal movements per year often declining to three or fewer.

3.5.4 Limitations and future work

Despite its improved performance, the random forest model faces limitations. In the eastern and southern regions current methods have proven less effective. These areas face unique challenges, including the uneven spatial distribution of grazing activities, the overlapping presence of wildlife such as Mongolian Gazelles, and the difficulty of detecting grazing signals in sparse and short vegetation. Moreover, the detection of breakpoints under the combined influence of grazing and wildlife activities is ecologically complex. This complexity is compounded by additional factors such as mining activities and wildfires, which can significantly interfere with remote sensing signals used to identify breakpoints (Serra-Burriel et al., 2021; Sun et al., 2024). Wildfires, in particular, can alter vegetation patterns at a landscape scale (Kerby et al., 2007), masking the impacts of grazing and wildlife activities in coherence time series and reducing the accuracy of breakpoint detection. As wildfires often coincide with dry seasons and can devastate pastureland, they indirectly influence herders' decisions regarding livestock movement and grazing intensity, further complicating the spatial distribution of grazing activities (Kazato & Soyollham, 2022).

Furthermore, as the random forest-based approach requires supervised learning, users must prepare appropriate training and validation datasets. The quality, representativeness, and spatial coverage of these data directly influence model robustness and generalization capability. In data-scarce environments like Eastern Mongolia, obtaining reliable ground truth information for training remains a challenge. Future research could explore semi-supervised or transfer learning strategies to alleviate data dependency.

Although our study focuses on Sentinel-1 coherence time series data, the proposed random forest-based breakpoint detection framework is not limited to SAR data. The method can be extended to other remote sensing time series datasets that capture vegetation dynamics, such as optical vegetation indices (e.g., NDVI from Sentinel-2 or Landsat). The key requirement is the availability of sufficiently dense and temporally consistent observations that reflect the vegetation responses to disturbances. However, data characteristics such as noise level, spatial resolution, and sensitivity to specific vegetation changes should be considered when applying the method to different sensor data.

3.6 Conclusion

This study provides compelling evidence that machine learning, specifically random forest, offers a powerful alternative to traditional methods for detecting grazing-induced vegetation breakpoints in Eastern Mongolia's rangeland. By leveraging Sentinel-1 SAR coherence time series, the random forest model achieved significantly higher detection accuracy of known herder movements (44%) compared to the widely used BFAST algorithm (28%), and revealed distinct seasonal breakpoint patterns aligned with traditional pasture rotation practices.

A key strength of our approach lies in its spatial generalization capability, which enables the transfer of learned patterns across diverse ecological zones and grazing contexts—highlighting its applicability for large-scale, data-driven rangeland monitoring. While some confounding factors such as wildfires, mining, or wildlife grazing may also influence the observed signals, our findings underscore the potential of random forest based frameworks for capturing subtle and seasonally structured vegetation dynamics linked to nomadic land use.

Overall, this study advances the integration of SAR time series and machine learning for ecological monitoring, offering new pathways to understand and manage rangeland systems under increasing environmental and socio-economic pressures.

3.7 CrediT authorship contribution statement

Shuxin Ji: Manuscript writing, methodology, data processing. Ganzorig Gonchigsumlaa, Sugar Damdindorj, Tserendavaa Tseren, Densmaa Sharavjamts, Amartuvshin Otgondemberel, Enkh-Amgalan Gurjav, Munguntsetseg Puntsagsuren, Batnaran Tsabatshir, Tumendemberel Gungaa, Narantsetseg Batbold, Lukas Drees, Bayarchimeg Ganbayar, Dulamragchaa Orosoo, Bayartsetseg Lkhamsuren, Badamtsetseg Ganbat, Myagmarsuren Damdinsuren, Gantogoo Gombosuren: Original questionnaire design and field investigation. Nandintsetseg Dejid and Thomas Müller: Provide guidance for delineating the scope of study areas. Batnyambuu Dashpurev and Thanh Noi Phan: Conceptualization, review & editing. Lukas Lehnert: Supervision, programming, review & editing.

3.8 Declaration of Competing Interest

The authors declare no conflict of interest in this paper.

3.9 Data available

The data that support the findings of this study are available from the corresponding author upon reasonable request.

3.10 Acknowledgments

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3.11 Appendix

Figure 3.8: Typical Winter camp in Eastern Mongolian Nomadic System

Table 3.2: Survey Questionnaires for Herder Household Interviews (2019, 2020, and 2022)

Year	**Link**
2019	https://docs.google.com/document/d/1ok7EEiEzZNvyuTUcPYE4amkeaLTbaiXI/edit?usp=sharing&ouid=115666775336645475325&rtpof=true&sd=true
2020	https://docs.google.com/document/d/1C7JneN5sZDvuitts1D6ketJ8FQxup9gt/edit?usp=sharing&ouid=115666775336645475325&rtpof=true&sd=true
2022	https://docs.google.com/document/d/1KdR5knuHkDAn8rGOnNnOqsGvuYbIAWkg/edit?usp=sharing&ouid=115666775336645475325&rtpof=true&sd=true

Tracking the ecological footprint of humans and wildlife in Eastern Mongolia

This paper is currently under review at *Ecosphere*

CHAPTER 4

TRACKING THE ECOLOGICAL FOOTPRINT OF HUMANS AND WILDLIFE IN EASTERN MONGOLIA

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This study developed a novel grazing pressure index by comparing remotely sensed and model-predicted aboveground biomass to quantify the combined impacts of livestock and wildlife in Eastern Mongolian grasslands from 2019 to 2021. Our analysis revealed a significant positive correlation between livestock density and proxy of biomass reduction(PBR), particularly in Khentii province, indicating its utility as an indicator of grazing pressure. While human population density showed a correlation only in 2021, the relationship between gazelle density and PBR varied across provinces, highlighting the complex interplay of factors influencing vegetation dynamics. This PBR index proves a valuable tool for monitoring combined grazing pressure in this vital ecosystem.

4.1 Abstract

The vast grasslands of Eastern Mongolia have supported wildlife and traditional pastoralists for thousands of years. The transition from a planned economy to a market economy has been accompanied by considerable changes in livestock numbers. It is essential to quantify the impacts of grazing on ecosystem functioning in this region, given the nomadic pastoralists' heavy reliance on natural resources to sustain their livelihoods, and the critical role played by these grasslands in terms of productivity and carbon sequestration. We tested the hypothesis that the combined grazing activities of livestock and wildlife (predominantly Mongolian gazelle Procapra gutturosa) had a detectable impact on vegetation dynamics in Eastern Mongolia from 2019 to 2021. To do this we devised an index of grazing pressure by calculating the difference in potential and actual aboveground biomass: subtracting estimated biomass from remote sensing and from the biomass predicted by the process-based ecosystem model LPJ-GUESS and analyzed the resulting differences in biomass in relation to livestock density, human population density, and gazelle density. The results showed that in 2020 and 2021 there was an overall significant positive correlation between livestock density and proxy of biomass reduction (PBR), an indicator of grazing pressure, and it was particularly evident in the western provinces. The human population density showed a significant positive correlation with PBR only in 2021. No significant correlation was observed between gazelle density and PBR overall, while among study areas a significant positive correlation was observed in Khentii, Sukhbaatar and Dornod, but not for the westernmost province of Tuv. Our results support the utility of PBR as an indicator of combined grazing pressure from livestock and wildlife in Eastern Mongolia's grasslands.

Key words: LPJ-GUESS; biomass proxy; Mongolian gazelle; *Procapra gutturosa*; livestock; ecological footprint

4.2 Introduction

In grassland ecosystems, the grazing activities of livestock and wildlife have significant impacts on vegetation growth and biomass, making it crucial to distinguish between their respective influences when assessing the impacts of grazing on the ecosystem. Livestock grazing is typically concentrated in specific areas, with livestock foraging behavior and population dynamics directly affecting changes in grassland vegetation cover and biomass at a more local scale (Cao et al., 2024; Lu et al., 2017). In contrast, the activities of wildlife (e.g., Mongolian gazelle Procapra gutturosa) are more unpredictable spatially and can involve migrations and foraging behaviors influenced by seasonal variations and ecological conditions, spanning hundreds of kilometers and causing broader-scale vegetation dynamics. When evaluating grazing intensity (Dejid et al., 2022), it is essential to consider the competition for resources and niche overlap between livestock and wildlife. For instance, in some areas, overgrazing by livestock may lead to soil erosion and vegetation degradation (Sainnemekh et al., 2022b; Q. Wang, 2014), while the foraging behavior of wildlife may exert localized pressure on specific plant species (Coughenour, 1991). Accurately distinguishing between these two influences not only helps to better understand grassland ecosystem functioning, but also provides scientific guidance for sustainable grazing management and wildlife conservation.

Assessing vegetation dynamics over large-scale geographic regions can be approached through two primary methods. The first, more commonly employed approach, combines remote sensing data with ground-based measurements to estimate changes in vegetation variables associated with their conditions. The second method involves using dynamic vegetation models to simulate ecological processes based on existing climate and soil data. For the latter, models such as LPJ-GUESS, a dynamic global vegetation model, simulate plant growth and aboveground biomass (AGB) production under the influence of multiple environmental factors, including climate, soil, water, and carbon dioxide concentrations, but often excluding biomass consumption by herbivores and anthropogenic land management (B. Smith et al., 2001). Consequently, such a prediction can be interpreted as a proxy for "potential natural biomass" (AGB_{pot}) in the absence of grazing. Such simulations provide a baseline, enabling us to understand the potential growth of vegetation as a function of the observed environmental conditions. In contrast, biomass estimates derived from remote sensing (AGB_{rs}) account for grazing, human land-use changes, and environmental factors affecting plant growth (Galidaki et al., 2017). AGB_{rs} measurements offer a more comprehensive understanding of ecosystem health and productivity by considering both natural factors and human influences, such as livestock grazing. By comparing the potential biomass simulated by the LPJ-GUESS model with the actual biomass derived from remote sensing, it might be possible to infer the combined effects of livestock and wildlife grazing on grassland ecosystems (Seaquist et al., 2009).

In this study, we focused on the grassland steppe of Eastern Mongolia, particularly in four provinces where the majority of Mongolian gazelles are found (Buuveibaatar et al., 2024; Olson, Fuller, Mueller, et al., 2010). Our analysis considered data collected between 2019 and 2021. Within this context, we hypothesized that the combined grazing intensity of livestock and wildlife are captured by the differences in AGB values between AGB_{pot} and AGB_{rs} (hereafter referred to as “proxy of biomass reduction, PBR”) in the grassland steppe of Eastern Mongolia, i.e. expecting a positive relationship between livestock density and PBR in areas of high grazing pressure. We also expected weaker or no correlation in regions with lower grazing pressure, particularly in the eastern part of the study area.

4.3 Data and methods

4.3.1 Study area

The study area is located in Eastern Mongolia, encompassing the provinces of Tuv, Khentii, Sukhbaatar, and Dornod (Figure 4.1). This region serves as a vital livestock grazing area and provides critical habitat for wildlife as well, including Mongolian gazelle and other species. Our analyses were conducted at the administrative level of ’bag’, which represents the smallest administrative unit in Mongolia. For this study, a total of 299 bags were included from these provinces, specifically comprising 79 bags from Khentii, 54 from

Tuv, 58 from Sukhbaatar, and 67 from Dornod. These administrative units exhibit considerable variability in their spatial extent; the bags within our study area have an average size of 107,619.5 hectares, with sizes ranging significantly from a minimum of 5,182 hectares to a maximum of 1,154,919 hectares. This substantial range in bag size is an important consideration when interpreting spatially aggregated density values. The total number of livestock in the region was more than 16.3 million in 2023, including horses, cattle, camels, sheep, and goats, according to the National Statistics Office (NSO) dataset (https://www.nso.mn/en/dissemination/73072997). According to a 2020 field survey, the number of gazelles in central and eastern Mongolia was estimated to be 1.99 million with a 95% confidence interval of 1.47 - 2.71 million (Buuveibaatar et al., 2024). Since the transition to a free-market economy in the 1990s, the number of livestock has increased significantly to meet export demand, resulting in a decline in pasture carrying capacity (Tumur et al., 2021). Vegetation quantity and quality is highly unpredictable both spatially and temporally, primarily influenced by variations in precipitation. During the study period (2019–2021), the region showed noticeable inter-annual variability in precipitation and temperature (Figure 4.10 and Figure 4.11). Apart from the well-known fenced railway corridor between Beijing and Ulaanbaatar, the region has no significant man-made physical barriers, making spatial overlap between livestock grazing activities and wildlife habitats highly possible. For this study, our analysis primarily focused on vegetation dynamics during the growing season, when biomass accumulation is most evident.

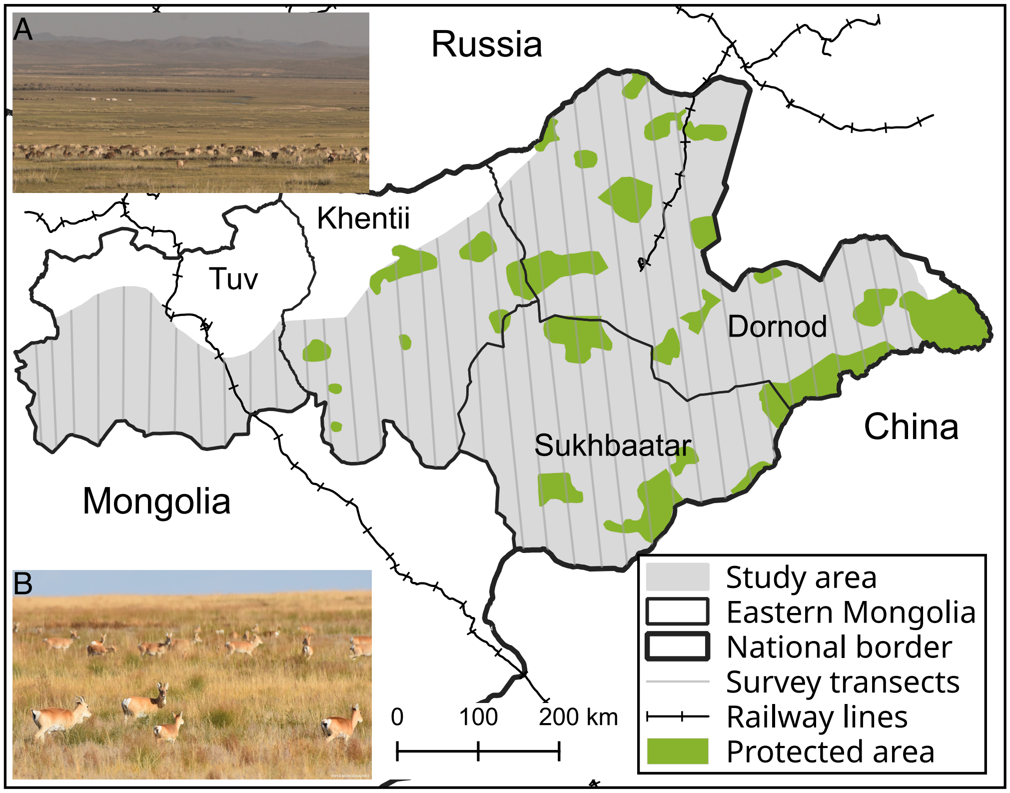

Figure 4.1: Study area (grey) in Eastern Mongolia covering a portion of the overall gazelle range with survey transects, protected areas, and mining areas shown. A: Livestock grazing (Photo by Lukas Lenhert); B: A group of Mongolian gazelle foraging (Photo by B. Buuveibaatar).

4.3.2 Data source

Satellite-derived biomass data

We used an aboveground biomass dataset for years 2019 to 2021 generated using machine learning applied to Sentinel 1 and Sentinel 2 data. The dataset was trained and validated against over 600 field-based measurements of aboveground biomass spanning central and eastern Mongolia (Ji et al., 2024). The spatial data at a 10 m resolution was resampled to a 0.1 ° resolution (using bi-linear interpolation) to be consistent with the biomass layer produced by the vegetation model (see subsection 4.3.3).

Human population, livestock and gazelle density

Since grazing pressure and human activity are likely major drivers of the difference between modelled AGB_{pot} and remotely sensed biomass AGB_{rs}, we tested the hypothesis that higher livestock density and human population density would increase the difference, while wildlife grazing (gazelles) would have a weaker or negligible effect. To examine this, livestock density, human population density and gazelle density were selected as potential drivers to explain the spatial variation in PBR indicated by the difference in AGB_{pot} and

AGB_{rs}, aiming to disentangle the respective contributions of anthropogenic and grazing pressure driven by wildlife and livestock.

Livestock density and human population density data were obtained from the Mongolian Statistical Yearbook (www.1212.mn). We calculated the livestock density, human population density, and gazelle density at the administrative level of bags to assess regional variations in human and livestock impacts on vegetation dynamics in the study area. To accurately quantify grazing pressures on grasslands, we converted the number of cattle, horses, camels, sheep, and goats into animal units (au), according to (Miao et al., 2021). In order to facilitate a direct comparison of the grazing impacts of these livestock species, we converted their numbers into livestock density by dividing the total animal units per bag by the area of each bag, which allowed for spatially explicit estimates of grazing pressure across the study area.

Design-based gazelle density estimates were obtained from vehicle-based distance sampling surveys (S. T. Buckland et al., 2015; S. Buckland et al., 2001) conducted across a 433,245 km^2 area in Central and Eastern Mongolia during May–June 2020 (Buuveibaatar et al., 2024). In addition, Generalized Additive Models (GAMs; (Wood, 2017)) were applied to these distance sampling data using the *mgcv* package in the R software to generate a Mongolian gazelle density surface across the study area. Transects were divided into 10 km segments with group counts assigned to each segment and the sampled area for each segment included as an offset term in the model to account for small variations in segment length. A second model to predict group size was fit to the number of gazelle recorded along each 10km segment with the number of groups included as an offset term in the model and conditioned on at least one group being recorded. Gazelle group density and group size were predicted across the entire study area at a spatial resolution of 1 km × 1 km based on location. The predicted gazelle group density was combined with the predicted group size to obtain a density surface for Mongolian gazelle. The average predicted gazelle density was 0.052 (95% Confidence Interval: 0.035–0.076) individuals per hectare.

4.3.3 Vegetation model

LPJ-GUESS

To simulate the AGB_{pot} in Eastern Mongolia, we used the LPJ-GUESS model (version 4.1), a dynamic global vegetation model designed to represent vegetation dynamics and ecosystem processes at regional and global scales (B. Smith et al., 2001), including nitrogen cycles (B. Smith et al., 2014). Given that the dominant vegetation type in the Eastern Mongolian Steppe is C3 herbaceous vegetation (Pyankov et al., 2000), only this plant functional type (PFT) was included in the simulations.

Grass growth was modeled using the daily grass module developed by Boke-Olén et al. (Boke-Olén et al., 2018), which is based on the framework originally proposed by Johnson and Thornley (Johnson & Thornley, 1983). This module accounts for the daily allocation of carbon to different plant organs, such as leaves, storage, and roots, where the original model calculates carbon allocation on a yearly basis. To ensure some biomass remained during the winter months, the decomposition of senesced leaves (dead standing biomass) was halted when temperatures dropped below 0 °C. Patch disturbances and fire dynamics were excluded from the simulations as they did not align with observed patterns in the region.

Finally, the peak aboveground biomass (AGB_{pot}) was calculated as the maximum green leaf biomass for each grid cell and year, leading to one spatial grid per year (2019-2021).

Model input

Daily climate data used to drive the model simulations, including air temperature, precipitation, and solar irradiation, were sourced from the ERA5-Land reanalysis database (Muñoz-Sabater et al., 2021). These data, originally provided at hourly time steps, were processed into daily values using the Climate Data Operators (CDO version 2.4.1) tool (Schulzweida, 2023). The dataset spans the period from 1950 to 2023, with a spatial resolution of 0.1 °.

Atmospheric CO2 concentrations were obtained as global annual values from Büchner and Reyer (Büchner & Reyer, 2022), while nitrogen deposition data were sourced as monthly values from the Atmospheric Chemistry and Climate Model Intercomparison Project (ACCMIP) (Lamarque et al., 2013). Additionally, static soil texture data based on Zobler (1986) was included as an input to the model at a 0.5 ° resolution.

To simulate vegetation establishment from bare ground and achieve equilibrium with environmental conditions, we conducted a 500-year spin-up. During this period, the first 30 years of climate data were repeatedly cycled, while CO2 concentrations and nitrogen deposition rates were maintained at their levels from the initial year of the climate dataset (1950).

4.3.4 Agreement between biomass estimates from LPJ-GUESS and remote sensing

In order to evaluate the relationship between modelled and remotely sensed biomass estimates, we examined the agreement between LPJ-GUESS outputs (AGB_{pot}) and remote sensing-based biomass (AGB_{rs}). Spearman's rank correlation coefficient (rs) was calculated to assess the consistency between the data and model outputs (rs[AGB_{pot} - AGB_{rs}]). The Spearman coefficient ranges from 1 to +1, where higher positive values indicate strong agreement, larger negative values reflect strong disagreement, and values near zero signify random variation. This coefficient is used to measure the association between two variables, such as AGB_{pot} and AGB_{rs}, with their scores ranked (McGrew Jr. Monroe, 2000). The selection of Spearman's coefficient was motivated by its ability to account for and mitigate any nonlinear relationships that could potentially distort the detection of a monotonic relationship between AGB_{pot} and AGB_{rs}. Given the limited sample size of data from 2019 to 2021, directly computing (rs[AGB_{pot} - AGB_{rs}]) may introduce considerable uncertainty. To mitigate this, we applied a 5 × 5 moving window approach across the entire raster, this means that for each pixel, the mean value of its surrounding 25 pixels (including itself) was calculated, effectively smoothing local fluctuations. By moving the window one pixel at a time, we generated a continuous surface of averaged values that captures local spatial patterns more reliably. This approach improves the robustness of the analysis by reducing noise and ensuring more stable correlation estimates (F. Gao & Zhang, 2021).

To assess the fundamental relationship between the biophysical potential and the observed biomass, and to ensure the coherence of these two datasets, we performed a correlation analysis between AGB_{pot} and AGB_{rs} across the study period (2019-2021).

4.4 Results

4.4.1 Data-model comparison

In terms of geospatial distribution, ($rs[AGB_{pot} - AGB_{rs}]$) showed strong consistency (greater than 0) in most areas of Dornod, Sukhbaatar, and Khentii, but showed inconsistency (less than 0) in the central and southeastern areas of Tuv and the southern area of Sukhbaatar (Figure 4.2).

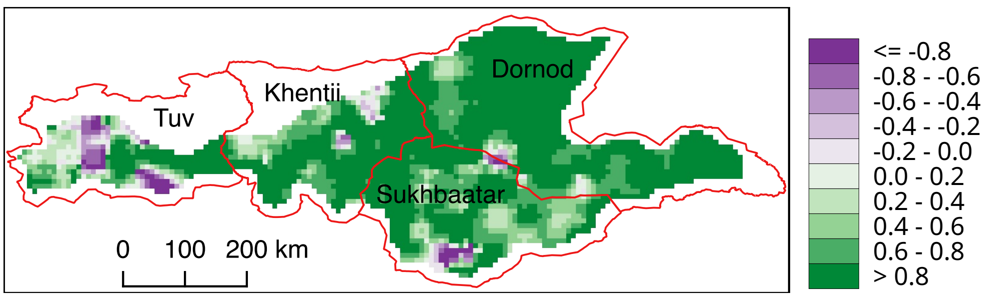

Figure 4.2: Spearmann rank correlation coefficient between AGB_{pot} and AGB_{rs} from 2019 to 2021.

The scatter plot (Figure 4.3) illustrates the relationship between AGB_{pot} and AGB_{rs} in multiple years (2019, 2020, and 2021) showing statistically significant positive associations between the two datasets ($p < 0.001$). The spread of data points around the regression line indicates variability in agreement between remote sensing estimates and model predictions, which may be influenced by differences in vegetation structure, model parameterization (e.g., uncertainty in the climate data i.e., ERA5-Land) and uncertainties in biomass retrieval.

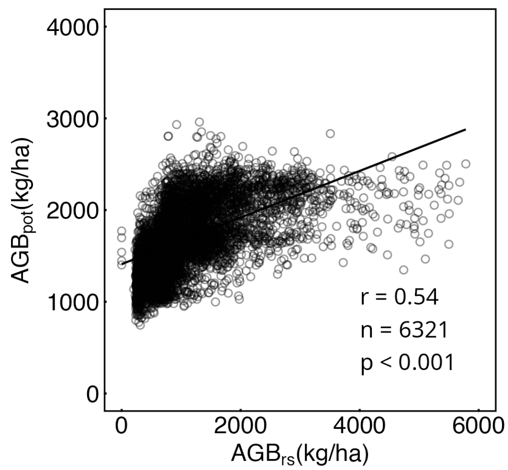

Figure 4.3: Correlation between AGB_{pot} and AGB_{rs} for biomass data of 2019-2021. Each point represents a spatial pixel, with the dots depicting individual biomass estimates and the regression line indicating the linear trend.

4.4.2 Factors influencing grazing intensity

In 2020 and 2021, a significant but weak positive correlation was observed between livestock density and PBR (Figure 4.4), indicating that as the number of livestock density per hectare of grassland increased, the PBR also increased ($p < 0.01$). In 2019, there was no statistically significant relationship between the variables. Human population density showed negative and positive correlation with PBR, but only in 2021 was the positive correlation significant. In 2020, no significant correlation was observed between gazelle density combined across all four provinces and PBR (Figure 4.4).

Across different aimags, livestock density had a consistently significant positive effect on the PBR in Khentii in 2019 and 2020 (the result was marginally significant in 2021, which was also the case for Sukhbaatar). Additionally, in 2019 and 2021, livestock density also exhibited a significant negative effect on the PBR in Tuv province (Figure 4.5). Regarding the impact of human population density across provinces, a significant negative correlation with PBR was observed only in Sukhbaatar in 2020 (Figure 4.6), while no clear positive or negative effects were found in other cases. A significant influence of gazelle density on the PBR was observed in Khentii, Sukhbaatar and Dornod, where an increase in gazelle density corresponded to an increase in PBR. However, no significant effect was found in Tuv (Figure 4.7).

Additionally, livestock density was strongly and significantly correlated with human population density across all years (2019–2021, $p < 0.001$), and negatively correlated with gazelle density in 2020 ($R = –0.28$, $p < 0.001$) (Table 4.1), indicating that areas with higher human and livestock presence tend to have lower wildlife abundance.

Table 4.1: Correlation coefficients among key drivers of PBR

	Human population_density vs. Livestock_density		Gazelle_density vs. Livestock_density
2019	R = 0.47	p <0.001	xxx
2020	R = 0.52	p <0.001	R = -0.28 p <0.001
2021	R = 0.50	p <0.001	xxx

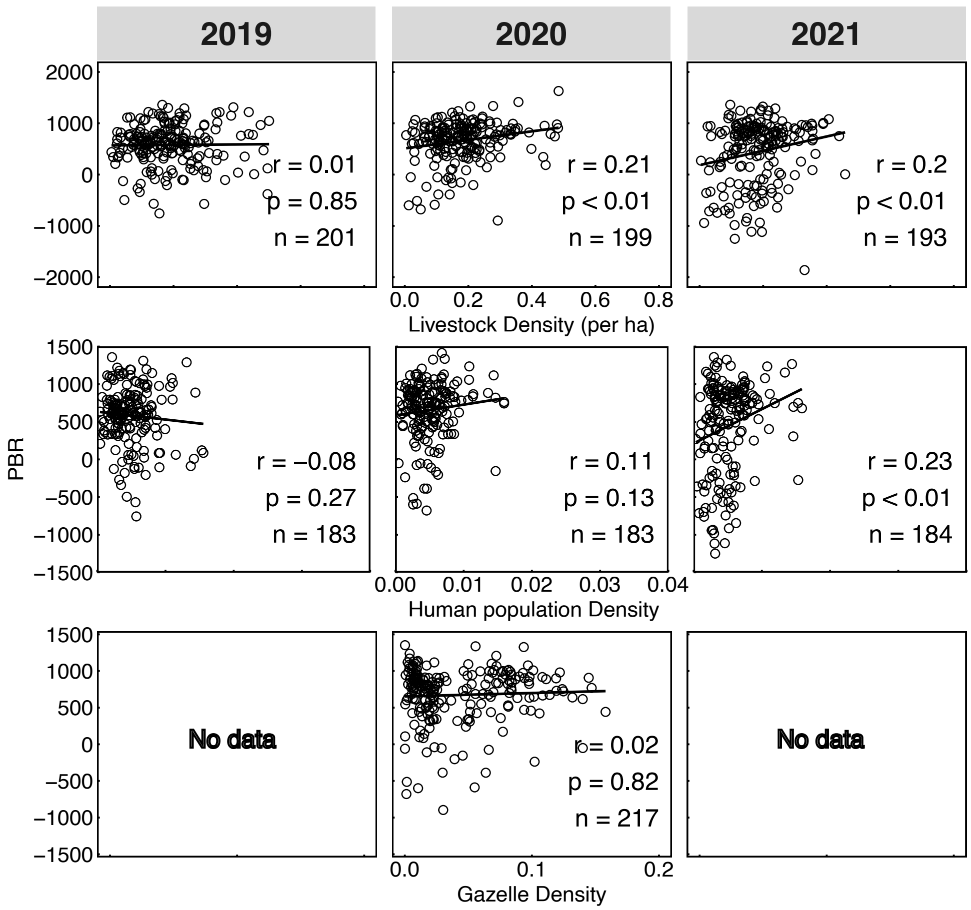

Figure 4.4: Correlation between proxy of biomass reduction with variables for 2019-2021 (with units per ha).

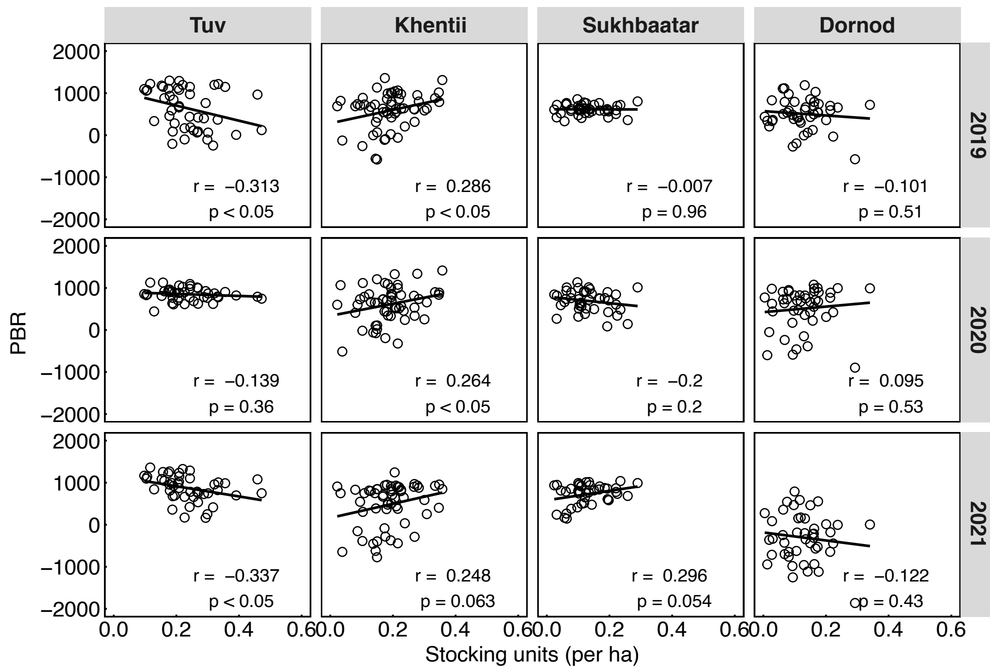

Figure 4.5: Correlation between proxy of biomass reduction and livestock density per aimag for 2019-2021 (ordered geographically from west to east).

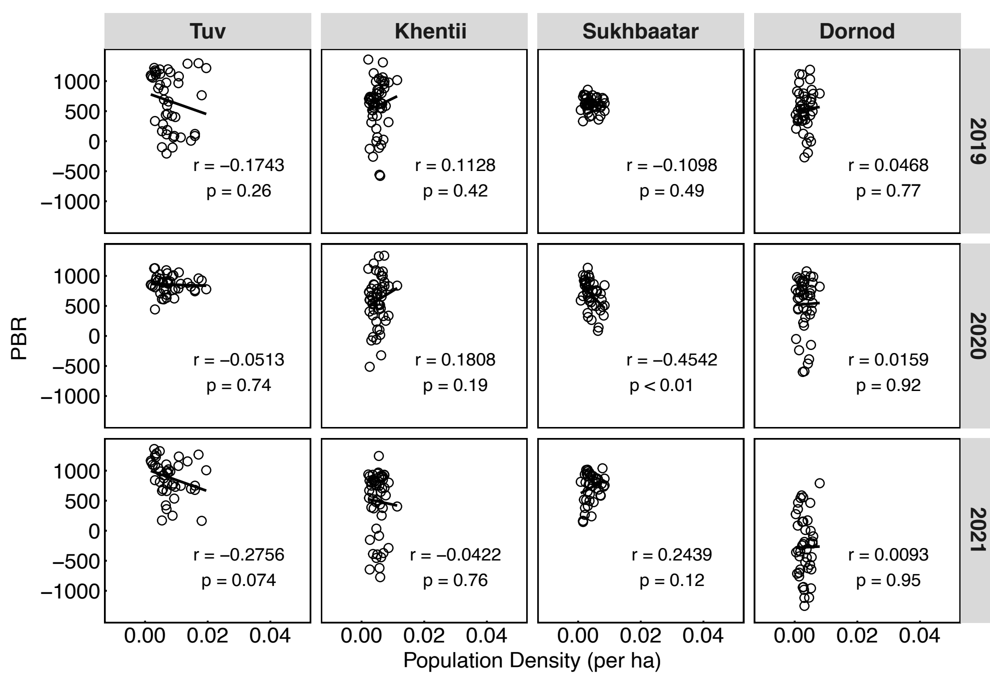

Figure 4.6: Correlation between proxy of biomass reduction and human population density per aimag for 2019-2021.

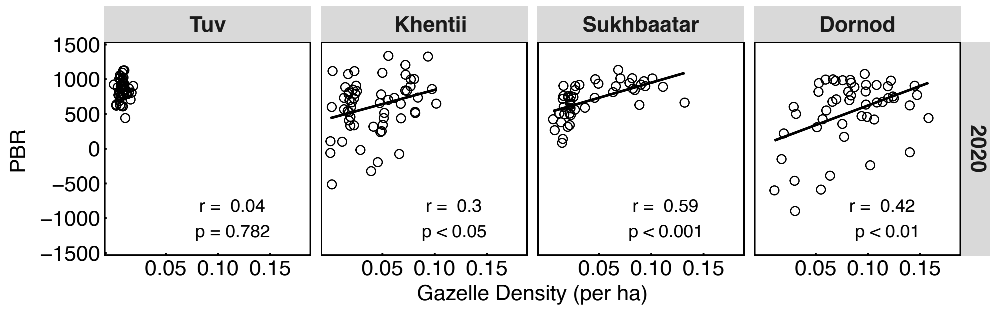

Figure 4.7: Correlation between proxy of biomass reduction and gazelle density per aimag in 2020.

4.5 Discussion

The observed positive correlation between AGB_{pot} and AGB_{rs} across multiple years underscores the overall consistency between these two datasets. However, the variability observed around the regression line suggests that several factors contribute to the discrepancies. Remote sensing retrievals may not fully capture vegetation structural attributes such as canopy height and species composition, which directly affect biomass estimates. On the other hand, model predictions may rely on simplified assumptions about biomass allocation and environmental drivers (e.g., precipitation variability, soil conditions), leading to systematic deviations. For example, in the northeastern part of the study region, the negative differences between RS-derived and modeled biomass in 2021 can be attributed to anomalous climatic conditions (Figure 4.9). Excess precipitation (Figure 4.10) likely enhanced vegetation growth, while anomalously low temperatures, particularly in autumn, winter, and spring (Figure 4.11), reduced evapotranspiration and increased water availability. These favorable conditions were reflected in the RS-derived biomass. However, the LPJ-GUESS simulations, which in this study only represent grass plant functional types, may systematically underestimate biomass accumulation in areas where tree and shrub cover contributes to vegetation productivity, thereby compounding the mismatch driven by the anomalous climate, thereby contributing to the observed difference. For the current analysis, this means that part of the observed mismatch between AGBpot and AGBrs is likely due not only to measurement uncertainty but also to structural limitations in how both approaches represent vegetation dynamics.

The significant relationship between livestock density and PBR highlights the importance of grazing pressure as a driver of grassland vegetation dynamics in Eastern Mongolia (Figure 4.4). While the observed positive correlation is relatively weak, it nevertheless points to measurable interactions between livestock management and biomass patterns. This relationship may partly reflect uncertainties in remote sensing–based biomass estimation or model assumptions, but it also underscores the necessity of accounting for grazing impacts when interpreting vegetation productivity. The significant negative effect of livestock density on PBR observed in Tuv province in 2019 and 2021 may reflect complex interactions between grazing intensity and environmental or management factors and needs to be studied in detail in future (Figure 4.5). For instance, variations in precipitation, land-use policies, or local conservation efforts may contribute to grassland resilience in some regions; while continuous grazing practices by pastoralists may limit the expected relationship between livestock pressure and biomass (B. Nandintsetseg et al., 2021; Oniki et al., 2024; Tsedev, 2021). However, an alternative explanation is also plausible. The observed pattern may reflect legacy effects of past land degradation, whereby heavily degraded areas now support lower livestock densities precisely because they are no longer suitable for grazing. In this case, the large PBR would not be due to increased current grazing pressure, but rather the result of historical degradation that led to long-term declines in vegetation productivity and a subsequent reduction in livestock use (Dashbal et al., 2023; Garchinbyamba & Kang, 2013). These two explanations are not mutually exclusive and highlight the need to consider both contemporary management and historical land-use legacies when interpreting vegetation dynamics in grazed ecosystems. It is also important to consider equilibrium versus non-equilibrium conditions in explaining the effect of livestock on vegetation. Under non-equilibrium conditions, characterized by low rainfall and high inter-annual climate variability, grazer populations cannot reach equilibrium with available biomass, because strong intermediate declines in vegetation prevent grazer populations from growing. Therefore, in such areas, the impact of livestock on vegetation is expected to be limited. In contrast, under equilibrium conditions, where rainfall variability is relatively low ($CV < 0.33$, roughly corresponding to forest steppe regions), grazer populations can reach equilibrium with their environment, and the effects of grazing on vegetation become more apparent.

The relationship between livestock density and vegetation dynamics in Eastern Mongolia should also be contextualized within the theoretical framework of equilibrium versus non-equilibrium rangeland dynamics. Classical equilibrium models posit that biotic interactions, particularly herbivore grazing, regulate vegetation biomass through density-dependent feedbacks, resulting in predictable grazing impacts ((Milchunas et al., 1988; Oesterheld et al., 1992)). Conversely, the non-equilibrium paradigm emphasizes the primacy of stochastic abiotic factors, such as precipitation variability, in driving rangeland dynamics, particularly in arid and semi-arid ecosystems ((Sullivan & Rohde, 2002)). In these environments, frequent droughts and high inter-annual climate variability can suppress livestock populations below the system's carrying capacity, decoupling grazing pressure from vegetation dynamics and rendering abiotic factors the dominant control ((Vetter, 2005)). In Eastern Mongolia, characterized by semi-arid grasslands and significant precipitation variability ((Bat-Oyun et al., 2016; C. Li et al., 2023)), non-equilibrium dynamics may predominate, potentially explaining the weak positive correlation between livestock density and PBR observed in our study (Figure 4.4). However, in regions like Tuv province, where negative effects of livestock density on PBR were noted in 2019 and 2021 (Figure 4.5), localized equilibrium dynamics may emerge due to more stable climatic conditions or intensive grazing management practices. These contrasting patterns suggest that grazing impacts in Eastern Mongolia are shaped by an interplay of contemporary management, and the degree to which local ecosystems align with equilibrium or non-equilibrium dynamics.

Human population density showed a weak positive correlation with PBR only in 2021, suggesting that direct anthropogenic pressures, apart from livestock grazing, may not be the primary driver of differences between AGB_{pot} and AGB_{rs} (Figure 4.4). Areas with higher population density also tend to have higher livestock density, indicating that the influence of population density on PBR may be confounded by grazing pressure. However, it is possible that indirect effects, such as land-use changes, urban expansion, or socio-economic activities linked to population density, could still play a role in shaping ecological differences (Allington et al., 2017; Korytnyi et al., 2023).

Similarly, no significant correlation was found between gazelle density and the PBR in Tuv, indicating that wildlife activities may not be a primary driver of the observed differences in this area (Figure 4.7). One potential explanation for this finding is that the overall impact of gazelle density may be overshadowed by stronger anthropogenic influences, such as livestock grazing and land-use changes, as well as a strong barrier effect caused by the Ulaanbaatar–Beijing Railroad, which may restrict the movement of gazelles and limit their grazing impact on certain areas (Ito et al., 2005, 2013). Additionally, the spatial distribution and high mobility of gazelle populations may lead to localized or transient effects that are not captured at the broader provincial scale. Supporting this view, gazelle density per hectare was lowest in Tuv Province (0.008 individuals/ha) in 2020, while Dornod Province in the far east exhibited a substantially higher density (0.079 individuals/ha), highlighting a marked spatial disparity in wildlife presence across the region (Figure 4.8). This contrast reflects two opposing gradients in grazing intensity: livestock density is higher in the more populated central and western regions, whereas gazelle density increases toward the less populated eastern steppe.

Overall, these findings emphasize the need for region-specific calibration of biomass estimation methods, considering both anthropogenic and ecological factors. Future research should incorporate finer-scale grazing intensity data, species-specific vegetation responses, and improvements in remote sensing algorithms to enhance biomass prediction accuracy. Additionally, integrating field-based biomass measurements with satellite observations could help disentangle the relative contributions of grazing, wildlife activity, and environmental variability to biomass distribution patterns.

4.6 Limitation

Our experimental design hypothesis is that all cases where the data model agreement is less than 0 are attributed to the direct impact of livestock grazing and wildlife activities on vegetation dynamics, but other factors may also play an important role in the changes in vegetation dynamics in some areas of Eastern Mongolia. One factor is the large-scale mining operations that are spread across the landscape. Eastern Mongolia hosts an expansive array of diverse mining operations, whose increasing proliferation is driving substantial environmental transformation, principally evidenced by widespread land degradation and ecological disturbance, dust, and pollution, which can affect soil quality, water availability, and microclimate, all of which can lead to changes in biomass (McIntyre et al., 2016; Park et al., 2020; Pecina et al., 2023a).

Regarding remote sensing data used as measured data, the production of the 10-meter resolution aboveground biomass map of Eastern Mongolia also experienced challenges, especially after the model was validated and the spatial accuracy of the product was verified, due to the "saturation" of vegetation indices generated by optical sensors and the decline in prediction accuracy in the transition zone at the edge of the study area, which to some extent caused a decline in product accuracy (Ji et al., 2024). However, this potential source of error is difficult to avoid.

Deviations between modelled and satellite-derived biomass values can also be caused by unrealistic climate input data for the vegetation model as well as inaccurate parameterization. This is potentially exacerbated by the relatively sparse network of meteorological stations in Mongolia. The consistency and robustness of our results suggest nevertheless that the general conclusions of our study are correct.

4.7 Conclusion

We tested the hypothesis that livestock grazing and gazelle foraging had a measurable impact on vegetation dynamics in Eastern Mongolia from 2019 to 2021. During the study period, livestock density exhibited a significant effect on PBR in 2020 and 2021, especially in western provinces Tuv and Khentii. The contribution of human population changes to variations in PBR is not significant. Gazelle density had no significant effect on PBR across the whole steppe while among the four provinces, a significant positive correlation was observed in Khentii, Sukhbaatar and Dornod, but not in the westernmost province of Tuv. Notable spatial discrepancies in PBR were observed in central and southern Tuv, the southern and northern parts of Sukhbaatar, and the border region between Sukhbaatar and Dornod. Our findings also highlight the need to refine remote sensing algorithms to better capture vegetation structural characteristics and to improve model calibration with respect to biomass allocation and environmental variability, in order to reduce differences between predicted and observed biomass estimates.

4.8 Acknowledgments

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4.9 CrediT authorship contribution statement

Shuxin JI: Writing - Original Draft, Jonas Van Laere: Writing - Review Editing, Thomas Hickler: Supervision and Revision, Bayarbaatar Buuveibaatar and Samantha Strindberg: Investigation, Thomas Müller, Nandintsetseg Dejid: Conceptualization, Investigation and Supervision. Lukas Lehnert: Conceptualization and Methodology and Supervision.

4.10 Declaration of Competing Interest

The authors declare no conflict of interest in this paper.

4.11 Data available

The data that support the findings of this study are available from the corresponding author upon reasonable request.

4.12 Appendix

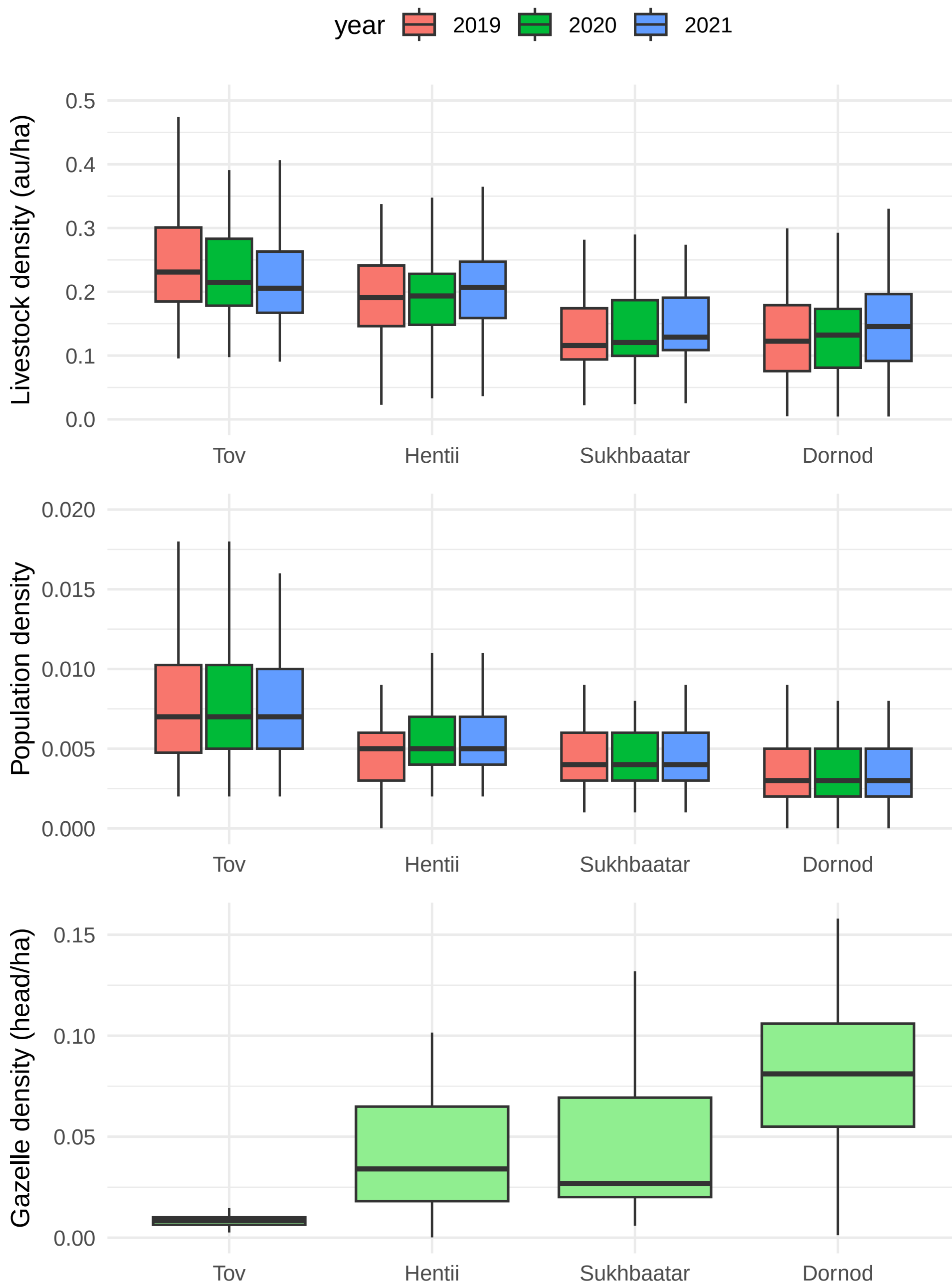

Figure 4.8: Livestock density, human population density and gazelle density in years

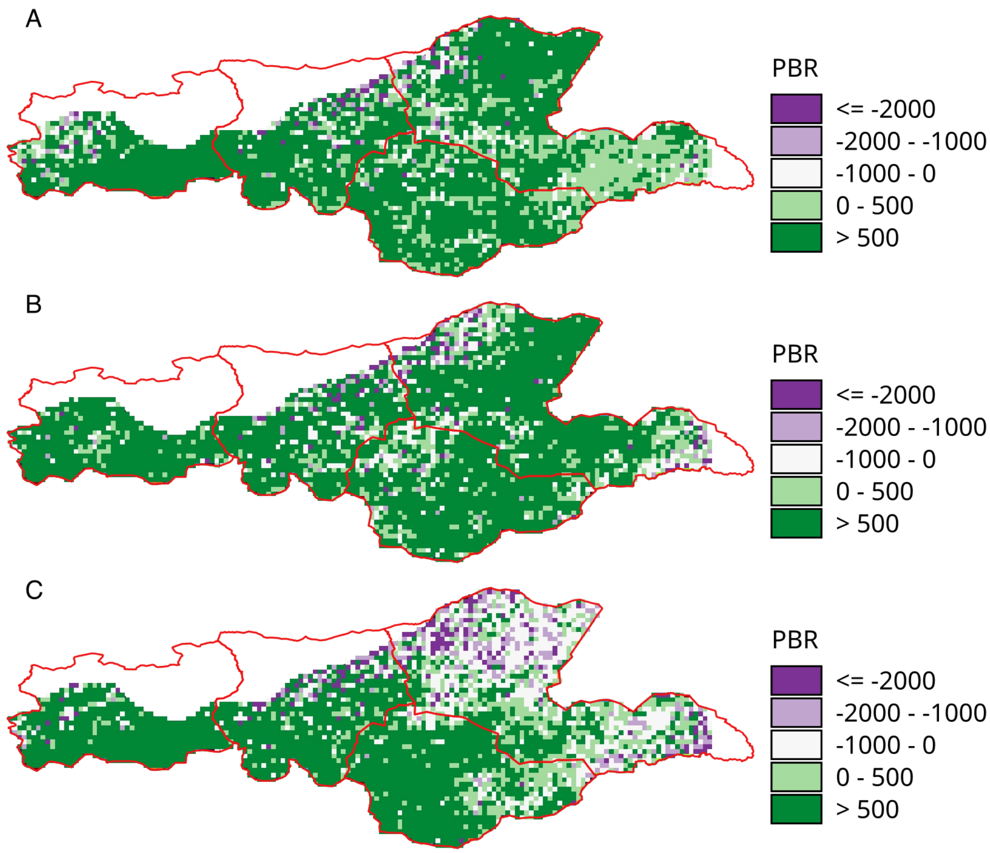

Figure 4.9: Proxy of biomass reduction in years (A: 2019, B:2020, C:2021)

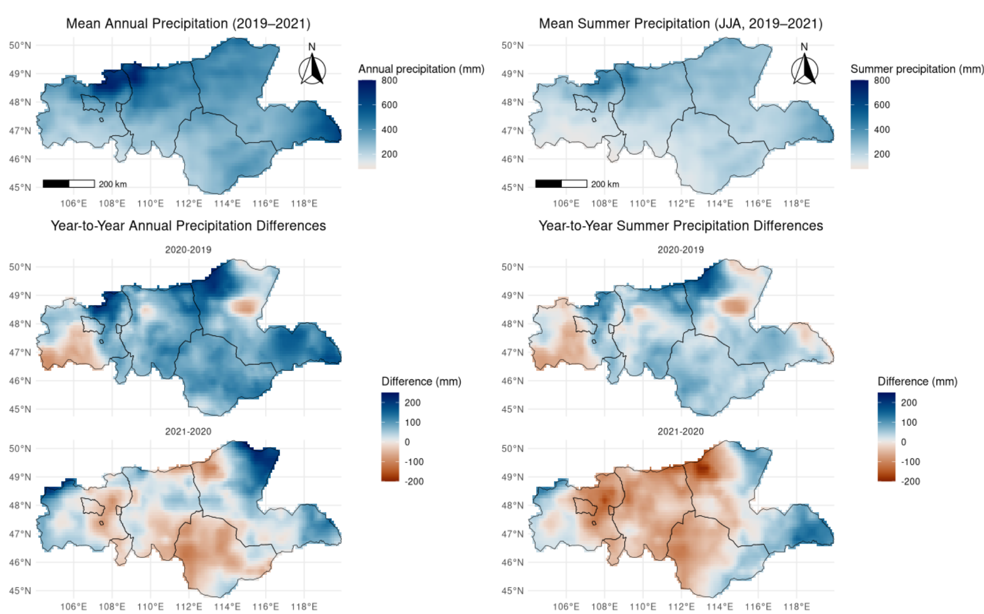

Figure 4.10: Precipitation changes in study area (data source: ERA5-Land).

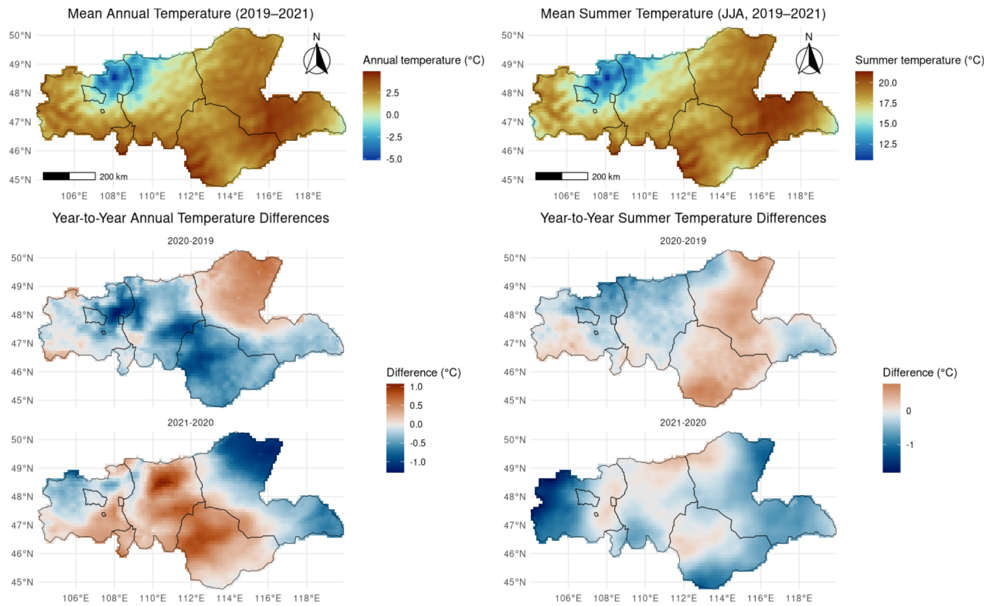

Figure 4.11: Temperature changes in study area (data source: ERA5-Land).

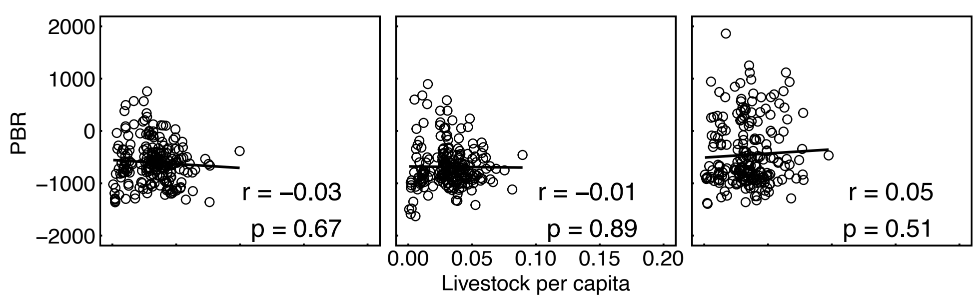

Figure 4.12: Correlation between PBR and human population density per aimag for 2019-2021.

CHAPTER 5

CONCLUSION AND OUTLOOK

5.1 Conclusion and outlook

5.1.1 Conclusion

This thesis thoroughly investigates land degradation dynamics within the vast grassland steppe of Eastern Mongolia, a region crucial for both wildlife and traditional pastoral livelihoods. Given the significant environmental and socioeconomic changes this ecosystem faces, the overarching aim of this work is to advance our understanding of grazing impacts from both human and wildlife populations, and to develop robust remote sensing methodologies for monitoring these impacts.

To lay the groundwork, this research initially focused on addressing a fundamental challenge in grassland ecology: accurately quantifying aboveground biomass (AGB) across large and environmentally diverse regions. This involved developing and validating a reliable, remotely sensed AGB product for central and eastern Mongolia, establishing a crucial baseline for subsequent ecological analyses.

Building on this capacity to estimate AGB, the investigation then delved into the complexity of detecting and attributing vegetation changes to specific drivers. This involved exploring how advanced satellite data, particularly Interferometric Synthetic Aperture Radar (InSAR), can be used to identify subtle vegetation breakpoints, thereby aiming to differentiate changes caused by livestock and herder movements from those resulting from natural climatic events.

Further integrating these insights, the research culminated in quantifying the overall grazing pressure exerted by both livestock and wildlife. This was achieved by devising and testing a novel index of grazing pressure—based on the difference between potential and actual biomass—and analyzing its correlation with various drivers to provide a comprehensive assessment of combined grazing impacts across the steppe.

Collectively, the research presented in this thesis addresses critical methodological gaps in remote sensing applications for grassland monitoring and provides essential ecological insights into the impacts of pastoralism and wildlife on the fragile Mongolian steppe, ultimately informing future sustainable land management strategies.

This conclusion presents the main findings of the thesis, addressing the questions outlined in Section 1.5.1.

Research question 1: Can we combine ground sampling data with remote sensing satellite data to generate a reliable aboveground biomass product covering a large area of the eastern Mongolian grassland?

Chapter 2 introduces a pioneering approach to accurately estimate aboveground biomass (AGB) in the vast and climatically diverse grassland steppe of central and eastern Mongolia. To achieve this, the study leveraged Random Forest (RF) modeling combined with multi-scale and multi-temporal optical (Worldview 2, Sentinel 2, and Landsat 8) and Synthetic Aperture Radar (SAR) (Sentinel 1) remote sensing data. A key contribution was the application of a novel dissimilarity index (DI) to derive the Area of Applicability (AOA) of the predictive model, ensuring the robustness and representativeness of the AGB product. The findings highlighted the superior accuracy achieved by combining Sentinel-1 and

Sentinel-2 data with RF, demonstrating the high potential of this approach for reliable AGB prediction across extremely large ecosystems. Significantly, the model proved applicable to over 72% of the steppe area, confirming its broad utility for large-scale grassland monitoring despite the challenging climatic gradients. This comprehensive assessment provides a crucial and validated baseline for understanding grassland productivity and its ecological dynamics.

Research question 2: How did vegetation breakpoints in the Eastern Mongolian rangeland manifest temporally and spatially between 2019 and 2021, and can InSAR coherence time series data effectively differentiate those caused by herder and livestock mobility from natural events?

Chapter 3 extends the thesis's focus from general biomass assessment to understanding the dynamic interplay between vegetation change and mobility patterns in the Eastern Mongolian rangeland. Recognizing that societal dependence on nomadic livestock farming makes herder movement crucial for pasture sustainability, this study explored the potential of Interferometric Synthetic Aperture Radar (InSAR) coherence time series data, in combination with optical imagery and weather information, as a tool for spatio-temporal grazing monitoring. A novel Random Forest (RF)-based method was developed to detect subtle breakpoints in vegetation condition, specifically designed to differentiate changes caused by livestock and herder movements from those attributable to natural events like snow and rainfall. The results demonstrated that the Random Forest method performed superior to the widely-used BFAST algorithm, indicating its ability to separate grazing-induced changes from natural phenomena. For instance, the RF model successfully detected 44% of summer camp movements compared to BFAST's 28%, though detecting winter movements proved particularly challenging. Breakpoints primarily occurred from April to June on summer pastures and during October, November, and the following February and March on winter pastures, aligning with seasonal herder movements. Spatially, the model predicted homogeneous summer and winter pasture patterns that generally agreed with known movement patterns in higher productivity areas (e.g., summer pastures along rivers, winter pastures in mountains). However, in drier and less intensively used regions, the agreement was less pronounced, suggesting insufficient evidence to definitively attribute all pasture breakpoints solely to herder movements, especially in the eastern and southern parts of the steppe ecosystem. This chapter thus presents a robust methodological framework for discerning the ecological imprints of mobile pastoralism, while also highlighting the complexities of attributing all vegetation changes in such dynamic environments.

Research question 3: How do livestock grazing and wildlife foraging influence vegetation dynamics in the eastern Mongolian Steppe?

Chapter 4 builds directly on the foundational biomass assessments and vegetation change detection by quantifying the comprehensive impact of grazing pressure from both livestock and wildlife in Eastern Mongolia. This study hypothesized that the combined grazing activities of livestock and wildlife (predominantly Mongolian gazelle) had a detectable impact on vegetation dynamics from 2019 to 2021. To investigate this, an innovative index of grazing pressure was devised by calculating the "biomass difference": subtracting the remotely sensed actual aboveground biomass (AGBrs) from the potential biomass predicted by the process-based ecosystem model LPJ-GUESS (AGBpot). This biomass difference was then rigorously analyzed in relation to livestock density, human population density, and gazelle density. The results revealed a significant positive correlation between livestock density and biomass difference in both 2020 and 2021, a trend particularly pronounced in the western study areas. Human population density also showed a significant positive correlation with biomass difference, though only observed in 2021. While no overall significant correlation was found between gazelle density and biomass difference, important regional insights emerged, with a significant positive correlation observed in Khentii, Sukhbaatar, and Dornod provinces, but not in Tuv. These findings robustly support the utility of biomass difference as a reliable indicator of combined grazing pressure from both livestock and wildlife within Eastern Mongolia's grasslands, offering a crucial tool for understanding and managing these complex human-wildlife-ecosystem interactions.

This thesis significantly advances the understanding and quantification of land degradation in the Eastern Mongolian steppe, with a primary focus on the nuanced impacts of grazing. It establishes a critical foundation by developing and validating a highly accurate, remotely sensed Aboveground Biomass (AGB) product, a crucial variable for monitoring grassland health across vast, climatically diverse regions. Furthermore, this research innovatively harnessed InSAR coherence time series data to detect and discern vegetation breakpoints, successfully differentiating changes induced by livestock and herder mobility from those resulting from natural climatic fluctuations. By integrating these advanced remote sensing techniques, the thesis provides a refined methodology for assessing vegetation dynamics under complex pastoral systems. Crucially, it then introduces and validates a novel "biomass difference" index to robustly quantify the combined grazing pressure from both livestock and wildlife, elucidating their spatially explicit impacts across the steppe. This comprehensive methodological suite offers a powerful toolkit for future integrations of multi-source satellite imagery in vegetation cover studies, contributing directly to the effective use of Mongolian pasture photo-monitoring data for producing reliable vegetation cover maps from regional to country-wide scales.

Overall, this thesis presents a pioneering approach to understanding grassland degradation by providing validated remote sensing products and ecological insights critical for sustainable land management in Mongolia. It contributes to a more granular understanding of how both natural processes and anthropogenic drivers, particularly grazing by livestock and wildlife, shape the fragile Eastern Mongolian steppe ecosystem. This knowledge is paramount for maintaining and developing sustainable land-use practices, directly impacting the welfare of a significant portion of the Mongolian population reliant on livestock productivity. The tools and methodologies developed in this thesis are highly scalable, utilizing readily available geospatial data for all of Mongolia, thereby offering the potential to extend land degradation mapping to other regions or the entire country. These advancements are especially timely given ongoing societal shifts in Mongolia, such as population concentration and reduced herder mobility, which are likely to exacerbate localized degradation in the future. With the robust products and insights generated, this thesis provides a vital framework for projecting future grassland status and informing adaptive management strategies in the face of evolving societal and climatic changes.

5.1.2 Outlook

This thesis synthesizes three interconnected research papers, each contributing to a deeper understanding of the vast and vital Mongolian Steppe Ecosystem. Paper 1 established a reliable, remotely sensed Aboveground Biomass (AGB) product for central and eastern Mongolia, leveraging the synergy of Sentinel-1 (SAR) and Sentinel-2 (optical) data with Random Forest (RF) and a novel Area of Applicability (AOA) assessment. Building on this, Paper 2 explored the intricate relationship between herder and livestock mobility and vegetation dynamics, developing a superior RF-based method to detect vegetation breakpoints that account for grazing influences, thus refining spatio-temporal grazing monitoring. Finally, Paper 3 devised a "biomass difference" index to quantify the combined impacts of livestock and wildlife grazing pressure on vegetation, identifying significant correlations with livestock density in specific regions.

The individual contributions of this thesis lay robust groundwork for future integrated analyses. A primary avenue for advancement lies in harmonizing the methodologies and insights gained across the three papers.

Enhanced AGB and Mobility Linkage: Paper 1 provides the foundational AGB estimates, while Paper 2 investigates mobility. Future research could explicitly link the detected mobility patterns (from Paper 2) with the observed AGB changes (from Paper 1's product) at finer spatio-temporal scales. This would allow for a more direct quantification of how specific movement events and grazing intensities impact AGB recovery and decline.

Refining Grazing Pressure Indicators: Paper 3 introduced the "biomass difference" index as a proxy for grazing pressure. Combining this with the refined mobility detection from Paper 2 could lead to a dynamic grazing pressure model. Such a model would not only indicate where pressure exists but also when and by whom (livestock/wildlife) it might have occurred, offering a more nuanced understanding of ecosystem response.

Unpacking Environmental and Anthropogenic Drivers: While Paper 2's RF method showed promise in separating weather-induced changes from grazing, further work could focus on disentangling the complex environmental and anthropogenic factors influencing AGB dynamics and breakpoint occurrences. This might involve integrating more detailed climate variables, soil moisture data, and land-use information into predictive models.

The methodology and results of this thesis demonstrate several promising new research directions with great potential for application:

Predictive Modeling of Pasture Resilience: By combining the AGB product, mobility data, and grazing pressure indicators, it's possible to develop predictive models of grassland resilience to varying grazing loads and climatic events.

Integrating Socio-Economic factors: Herder movement patterns (Paper 2) are driven by a complex interplay of forage availability, water access, market forces, and traditional knowledge. Future research should integrate socio-economic data (e.g., household demographics, market prices, policy changes) with the remote sensing-derived ecological insights to build more comprehensive socio-ecological models of pastoral systems.

Wildlife-Livestock Coexistence and Management: Paper 3's findings on gazelle impacts, though less conclusive overall, highlight regional variations. Further studies could employ advanced spatial statistics or species distribution models to better understand competitive or facilitative interactions between wildlife and livestock, supporting integrated conservation and management strategies.

Beyond AGB: AGB is a key indicator, but grassland health encompasses more. Expanding the suite of remote sensing products to include metrics for plant functional types, carbon fluxes, or water use efficiency could provide a more holistic view of ecosystem functioning under grazing pressure.

The availability of fine-grained ground-truth data for model validation, the inherent complexity of unraveling the intertwined drivers of natural systems, and the computational demands of dealing with multi-source, large-area remotely sensed time series will all present significant challenges. Within the challenges lie great opportunities. The acceleration of remote sensing data acquisition (e.g., upcoming missions with higher temporal/spatial resolution, the emergence of new types of sensors), advances in machine learning algorithms (e.g., deep learning for time-series analysis), and increased computational power provide powerful tools to overcome current limitations. In addition, enhanced communication and cooperation between disciplines is essential, and interdisciplinary cooperation between remote sensing scientists, ecologists, social scientists and local communities plays an important role in the development of programs that are truly applicable to the sustainable development of local environments.

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