

Dissertation

Submitted to the
Combined Faculties of Mathematics, Engineering and Natural
Sciences
Heidelberg University, Germany
for the degree of
Doctor of Natural Sciences (Dr. rer. nat.)

Presented by
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From: Ulaanbaatar, Mongolia
Oral examination: June 26th, 2025

INAUGURAL-DISSERTATION

zur

Erlangung der Doktorwürde

der

Naturwissenschaftlich-Mathematischen Gesamtfakultät

der

Ruprecht-Karls-Universität, Heidelberg

Vorgelegt von

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aus: Ulaanbaatar, Mongolei

Tag der mündlichen Prüfung: Juni 26, 2025

Hydrological responses to climate change and wildfire disturbance in northern Mongolia

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Zusammenfassung

Zusammenfassung Der Norden der Mongolei bildet als Übergang zu den ariden Steppen Zentralasiens den südlichen Rand des borealen Waldes Sibiriens. Diese semiaride Region ist besonders anfällig für den Klimawandel, Intensivierung der Landnutzung und Umweltdegradation. Die borealen Wälder der nördlichen Mongolei sind aufgrund von Abholzung und Waldbränden stark bedroht, wurden durch Abholzung und Waldbrände stark dezimiert: Von den insgesamt rund 14,2 Mio. ha sind bereits etwa 13% von Waldbränden betroffen.

Das nördlich von Ulaanbaatar gelegene Sugnugur-Tal, befindet sich in einem Übergangsgürtel zwischen Steppe, borealem Wald und der alpinen Tundra des Khentii-Gebirges. Dieses erstreckt sich von Sibirien bis in die Mongolei und erreicht Höhen von bis zu etwa 2 800 m ü. NN. Die westlichen Hänge des Gebirges entwässern in das entwässern in das Selenge–Baikal System und sind daher eine wichtige regionale Süßwasserquelle.

Das Klima ist stark kontinental-semiarid. Zwischen 1980 und 2022 betrug der mittlere Jahresniederschlag weniger als 330 mm; im Zeitraum 1980–2001 lag er bei rund 350 mm, von 2001 bis 2022 sank er auf etwa 300 mm. Nahezu 90 % des Niederschlags fallen im Sommer (Mai bis Oktober). Über den gesamten Zeitraum (1980–2022) lag die durchschnittliche Jahrestemperatur bei etwa $-2,7^{\circ}\text{C}$ und zeigte einen Aufwärtstrend von ca. $0,04^{\circ}\text{C}$ pro Jahr. Im Winter (Oktober–März) betrug die mittlere Temperatur etwa -14°C mit einer ähnlichen Steigerung von rund $0,06^{\circ}\text{C}$ pro Jahr. Diese klimatischen Veränderungen – insbesondere reduzierte Niederschläge und höhere Temperaturen im zeitigen Frühjahr – können das Verhalten von Waldbränden erheblich beeinflussen.

Im Sugnugur-Tal laufen zahlreiche hydro-ökologische Prozesse ab, die für die mongolischen Wasserhaushalte typisch sind, darunter Schneespeicherung, Permafrost und Waldbedeckung. Obwohl Teile des Gebiets nahezu unberührte boreale und alpine Ökosysteme aufweisen, haben menschliche Einflüsse, allen voran Waldbrände, zugenommen. Seit 2000 behindern wiederkehrende Brände die natürliche Regeneration und zerstören Samenbanken. Über Veränderungen der Landbedeckung hinaus beeinflussen diese Feuer auch die lokalen hydrologischen Dynamiken. Ein zentrales Ziel dieser Arbeit war daher, die zeitliche Entwicklung Von Gebirgswäldern im Einzugsgebiet unter verschiedenen Brandregimen zu untersuchen.

Erste Ergebnisse aus Monitoring-Transekten im Sugnugur-Tal zeigten, dass Waldbrände die Quellgebietsfunktion deutlich beeinträchtigen und somit die Wasserverfügbarkeit in den ariden Steppenausläufern des Khentii-Gebirges verringern. Wiederholte Brände verzögern die Walderholung und begünstigen schnellwüchsige Arten, was die Biodiversität mindert. Der Verlust der organischen Bodenoberfläche erhöht die Sonnenstrahlungsaufnahme im Boden und führt zu höheren Bodentemperaturen.

Diese abgelegenen Wälder sind für die lokalen Gemeinden unverzichtbar, die auf Holz zum Heizen und Kochen, auf Pinienkerne als Einkommensquelle und auf bewaldete Flächen als Weidegebiete angewiesen sind. Dennoch ist das Ausmaß menschlicher Einflüsse, insbesondere durch Feuer, bislang schlecht dokumentiert, was die Entwicklung wirksamer Schutzmaßnahmen erschwert.

Durch die Kombination von Feldbeobachtungen mit dem hydrologischen TRAIN-Modell (TRANspiration and INterception) zielt diese Arbeit darauf ab, die regionale Datenverfügbarkeit zu erhöhen und zu analysieren, wie Waldbrände über ihre Auswirkungen auf die Wälder lokale Wasserhaushalte prägen. Die Ergebnisse schließen eine wichtige

Wissenslücke für die nördliche Mongolei, wo bislang wenig über die hydrologischen Folgen von Waldbränden bekannt ist.

Abstract

Northern Mongolia marks the southern edge of Siberia's boreal forest, where it transitions into the arid Central Asian steppes. This semi-arid region is highly susceptible to climate change, land-use intensification, and environmental degradation. Mongolia's boreal forests, primarily found in the north, have been severely diminished by logging and wildfires: Of the ~14.2 million ha, ~13% has been affected by fires.

Sugnugur Valley, situated north of Ulaanbaatar, lies within a transitional belt of steppe, boreal forest, and the alpine tundra of the Khentii Mountains. This mountain range extends from Siberia into Mongolia, reaching elevations of ~2800 m a.s.l. Its western slopes feed into the Selenge–Baikal drainage system, making it an important regional freshwater source.

The area has an intensely continental semi-arid climate. Between 1980 and 2022, the average annual precipitation was <330 mm. However, this increased to 350 mm during 1980–2001 and declined to 300 mm during 2001–2022. Nearly 90% of rainfall occurs during summer (May to October). Over 1980–2022, the annual mean air temperature was roughly -2.7°C , with an upward trend of $\sim 0.04^{\circ}\text{C}/\text{year}$. In winter (October–March), the mean temperature reached around -14°C , showing a comparable increase of $\sim 0.06^{\circ}\text{C}/\text{year}$. These changes in climate, including decreased precipitation and increased temperature in early spring, can greatly affect wildfire behavior.

Sugnugur Valley supports numerous crucial hydro-environmental processes characteristic of Mongolia's hydrological regimes, such as snow storage, permafrost, and forest cover. Although parts of the area exhibit near-pristine boreal and alpine ecosystems, human impacts, particularly wildfires, have increased. Since 2000, recurrent wildfires have hindered natural regeneration and destroyed seed banks. Beyond altering land cover, these fires also affect local hydrological dynamics. One key objective of this study was to explore the temporal evolution of watershed forests under various wildfire regimes.

Initial findings from monitoring transects across Sugnugur Valley showed that forest fires strongly determined headwater function, in turn diminishing water availability in the arid steppe lowlands of the Khentii Mountains. Repeated wildfires retarded forest recovery and promoted the dominance of fast-growing species, thereby decreasing biodiversity. The loss of the organic surface layer increased the soil absorption of solar radiation, increasing soil temperatures.

These remote forests are crucial for local communities that depend on wood for heating and cooking, pine nuts for income, and forested areas for grazing. Nevertheless, the degree of human influence, especially wildfires, remains poorly documented, limiting the development of effective conservation measures.

By combining field observations with the TRANspiration and INterception (TRAIN) hydrological model, this thesis aimed to increase regional data availability and analyze how wildfires shape local water regimes through their effects on forests. The outcomes of this study fill an important knowledge gap in northern Mongolia, where little is known of the hydrological impacts of wildfires.

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Chapter 1

1 Introduction

1.1 Background

The global occurrence of large forest fires has increased annually largely due to warming temperatures, altered rainfall patterns, and the resulting changes in ecosystem functions. Wildfires were a major environmental challenge in the 20th century, causing the loss of ~126 million km² of global forests, especially in boreal regions (Hansen et al., 2013; Li et al., 2020). In the first two decades of the 21st century, ~1.2 million km² of forest cover was lost (Figure 1.1). Past data, current trends, and model simulations have predicted extended periods of warmer and drier conditions, which are likely to lower biofuel moisture levels and prolong fire seasons, thereby increasing wildfire frequency and distribution compared to those in the 20th century (Halofsky et al., 2020). As the climate warms, the most important drivers of forest loss and ecosystem shifts appear to be the combined effects of fires and drought, human-induced ignitions, and timber extraction. Hotter drier weather also increases the likelihood of recurring fires (reburns), which can affect new growth and species composition. The hottest and driest areas may be especially vulnerable to regeneration failure. Over the past two decades, wildfires have become both more common and extreme, and forecasts suggest that the incidence of severe fires could rise by up to 14% by 2030, 30% by the mid-century, and 50% by its end (Li et al., 2021). By then, northern high-latitude regions are expected to experience more severe and longer fire seasons (Flannigan et al., 2013). In Canada, for example, 80% of wildfires are caused by lightning (Amiro et al., 2000; Tymstra et al., 2020), whereas 80–95% of wildfires in northern Mongolia are caused by humans (Goldammer, 2007). The wildfire regime in Mongolia is consistent with the global trend: Forest fires have grown more frequent and intense since the 1990s, coinciding with major shifts in both environmental and economic policies during a politically turbulent period. These changes opened forested areas to more human activity and relaxed regulations in certain markets (Goldammer, 2007). Because fires and anthropogenic disturbance affect different environmental factors in various ways, detailed data collection and analysis are vital for characterizing environmental changes, particularly in remote poorly documented mountainous forests.

1.2 Forest hydrology and wildfires

Forest ecosystems greatly affect the water balance structure and moisture redistribution between evapotranspiration (ET) and runoff (Sun & Vose, 2016). Forest vegetation controls ET and, thereby, impacts soil hydrology. The complex dynamic relationship between forest hydrology and wildfires strongly determines the health and function of forest ecosystems. Although wildfires naturally occur in many forested regions, the amplification of their frequency and intensity by climate change and human activities can disrupt essential hydrological processes such as interception, ET, infiltration, and runoff, with both immediate and long-term consequences. Importantly, however, the scale and nature of these disruptions

differ across ecosystems. Bowd et al. (2018) noted that the hydrological impacts of wildfires are not uniform but vary widely depending on vegetation type, soil composition, topography, and climate. Understanding how forests respond to these disturbances, particularly the hydrological effects in mountainous headwater areas, is essential for developing appropriate fire rehabilitation and long-term management policies (Jones et al., 2022).

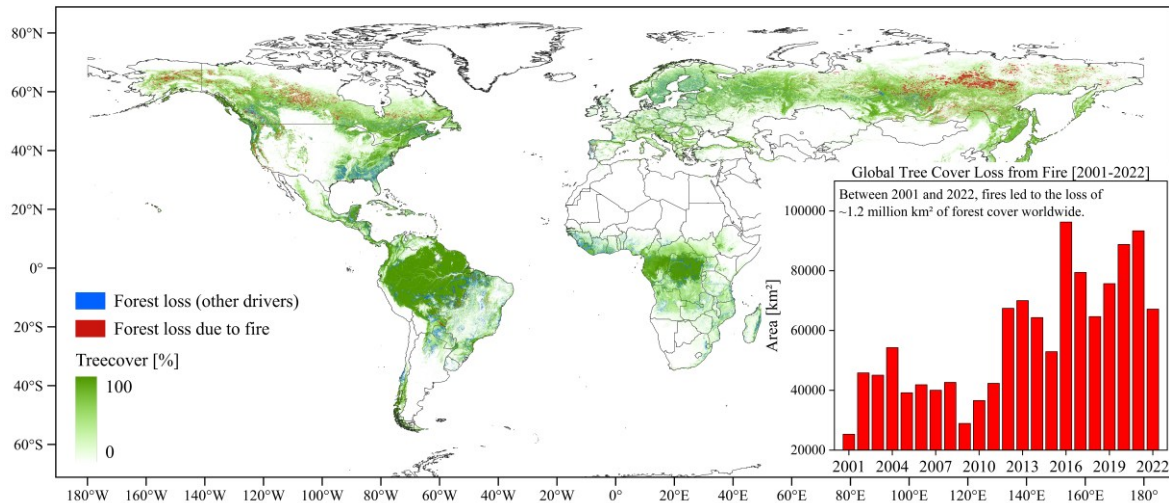


Figure 1.1: Global forest cover in 2000 and accumulated changes during 2000–2022. Red and blue indicate forest loss caused by fire and other factors, respectively. The percentage tree cover represents forest density. The bottom right graph displays the annual global tree cover loss caused by fires from 2001 to 2022. Data source: Hansen et al. (2013).

Vegetation plays a crucial role in rainfall interception: trees and plants capture rainfall on their leaves, branches, and stems, thereby reducing the amount of water reaching the soil surface. The removal of vegetation through wildfires inhibits interception and promotes surface runoff, soil erosion, and flash flooding, especially during intense rainstorms (Kopp, 2016; Kopp et al., 2017; Munkhjargal, 2020). The loss of canopy cover also accelerates soil drying by promoting solar irradiation of the forest floor, inhibiting post-fire recovery, particularly in regions prone to heavy storms. In boreal and temperate forests, the removal of the canopy can greatly alter rainfall partitioning, accelerating water transfer to the soil surface and disrupting the hydrological balance (Kharuk et al., 2021). The adverse effects are even more pronounced in certain ecosystems such as the Siberian taiga, where frequent fires greatly accelerate vegetation loss, increase surface runoff, and alter soil moisture (SM) dynamics. Vegetation is vital for protecting the permafrost zones of northern Mongolia and Siberia (Kharuk et al., 2021). Frequent severe wildfires cause rapid permafrost thawing, reducing soil water retention capacity and exacerbating runoff-related issues. Permafrost degradation may have profound implications for regional hydrology (Han, 2021). Wildfires drastically reduce ET by removing vegetation, which, coupled with increased evaporation from exposed soils, disrupts local hydrological cycles and the regional water balance structure (Ibáñez, 2022). ET can drop by up to 50% immediately after a wildfire, particularly in water-scarce semi-arid and arid ecosystems (Bowd et al., 2018). Lower ET can lead to higher surface temperatures, accelerating soil drying and increasing erosion risk. Owing to the important role of forests in regulating atmospheric moisture, the destruction of large areas can contribute to drier regional conditions, generating a positive feedback loop that exacerbates drought and fire occurrence (Kharuk et al., 2021; Rego et al., 2021). In the semi-arid regions of Mongolia and Siberia, the

reduction in ET following wildfires has been linked to changes in SM levels, directly impacting plant regeneration and overall ecosystem recovery. Han (2021) observed that prolonged droughts and higher post-fire temperatures have retarded vegetation recovery in these areas, prolonging the reductions in ET and further destabilizing the hydrological cycle. Wildfires may increase soil hydrophobicity (water repellency), which greatly reduces water infiltration and increases surface runoff. High-intensity fires can vaporize organic soil compounds that then condense on cooler soil particles to form a water-repellent layer that prevents infiltration. This is especially problematic in areas with steep slopes and thin soils, where poor infiltration can lead to severe erosion and sediment loss during rainstorms (Kharuk et al., 2021). Indeed, Kopp et al. (2017) found that vegetation loss combined with soil hydrophobicity exacerbates erosion risk in regions such as the Siberian taiga and Mongolia's mountainous areas, leading to long-term changes in hydrological patterns.

In fire-prone ecosystems, hydrophobic soil layers can persist for years, depending on fire severity and vegetation type (Rego et al., 2021), delaying ecosystem recovery and increasing the risk of flash floods and landslides (Munkhjargal, 2020). This lasting effect disrupts the natural geohydrological cycle by promoting surface runoff and erosion, reducing water availability for new plant growth, and leading to long-term landscape degradation and river/lake sedimentation (Bowd et al., 2018). In Mongolia's Khentii Mountains, increased wildfire frequency has been associated with hydrophobic soils and increased river/stream sedimentation (Kopp et al., 2017). Similarly, in Siberia, fires in larch and pine forests have altered the soil structure and increased runoff, affecting long-term water quality and ecosystem health (Kharuk et al., 2021). The burning of vegetation and organic matter also disrupts the soil nutrient balance and releases nutrients such as nitrogen and phosphorus, which may be removed by runoff and transported into waterways, depleting soil nutrients and causing eutrophication. Sedimentation and eutrophication can reduce water quality, affecting aquatic life and water supplies. Munkhjargal (2020) indicated that sediment loading can alter the physical structure of the river/stream, leading to long-term changes in flow patterns and increased flood risks. Since hydrophobic soils and increased surface runoff reduce ground infiltration, groundwater recharge is inhibited after wildfires (Kopp et al., 2017). In the permafrost regions of Siberia, wildfires further complicate groundwater recharge by accelerating permafrost thaw, reducing the soil's water-holding capacity, limiting groundwater recharge, and promoting surface water loss (Han, 2021). Reduced groundwater recharge affects surface water systems by reducing the baseflow of rivers and streams, especially during dry seasons and droughts, thereby altering the physical characteristics of the riparian system and reducing habitat availability (Bowd et al., 2018). In Siberia, the combined effects of permafrost degradation and wildfires have led to notable changes in both surface and subsurface water dynamics (Kharuk et al., 2021).

The long-term effects of wildfires on forest hydrology are closely linked to the rate of vegetation recovery. In boreal forests with relatively quick regrowth, the hydrological impacts may be short-lived, with canopy cover and ET levels returning to normal within a few decades (Ibáñez, 2022). However, in semi-arid Mongolia, where recovery is slower and fires are more frequent, the impacts can persist much longer (Munkhjargal, 2020). With repeated wildfires, the cumulative effects of vegetation loss, soil degradation, and altered hydrological cycles can cause long-term ecological damage (Figure 1.2), particularly in areas with fragile soils and limited water resources, which are sensitive to the positive feedbacks between soil degradation, runoff, and erosion.

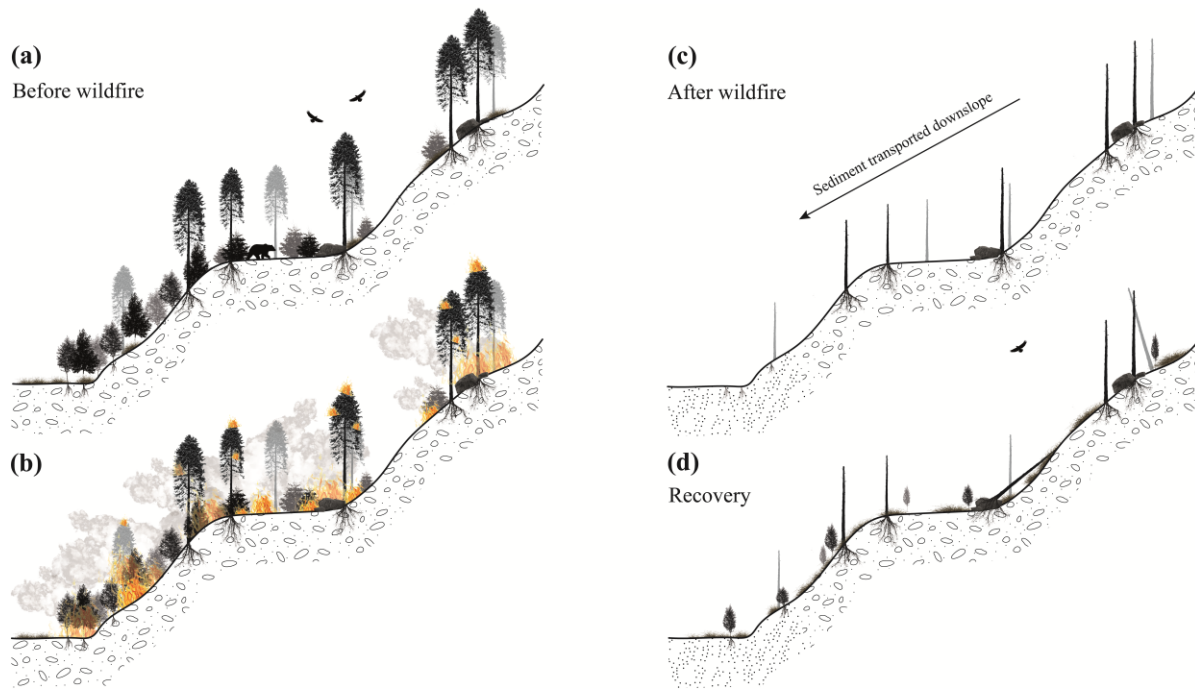


Figure 1.2: Scheme of forest structure under different events. (a) Before wildfire, (b) disturbance such as wildfire, (c) after wildfire, and (d) regeneration.

1.3 Aim and objectives

This study aimed to improve data availability on wildfires in an underreported region and elucidate the changes in ecohydrological processes in the heterogeneous headwater areas on the western slope of the Khentii Mountains, northern Mongolia.

We addressed the following objectives:

- (1) Identify ecosystem changes in this data-scarce region**
 - a.** Examine forest structural parameters under different conditions in steppe, unburned, partly burned, and burned forests.
 - b.** Analyze historical changes in forests under climate change, focusing on wildfire impacts and behavior.
- (2) Identify the long-term changes in the water balance of Mongolian taiga forests**
 - a.** Explore historical hydrological dynamics by simulating the water balance using the TRAnspiration and INterception (TRAIN) model.
 - b.** Extend the applicability of the TRAIN model by incorporating historical wildfire events to examine the impacts of both single and repeated wildfires on the water balance.

Chapter 2

2 Methodology

2.1 Historical context to study region

The boreal forests of northern Mongolia are vital for maintaining regional ecosystem functions and water supply. The Khentii Mountains serve as a transitional zone between the forestland and dry steppes. The Siberian boreal forests in this region, forming the southern border of the Siberian taiga (Ishikawa et al., 2018), are particularly sensitive to climate warming (Mühlenberg et al., 2012; Kopp et al., 2014). The Khentii Mountains have historically played important roles in glaciation, featuring various glacial landforms such as moraines, hills, and glacial lakes (Orkhonselenge et al., 2022). In northern Mongolia, a significant warming trend has been documented over the past 47 years, accompanied by a decrease in summer precipitation (Dulamsuren et al., 2010). Consequently, the frequency of regional droughts has increased in recent years (Natsagdorj, 2014). The associated alterations in water regimes and increasing temperatures have also promoted regional forest fire occurrence (Natsagdorj, 2014; Tyukavina et al., 2022).

Forest cover loss, a major adverse effect of climate warming, may accelerate permafrost degradation (Miner et al., 2022). The forest cover in the transition zone between the boreal and dry mid-latitude climates of the Northern Hemisphere plays a crucial role in determining the distribution of permafrost, in turn directly and indirectly influencing the surface energy balance (Dulamsuren et al., 2010). Vegetation cover protects soil from overheating and permafrost from melting during the summer (Sharkhuu & Anarmaa, 2012). The boreal forests of the Khentii Mountains promote the persistence of permafrost by blocking incoming shortwave radiation (Dashtseren et al., 2014; Ishikawa et al., 2018). Since the 1960s, droughts have decreased the forested area of northern Mongolia by 26% and the biomass of pastures by 20–30% (Batjargal and Enkhjargal, 2013). Mongolian forests are also negatively affected by anthropogenic disturbances (both direct and indirect), including large-scale illegal logging (which promotes forest fragmentation), fire regime changes due to fire suppression, and overgrazing (Hansen et al., 2020). As indicated by the Food and Agriculture Organization (Gradel et al., 2019), the area of harvested forestland significantly exceeds the reforested area, decreasing the total annual forest area and reducing ecosystem resilience to severe disturbances (Xu et al., 2020).

By the end of the century, the severity and duration of the fire season are expected to increase worldwide, most notably in the northern high latitudes (Flannigan et al., 2013). Indeed, the frequency and severity of forest wildfires has increased worldwide over the past 20 years (Potapov et al., 2022). Wildfire was the main driver of tree cover loss in 2001–2021, during which the forest cover in Mongolia declined to 4350 km², equivalent to an 11% decrease in tree cover since 2000 (Słowiński et al., 2022). The largest burned areas were recorded during this time. In early April 2009, nearly 50 fires were reported and, at the end of 2009, 791 km² of forest cover was affected. This increase in wildfire frequency is a major problem in the Khentii Mountains (Munkhjargal et al., 2020a) and affects regional forest composition and permafrost. Unfortunately, the effects of wildfires in combination with

anthropogenic damage on environmental parameters are highly variable and poorly documented.

2.2 Study area

The study area features the southern edge of the Siberian Forest and transition zone between a vast steppe area. The Siberian Forest stretches from northern Mongolia towards the northern border of Russia. Mongolian forests occur predominantly in the north, between the Siberian and Central Asian taiga (Figure 2.1). This region transitions between the steppe, boreal, and alpine tundra of the Khentii Mountains. The mountain range (elevation: 1700–2500 m a.s.l.) is divided into two regions, Baga and Ikh Khentii, with Mount Asralt Khairkhan (2800 m a.s.l.) being the highest peak. The terrain consists of rounded mountaintops and steep slopes that are highly dissected by river valleys (Orkhonselenge et al., 2022).

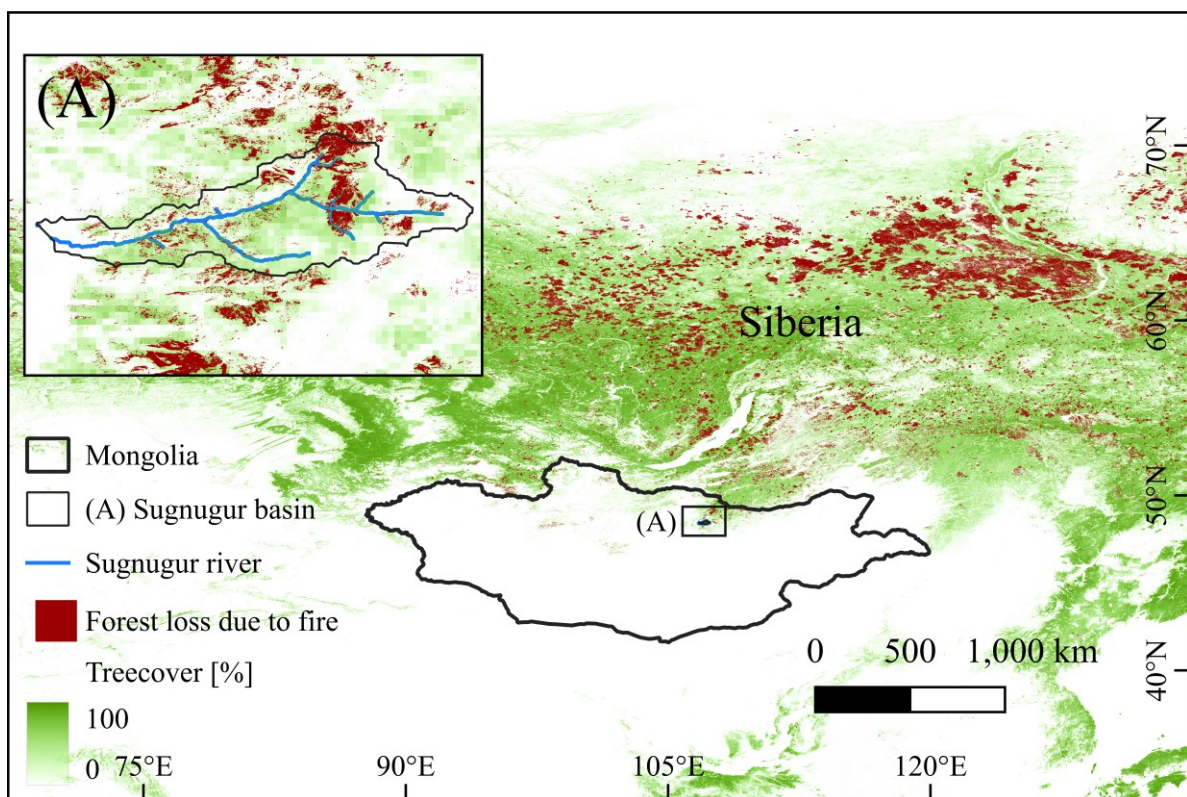


Figure 2.1: Base map showing tree cover and accumulated forest loss due to fire (2000–2021). (A) Siberian Forest cover and forest loss due to fire in the Sugnugur Valley study area, northern Mongolia. Forest dataset: Hansen et al. (2013). Data source: hydrosheds.org

The Khentii Mountains are isolated from one another by intermountain depressions. The western slopes are part of the Selenge–Baikal river drainage system—the primary local freshwater source (Menzel et al., 2011). The Ikh Khentii range comprises the headwaters of the Kherlen, Onon, and Minj rivers, and Sugnugur Valley contributes greatly to baseflow in the Kharaa River (Menzel et al., 2011). The mid-elevation mountains are forested (Figure 2.2), while the mountaintops are covered by stones, rocks, and loose weathered geological features (Figure S1). Rainfall is the primary source (56–75%) of runoff (Myagmarjav & Davaa, 2014). The area has a highly continental semi-arid climate, with an average annual precipitation of 250–400 mm (mostly during the summer months) (Menzel et al., 2011). The Khentii

Mountains are dominated by boreal forests and forest–steppe mosaics, with intermittent permafrost (Kopp et al., 2017). The northerly facing slopes maintained cool and moist soil conditions and were sheltered by dense taiga, mainly comprising *Pinus sibirica*, *Larix sibirica*, and *Betula platyphylla*, along with a thick layer of mosses and shrubs, mainly *Ledum palustre* and *Vaccinium vitis-idaea*. Although the boreal and alpine ecosystems are largely undisturbed, the region experiences various anthropogenic effects, particularly from forest fires.



Figure 2.2: Drone photograph of the upper Sugnugur Valley in the Khentii Mountains captured on September 11, 2022, by the author.

2.2.1 Site selection

We selected two relatively comparable study sites. The main study site was located in Sugnugur Valley, northern Mongolia (latitude: 48° N), and the second was located in the Black Forest, southwestern Germany (latitude: 48° N). The second study site is discussed in Chapter 3. The Sugnugur Valley study area is located in southern Siberia (48° N, 107° E).

2.2.2 Sugnugur Valley

Sugnugur Valley has an area of ~483 km², elevations of ~1000–2700 m a.s.l. (Figure 2.3), and is underlain by granite and gneiss bedrock, though the floodplain itself consists primarily of sedimentary deposits. The river course flows mainly from east to west. This area comprises the main tributaries of the Kharaa River. The study area consisted of natural, partly burned, burned, and disturbed forests. Higher-elevation vegetation communities were characterized

by alpine scree and sparsely vegetated areas; vegetation cover and species richness gradually increased with decreasing elevation (Figure 2.2).

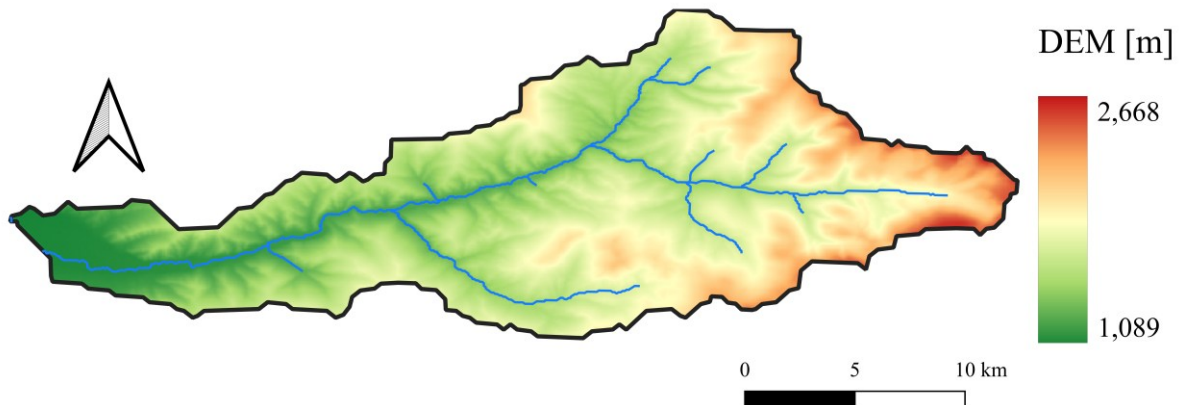


Figure 2.3: Digital elevation model (DEM) of the Sugnugur Valley study area.

Temperatures in summer and winter average around 12 °C and −20 °C, respectively. Seasonal temperatures show high variation and peak at ~14 °C in July before gradually decreasing to −3 °C in October. December (−25 °C) is the coldest period, followed by January (−23 °C) and February. The mean annual monthly temperature is −2.8 °C (−19 °C; reference period 1980–2022, ERA5-Land, Figures 2.4, 2.6, and 2.7). This area has relatively consistent wind conditions: Starting from early spring, windspeed increases from ~0.8 m/s to 1 m/s. Towards summer, windspeed gradually decreases to a mean of 0.7 m/s. Mean monthly relative humidity decreases to 50% in spring and increases towards summer. Solar radiation peaks around late spring and gradually declines towards winter to ~800 W/m². Based on the historical monthly mean for 1980–2022, precipitation is concentrated to May–September, particularly June, July, and August, where it peaks around 60 mm. Total annual precipitation is about 310 mm (Munkhjargal et al., 2020a), approximately 2/3 of which is concentrated to the summer months (Figures 2.5, 2.6, and 2.7).

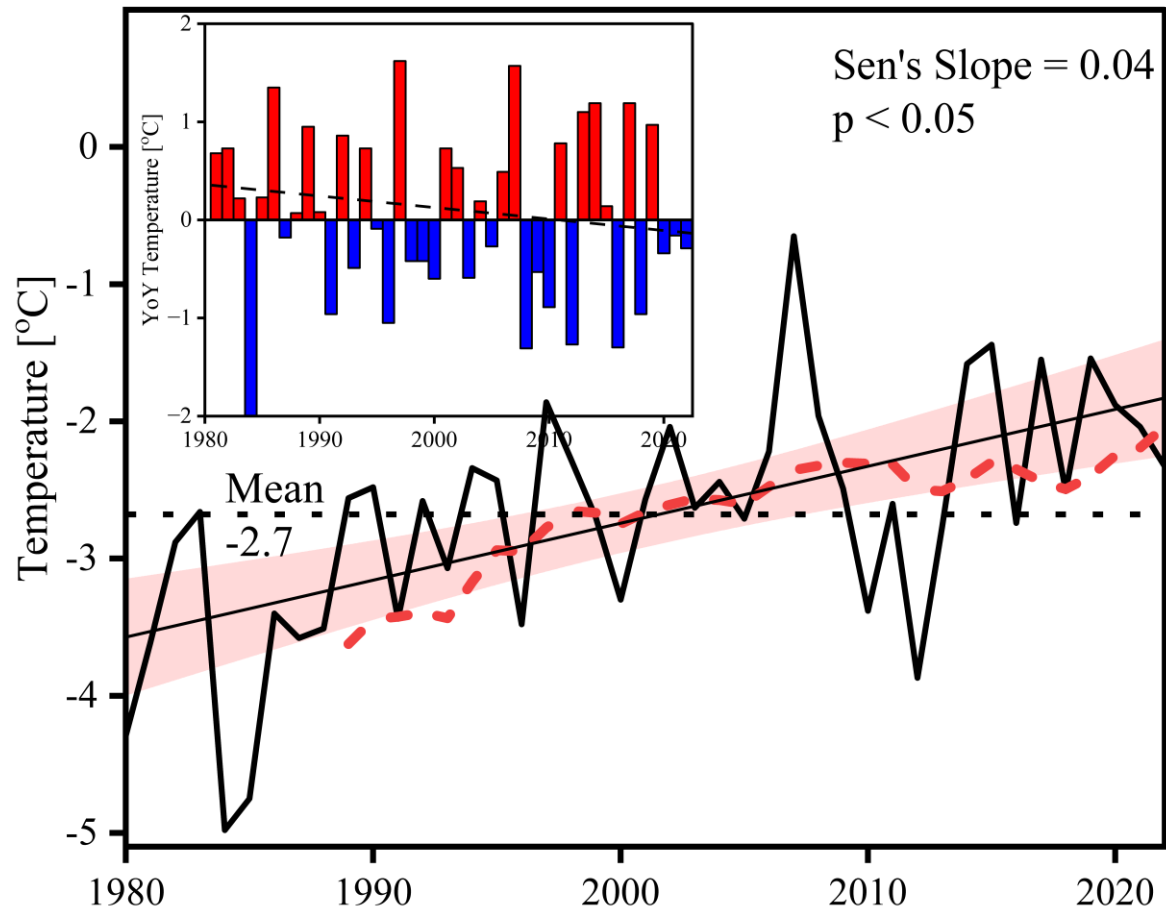


Figure 2.4: Time series of annual mean temperature (°C) during 1980–2022 (blue line). The black solid line indicates a positive linear trend, revealing a gradual increase in temperature with time, consistent with the positive Sen's slope. The grey shading around the trend line represents the 95% confidence interval. The black dotted line marks the long-term average temperature, providing a reference for annual deviations. The red dashed line shows the 10-year moving average, smoothing out short-term fluctuations and emphasizing the longer-term trend. Data source: ERA5-Land.

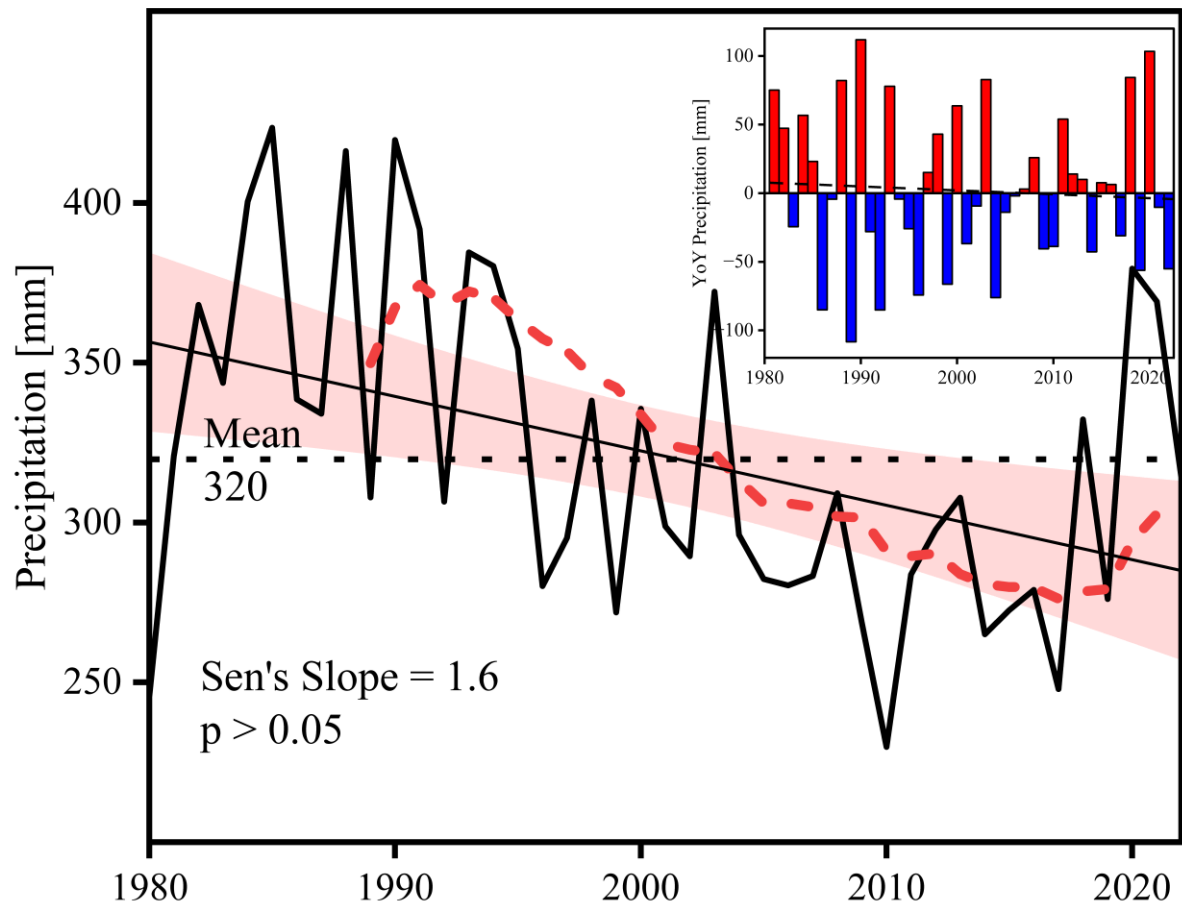


Figure 2.5: Time series of annual precipitation (mm) during 1980–2022 (blue line). The black solid line indicates a linear downward trend in precipitation with time, consistent with the negative Sen's slope. The grey shaded area around the trend line denotes the 95% confidence interval. The black dotted line across the plot indicates the long-term average precipitation, providing a reference for annual deviations. The red dashed line represents the 10-year moving average, which smooths out annual variations to highlight the broader trend. Data source: ERA5-Land.

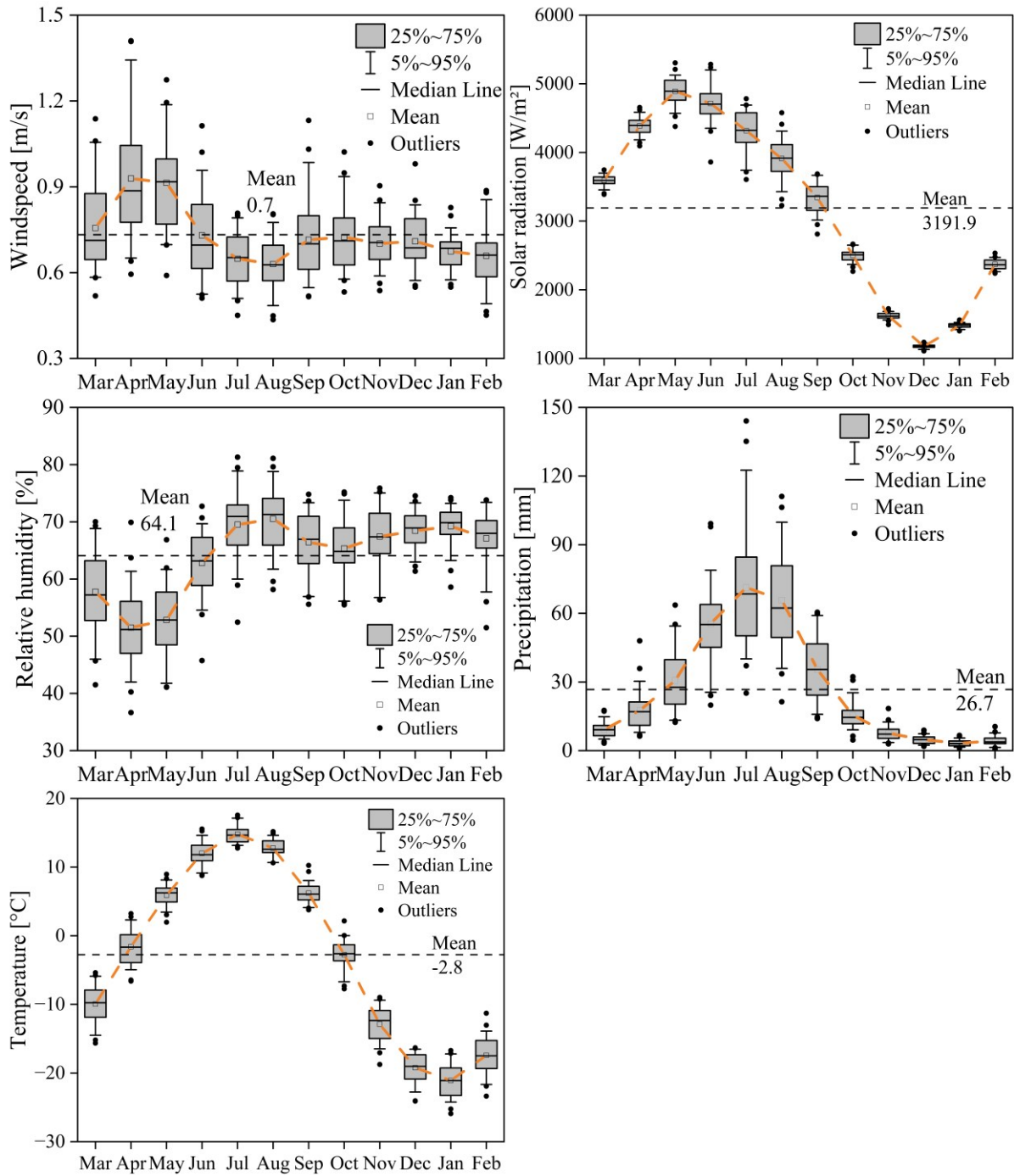


Figure 2.6: Intra-annual mean monthly windspeed, air temperature, precipitation, relative humidity, and solar radiation during 1980–2022 in Sugnugur Valley. These parameters were extracted from a global reanalysis ERA5-Land dataset.

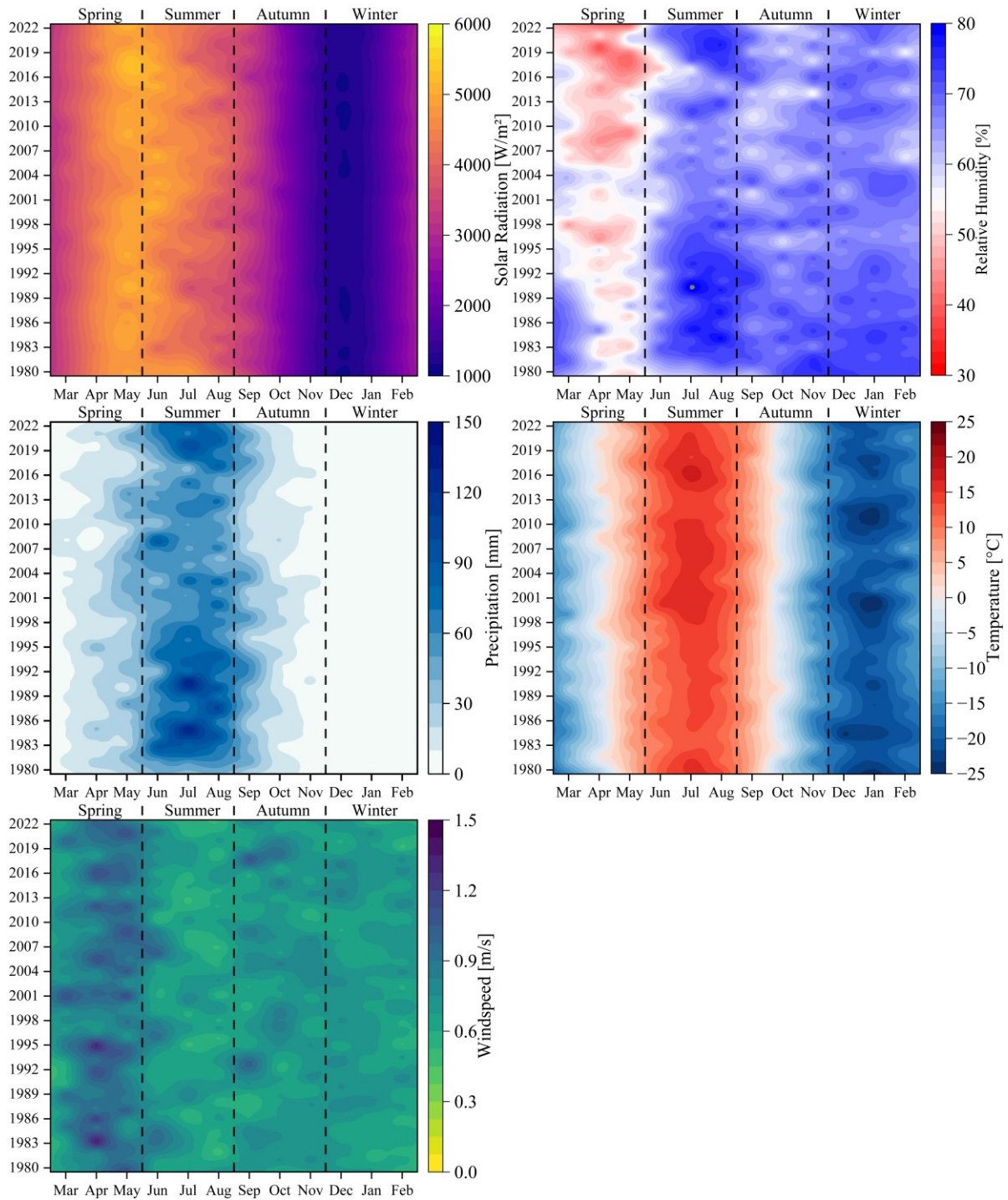


Figure 2.7: Contour plots of annual variation in monthly solar radiation, relative humidity, precipitation, temperature, and windspeed during 1980–2022 in Sugnugur Valley. Each plot is divided into four seasons.

2.3 Data sources

2.3.1 Objectives

Continuous and well-documented observational data are important for hydroclimatic research. Data are especially limited for remote regions with harsh climates, which limit their accessibility and the functioning of instruments for recording certain hydroclimatic variables. Heterogeneous land structures create many uncertainties in the characterization of climate

variables. The elevational differences (>1000 m a.s.l.) and sharp incline of the mountains complicate monitoring of the complete area. To address these limitations, we combined field investigations and global gridded reanalysis datasets, which provide spatially and temporally continuous data integrating historical observations. The field investigation was important for supplementing real-world data and validating the reanalysis products. In the following sections, we describe the hydrological and meteorological data sources.

2.3.2 Meteorological dataset

Since 2010, the Hydrology and Climatology Group at Heidelberg University has operated a monitoring program in northern Mongolia (Figure 2.8) to elucidate the effects of climate change and human activities on water resources in semi-arid environments. The station in Sugnugur Valley (~ 1200 m a.s.l., $48^{\circ}24'55''$ N, $106^{\circ}56'21''$ E) is situated ~ 100 km north of Ulaanbaatar (Menzel, 2014), which is convenient for recording the local hydro-environmental conditions of the mountainous headwater system, including snow storage, permafrost, and forest cover. The station is self-sustained by solar panels and continuously measures a range of variables (Minderlein & Menzel, 2015). In our study, the meteorological dataset was used as a reference and to validate the global gridded reanalysis datasets.



Figure 2.8: Hydroclimatic (Xoxoo) station (established in 2010). The station was founded and is supervised by the Hydrology and Climatology Group, Heidelberg University.

2.3.2.1 Ground observations

To observe the daily development of snow and river ice cover in Sugnugur Valley (Figure 2.9), we employed a wildlife camera (~1600 m a.s.l., 48°27'10" N, 107°11'61" E). To gain a general overview of the valley, the camera was installed in a south-easterly direction, and the capture frequency was set to one image every 12 h.

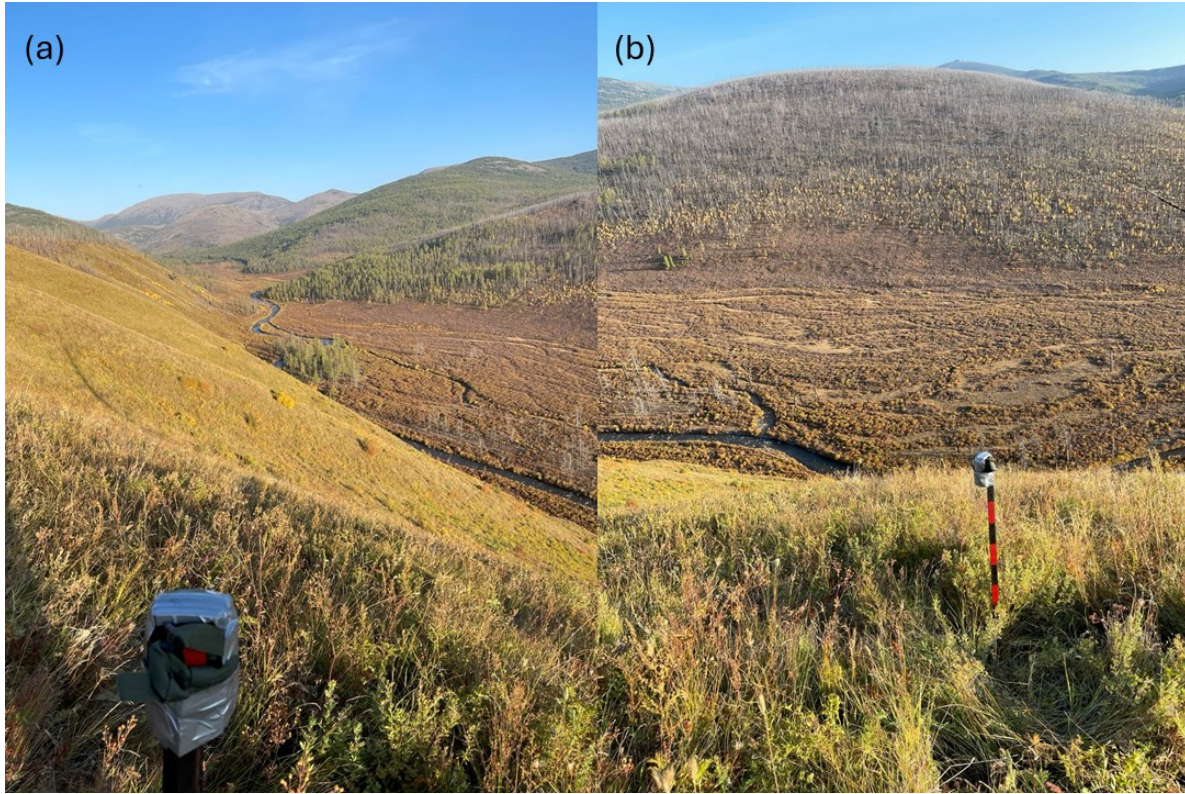


Figure 2.9: Installation of wildlife camera in Sugnugur Valley. (a) South-easterly direction of camera lens. (b) Immediately surrounding area.

2.3.3 Global gridded meteorological datasets

Because of the sparse distribution of the meteorological station network in northern Mongolia, limited data availability, and high spatial variability (Munkhjargal et al., 2020a), we employed multiple global gridded datasets to address the inherent uncertainties. Meteorological datasets were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). ET data were downloaded from the Global Land Evaporation Amsterdam Model (GLEAM). Root zone SM (RZSM) data were derived from Soil Moisture Active Passive (SMAP) and GLEAM. Snow products were obtained from Moderate Resolution Imaging Spectroradiometer (MODIS). Table 2.1 provides details on the spatial resolution, time step, and source information of the data, which include hourly to yearly time series and were extracted at the basin scale. The average time series for the entire basin were used to create seasonal and annual series for statistical analysis. For comparison, the datasets were interpolated to a resolution of 1×1 km.

2.3.3.1 ERA5-Land dataset

ERA5 represents the fifth-generation reanalysis by the ECMWF. It is a detailed global climate dataset that offers hourly recordings of various atmospheric, land, and oceanic variables. The reanalysis combined historical observations with advanced weather models to create a consistent long-term record (Muñoz Sabater, 2019). The public ERA5-Land dataset, available from 1950 to 5 d before the current date, provides high-resolution hourly data on surface variables. It is a refined version of the land component from the ERA5 climate reanalysis, featuring a finer resolution of ~9-km grid spacing. Additionally, ERA5-Land offers information on uncertainties for all variables, though at lower spatial and temporal resolutions. The ERA5-Land climatological data for 1980–2022 were used for the TRAIN model to simulate ET.

2.3.3.2 GLEAM dataset

GLEAM 3.8a is used to estimate land evaporation or ET by integrating satellite observations with a range of data-driven algorithms (Martens et al., 2017). GLEAM provides detailed assessments of various evaporation components, including transpiration, soil evaporation, interception loss, and open-water evaporation (Miralles et al., 2011). It operates at a high latitude–longitude resolution of 0.1° and offers continuous daily records from 1980 to present. GLEAM ET and RZSM data were used to validate the ET simulated by the TRAIN model.

2.3.3.3 SMAP

The SMAP satellite, launched in January 2015, has been collecting SM data since March 31, 2015 (Entekhabi et al., 2010). SMAP uses a combination of radar and radiometer images to estimate surface SM (Colliander et al., 2017). The strategic use of SMAP SM data can improve RZSM estimation by improving the physical constraints in SM models (Mladenova et al., 2019). The RZSM product from the SMAP dataset was used to compare the RZSM simulated using the TRAIN model.

2.3.3.4 Terra and Aqua satellite

MODIS operates on two platforms, Terra (MOD10A2) and Aqua (MYD10A1), both of which provide parameters related to snow cover. These platforms offer a global daily composite of snow cover at a resolution of $0.05^\circ \times 0.05^\circ$ (Hall et al., 2019; Riggs et al., 2021). MODIS sensors observe the Earth's surface across 36 spectral bands, ranging from visible to infrared wavelengths, which makes them particularly effective in monitoring environmental variables, including snow cover, vegetation cover, land use, and ocean color (Justice et al., 2002; Hall et al., 2019). One of the most widely used products of MODIS is the snow cover datasets, specifically the MOD10A1 (Terra) and MYD10A1 (Aqua) daily snow cover maps. These products utilize the Normalized Difference Snow Index (NDSI) to discriminate between snow-covered and snow-free areas, offering critical data for hydrological studies, climate change monitoring, and water resource management (Hall et al., 2019; Riggs et al., 2021). Despite their advantages, the use of MODIS snow products is limited by cloud contamination and snow misclassification, which can obscure up to 63% of the Earth's surface in some regions (Parajka & Blöschl, 2008; Dong & Menzel, 2016). Various methodologies have been developed to address these challenges and enhance the reliability of MODIS-derived snow cover information, such as combining Aqua and Terra datasets, spatial and temporal gap-filling, and integrating meteorological data (Gafurov & Bárdossy, 2009; Dong & Menzel, 2016).

The current study employed daily snow cover maps (MOD10A1 and MYD10A1) for January 1, 2003–December 15, 2022. A total of 14,578 MODIS snow cover images were downloaded through Google Earth Engine (<https://developers.google.com/earth-engine/>). The Terra and Aqua products were used to estimate the spatial distribution and duration of snow cover. These estimates were validated with the meteorological data and compared with the TRAIN snow cover simulation.

2.3.3.5 Runoff observations

Given the limited historical data for the study site, we used data for nearby comparable basins, such as Kharaa, Baruun Kharaa, and Tuul, to compare the recorded and simulated river runoff. Due to the characteristic presence of river ice during the cooler periods, large uncertainties exist in daily river runoff; however, these can be reduced by aggregating daily data at monthly, seasonal, or annual scales (Han et al., 2022). Accordingly, this analysis was based mainly on seasonal and annual data aggregated from monthly records. To compare the magnitude of river runoff (runoff per unit area) between basins, streamflow data were converted from m^3/s to $\text{L}/\text{s} \cdot \text{km}^2$ (specific runoff) for monthly and annual time series. However, the records of each basin cover different periods, and some datasets are available only at monthly or yearly resolutions. The majority of the data were provided by the Hydrology and Climatology Group at the Heidelberg University.

Table 2.1: Dataset descriptions.

Data set	Data category	Dataset	Resolution	Frequency	Period	Website
Global gridded data	Temperature (T)	ERA5-Land	$0.1^\circ \times 0.1^\circ$	Hourly, daily, monthly, and yearly	1950-2022	https://cds.climate.copernicus.eu/
	Precipitation (P)					
	Windspeed (u)					
	Dewpoint temperature (Tdew)					
	Global radiation (Rd)	ERA5-Land GLEAM SMAP	$0.1^\circ \times 0.1^\circ$	Daily	1980-2022	https://www.gleam.eu / https://cds.climate.copernicus.eu/
	Root zone soil moisture (RZSM)				2015-2022	
	Evapotranspiration (ET)				1980-2022	
	Digital Elevation Model (DEM)	SRTM	90 x 90 meters		2000	https://www.opentopography.org
	Plant Available Soil Water	ETH Zurich	1 x 1 km		2023	https://zenodo.org/records/8091791
	Hydraulic Conductivity				2020	https://zenodo.org/records/3935359
Remote sensing	Aspect and slopes	GEE			2023	https://earthengine.google.com/
	Snow cover	Terra (MOD10A2) Aqua (MYD10A1)	$0.05^\circ \times 0.05^\circ$	Daily	2000-2022 2002-2022	https://terra.nasa.gov/data/modis-data
Meteorological station data	Temperature (T)	Climate and Hydrology Group at Universität Heidelberg	Station	Daily	2012-2020	upon request from Climate and Hydrology group
	Precipitation (P)					
	Snow height			Daily, monthly, and yearly	1950-2012	
	Radiation (Rd)					
	Runoff (Q)					

2.3.3.6 Digital elevation map

A DEM representing the topographic surface of the Earth without extraneous features such as vegetation or man-made structures was generated using Shuttle Radar Topography Mission images (www.opentopography.org) as the foundation for a cartographic map. A shapefile of Sugnugur Valley was generated using a water basin layer (www.hydrosheds.org).

2.3.3.7 Global plant-available soil water dataset

The plant-available soil water dataset (version 3, 1×1 km resolution) was procured from ETH Zurich (Gupta et al., 2023). The potential plant-available soil water was calculated as the difference between the wilting point and field capacity.

2.3.3.8 Global hydraulic conductivity dataset

We used a global hydraulic conductivity map (1×1 km resolution, GeoTIFF format) developed using advanced machine learning and remotely sensed surrogate data such as terrain, climate, vegetation, and soil covariates (Gupta et al., 2020).

2.3.3.9 Aspect and slope dataset

The geographical aspect and slope data were obtained using Google Earth Engine (<https://developers.google.com/earth-engine/>). The platform provides a combination of different datasets and allows for the interpolation of small- to large-scale datasets, for a given format and coordinate reference system (CRS).

2.3.4 Study period and dataset evaluation

Several reference periods were chosen to assess the long-term hydroclimatic changes during 1980–2022, with the start and end years selected based on data availability. We divided the 42-year period into two 21-year segments (1980–2000 and 2001–2022) to determine changes in both average and extreme hydroclimatic conditions within a nonstationary Earth system. A high-resolution forest fire dataset for 2001–2022 was used to elucidate the impacts of wildfires on hydrological regimes and, combined with historical climatological data, corresponding changes in wildfire behavior.

Gauge-based observations, field measurements, and gridded data were used. Observational datasets are critical for validating global gridded datasets; however, they are limited by the inherent uncertainties arising from spatial heterogeneity in hydroclimatic conditions, point-scale measurement errors, and systematic biases introduced by complex topography (Barstad et al., 2007).

Due to limited data availability, we used river discharge data for the nearest comparable basins. Most datasets did not fully cover the study period of 1980–2022.

The field measurements comprised various essential forest parameters, including forest type, leaf area index (LAI), species composition, and tree height, which are useful for comparing the impacts of forest damage caused by wildfires, human disturbances (e.g., pine nut collecting), and grazing. However, most forest and field parameters are available only for late summer or early autumn, when the growing season has stabilized. Consequently, these measurements are heavily dependent on seasonality and require consistency in the timing of data collection. Specifically, to accurately assess changes in forest conditions, it is essential to collect measurements at the same locations and during the same time of year.

Grid-based data have improved the estimation of hydroclimatic changes in data-scarce regions (Hrachowitz et al., 2013). These datasets are uniformly processed using consistent standards and methodologies across both temporal and spatial scales, enabling evenly distributed regional estimates with complete temporal coverage. However, although these datasets are relatively accurate compared to the observed datasets, most of the products are generated at a coarse resolution, including the gridded data for Sugnugur Valley. Therefore, we interpolated the data to a resolution of 1×1 km. Our combined research strategy incorporating observational data, field measurements, and global gridded datasets helped reduce uncertainties arising from the heterogeneous structure and frequent wildfires in the study area.

2.4 Model simulations

We employed the distributed TRAIN model to identify hydrological responses in intensive wildfire periods (2001–2022) compared to those in no or less frequent wildfire periods (1980–2000). The TRAIN model is a comprehensive hydrological model, developed by Menzel in the mid-1990s (Menzel 1996, 1997), based on soil–vegetation–atmospheric transfer structures

and has been extensively applied and validated in various regions, including Switzerland, southwestern Germany (Tijdeman & Menzel, 2021; Wang et al., 2023), and southern Siberia (Han et al., 2022). TRAIN integrates detailed field data associated with water and energy balances across different surface types, such as snow cover, ET, interception, SM, and runoff. This allows the simulation of water budget components at multiple spatial and temporal scales, with hourly to daily resolutions. TRAIN requires key meteorological inputs (i.e., station observations and reanalysis estimates) including precipitation, global or net radiation, soil heat flux (if available), air temperature, relative humidity, and windspeed. Additionally, the model relies on information about soil depth, soil water-holding capacity, LAI, and vegetation height. Where LAI or vegetation height data are unavailable, TRAIN makes standardized assumptions based on typical vegetation patterns. The model outputs encompass various hydrological variables, such as interception evaporation, transpiration, total ET, RZSM, percolation, runoff, and snow cover. The TRAIN model generally considers four processes: snow storage change, interception and ET, SM change, and runoff generation (Figure 2.10). TRAIN is specifically developed for simulating ET and SM dynamics. Transpiration is calculated using the Penman–Monteith equation, incorporating canopy resistance (Menzel, 1996). According to Menzel (1997), the maximum amount of water that can be stored in the canopy depends on seasonal LAI. Information about LAI and vegetation height can be input directly or estimated from typical values. In our case, LAI and vegetation parameters were obtained from field measurements. The model simulates interception evaporation occurring at varying intensities based on both the current accumulation of water on the canopy and prevailing weather conditions (Wang et al., 2023). SM content and percolation were determined using a conceptual approach derived from the HBV model (Bergström, 1995). This study elaborates on the applicability of the TRAIN model for simulating forest cover changes due to wildfire. The impacts of wildfire were only analyzed for 2001–2022 because of the dataset range. Some of the input data (i.e., LAI, vegetation height, and soil depth) were obtained from the field measurements. For more information on the TRAIN model and its applications, please refer to Han et al. (2022) and Wang et al. (2023).

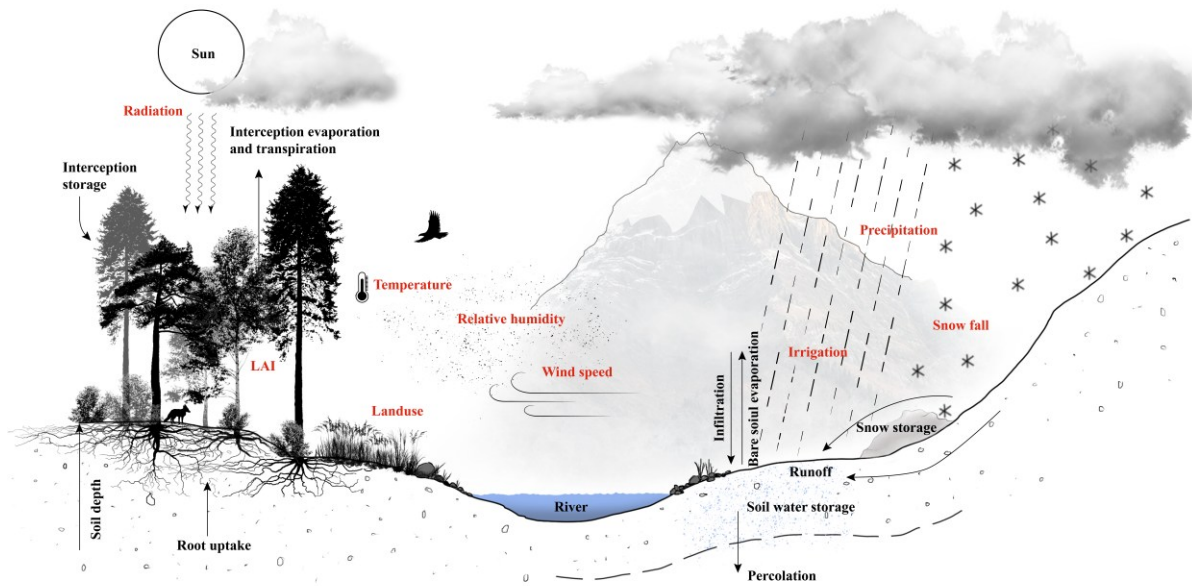


Figure 2.10: Schematic representation of TRAIN model simulation. Red terms indicate model inputs, including meteorological (precipitation, temperature, relative humidity, windspeed, and radiation), landcover (LAI and vegetation height), and soil variables (soil type, soil depth, and field capacity; for more details, see the user manual for the TRAIN model, version 6, written by Prof. Dr. Menzel, July 2024) (Menzel, 2024). Graphical illustration prepared by the author.

2.5 Validation of ET and RZSM data

We applied water balance closure to validate both the global gridded reanalysis (ERA5-Land, SMAP, and GLEAM) and model-simulated ET and RZSM data. First, we conducted spatial analysis to assess the performance of the TRAIN model. Accordingly, we compared the TRAIN ET outputs versus those of ERA5-Land and GLEAM. For the RZSM, we compared the TRAIN output versus the SMAP and ERA5-Land estimates. We simulated unchanging landcover for 1980–2022, assuming no wildfires, and found that the TRAIN ET estimates showed a strong basin-averaged correlation (~ 0.8) with both the GLEAM and ERA5-Land data. The TRAIN simulation of RZSM also showed a strong correlation (~ 0.7) with the ERA5-Land and SMAP data, while a lower correlation was observed with the GLEAM data (~ 0.5). We selected five sample points to further evaluate the performance of the TRAIN model in simulating ET and RZSM on a point scale. In general, the TRAIN model reasonably simulated ET and RZSM across the study area. Thus, the simulated data are representative of the regional conditions and can be used for elucidating the impacts of wildfires. We discuss the results of the spatial and point analyses of each product in Chapter 6.

2.6 Statistical analysis

In each chapter, we only present the statistical methods used for achieving the current objective. To avoid confusion, the discussion of the statistical methods has been separated into major and minor components corresponding to each chapter.

2.7 Trend detection

Trend detection for the hydroclimatic time series data was performed in two steps. First, the trend magnitude was determined using both ordinary linear regression and Sen's slope (Sen, 1968). Second, nonparametric data were assessed using the Mann–Kendall (MK) test, recommended by the World Meteorological Organization (Kendall & Gibbons, 1975), with statistical significance set at $p < 0.05$. The MK test is among the most widely used and robust methods for detecting long-term trends in hydroclimatic time series (Han et al., 2022; Wang et al., 2023). Its performance relies on the absence of serial correlations. Owing to the strong seasonality of the hydroclimatic regimes of the Sugnugur basin, the variables were assumed to be serially independent.

2.8 Moving average approach

We applied a 10-year moving average to analyze the long-term time series and reduce bias caused by year-to-year variations and extreme conditions in individual years. This approach effectively accommodates the oscillatory patterns in the hydroclimatic series and can detect potential relationships among hydroclimatic variables.

Chapter 3

3 Selection of optimal method for detecting leaf area index: Line quantum sensing versus hemispherical photography

3.1 Study objective

This chapter, along with Chapter 4, concentrates on selecting the most suitable technique for detecting LAI in the Black Forest (south-west Germany) for use in Sugnugur Valley (northern Mongolia). Both study sites are located around 48 °N with comparable geographical and topographical features. The Black Forest is well-documented compared to the data-scarce northern Mongolia, allowing us to compare, validate, and select the most suitable LAI estimation techniques. The accurate and reliable estimation of LAI in this chapter contributes to the data used in Chapter 5 and provides input for hydrological modelling in Chapter 6.

3.2 Importance of LAI

Forest cover, structure, function, and species composition influence hydrology through the partitioning of precipitation into ET and streamflow. The LAI, a crucial parameter in process-based models of vegetation cover responses, describes the projected leaf area per unit ground area and is an important ecohydrological driver in forests. It is the primary parameter for assessing the structural properties of forests and thus essential for modeling water cycles in forest stands (Schulze, 1982; Hyer & Goetz, 2004). It is generally accepted that leaves make up the largest portion of the canopy surface (Running & Coughlan, 1988), serving as the main site of energy production, net photosynthesis, mass exchange, canopy interception, transpiration, and other biological functions (Chen et al., 1999; Singh, 2021). Therefore, LAI influences dry deposition, ET, and CO₂ flux.

Accurate and reliable estimation of forest parameters are important to accurately simulate water balance. Because some LAI estimation techniques are unsuitable for use in our geographically complex study site, we modified previously validated techniques, tested and improved their performance in the Black Forest, and, based on their adaptability and reliability, selected the most suitable technique. Due to time constraints, the remote location of our study site and limited availability of transportation for fieldwork equipment motivated our selection of comparatively comprehensive and rapid techniques. This chapter discusses the estimation of LAI, forest structure, and species composition in various forest types.

3.3 LAI estimation techniques

LAI can be estimated using direct methods, such as destructive sampling or leaf litter collection (Watson, 1947; Breda, 2003; Liu et al., 2015), or indirect methods (Ferment et al., 2001), such as inclined point quadrat sampling or allometric techniques (Jonckheere et al., 2004; Casa et al., 2019). Direct methods for estimating forest LAI are considered precise, reliable, and useful for validating s (Casa et al., 2019). However, their applicability is limited by their time, labor, and operational requirements; therefore, we applied indirect techniques, which are generally faster than direct methods and can be automated for increased sample

size. Indirect LAI estimation based on light transmission differences between vegetation and other natural cover types is particularly useful for large-scale spatiotemporal studies (Parker, 2020).

Indirect non-contact methods provide real-time LAI data based on both gap fraction and gap size distribution analyses. The gap fraction reflects the variations in light measurements above and beneath the canopy, whereas gap size reflects the ratio between open and canopy-covered areas (Madgwick & Brumfield, 1969). Hemispherical photography (HP), a field-based remote sensing technique for characterizing biophysical canopy structure through light attenuation and contrast measurements, was used to estimate gap size and forest cover (Figure 3.1). HP is useful for determining the arrangement, position, extent, size, frequency, density, and distribution of canopy gaps, and can capture the species-, site-, and age-specific attributes of the canopy with a 180° viewing angle (Wang et al., 2021). HP is effective for measuring different components of the canopy structure, but cannot be applied under direct sunlight due to over-exposure and the resulting distortion. Therefore, HP may underestimate LAI during some times of day (Chianucci et al., 2015). Gap fraction-based methods such as line quantum sensing (LQS) take ground-based measurements of the total, direct, and diffuse radiation transmittance to the forest floor (Lang, 1987). Light interception can be estimated above the canopy or, for tall stands, in a nearby open area (Monsi & Saeki, 2004; Wang et al., 2018). These methods assume that the total amount of radiation captured by a canopy layer depends on incident irradiance, canopy structure, and optical properties (Tan et al., 2020). The assumptions of the Beer–Lambert law are considered to hold in describing the link between LAI and gap probability (Pierce & Running, 1988; Pokovai & Fodor, 2019) as follows:

$$I = I_0 * e^{-K(LAI)}. \quad (1)$$

Equation 1 was transformed to:

$$LAI = \frac{-\ln\left(\frac{I}{I_0}\right)}{K}, \quad (2)$$

where I is the average below-canopy photosynthetically active radiation (PAR), I_0 is the average total incoming PAR, and K is the light extinction coefficient (Tan et al., 2020). This equation is based on the assumption that the LAI does not vary with the angle of incoming radiation on the canopy, leaf inclination angles are distributed in a spherical random manner, and plant leaves are arranged randomly within the canopy (Jarvis & Leverenz, 1983).

Recently, LAI estimation methods assuming the Beer–Lambert law have been applied by large-scale forest monitoring agencies (Tan et al., 2020), and are accepted for engineering and research applications owing to their reliable estimation of average canopy conditions (Rogers et al., 2021). These methods depend on a specific K -value, which is further complicated by the variation in solar radiation due to cloud cover. Appropriate K -values must account for site- and species-specific characteristics, including leaf angle, form, and clumping. Pierce and Running (1988) proposed the use of a constant K of 0.52 for coniferous species, based on measurements reported by Jarvis and Leverenz (1983). However, since K inherently varies based on stand structure and canopy architecture, a unique K should be selected for any given stand (Ludemann, 2010).

Despite the clear advantages of methods such as LQS, including rapid turnaround and reproducibility, K -based estimates are limited by their high variability and unvalidated accuracy compared to more established methods. For example, investigations requiring finer details on canopy structure (i.e., angular distributions of foliage) or light penetration (i.e., bidirectional gap fraction) may benefit more from HP owing to its spatial discrimination ability (Jonckheere et al., 2004). However, LQS may be more advantageous for LAI estimation in croplands and forests (Yousefpour et al., 2010). LAI estimates obtained via HP and LQS have not been thoroughly compared in environments with complex structures, such as protected and managed temperate coniferous forests. Furthermore, the reliability of K is unclear in these forest types.

In this study, LAI was estimated using LQS for two temperate coniferous forest sites and compared against the standard HP estimates. We assessed the accuracy of the LQS-based LAI values associated with different K -values for each site and selected the optimal value. The primary objectives of this study were to determine (1) the performance of LQS for accurately estimating LAI in a temperate coniferous forest from transmittance measurements, and (2) how K affects measurement accuracy between differing stand structures (managed versus protected forests). We sought to enhance the precision of the LQS technique by incorporating corrections based on raw quantum sensor data collected under variable light conditions. Our results indicate that the application of stand-specific K -values can effectively address the limitations associated with LQS-based LAI estimation.



Figure 3.1: Hemispherical photograph at Hundseck, Black Forest, Germany.

3.4 Field measurements in the Black Forest

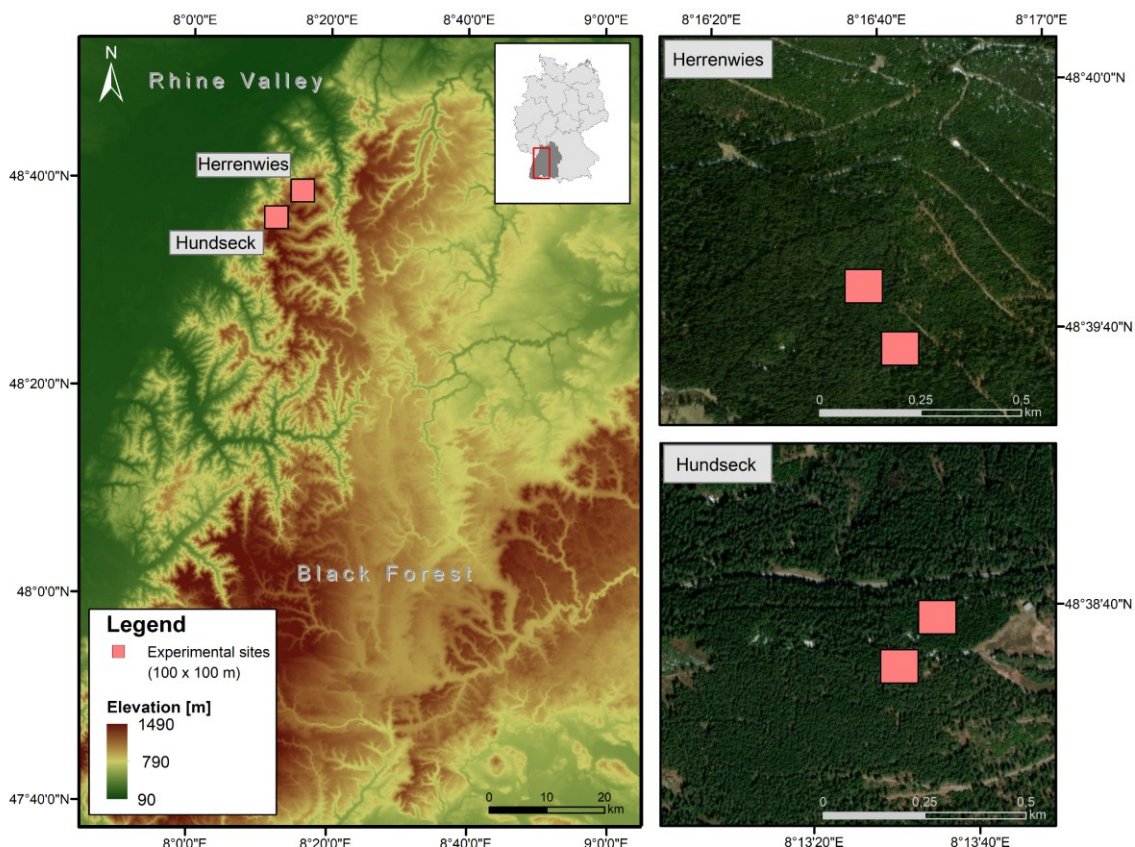
The Black Forest study site is located in the topographically heterogeneous Upper Rhine region and spans across several mountains, including the Black Forest mountains in the east and Vosges mountains in the west. The forest maintains a low average altitude of 800–1500 m a.s.l. (Figure 3.2). The region is bordered to the west and south by the Rhine Valley, extending ~160 km in length and averaging ~50 km in width. As with other low mountain ranges in Central Europe, the Black Forest is both ecologically significant and increasingly vulnerable to environmental challenges associated with drought (Tijdeman & Menzel, 2021) and diminished snow cover (Dong & Menzel, 2019). Mean temperatures in the region range from 4 to 6 °C, with annual precipitation varying between 1700 and 2000 mm depending on altitude

(Ludemann, 2010). The area is characterized by dense extensive forests comprised of ~80% coniferous species (spruce, fir, and pine) and ~20% deciduous species (beech, birch, and oak) (Yousefpour et al., 2010). Our study sites were located in a large-scale managed forest at Hundseck (953 m a.s.l.) and protected forested area of Herrenwies (875 m a.s.l.) in the northern Black Forest (Table 3.1).

Table 3.1. Dates of photographs and LQS measurements

Site name	Longitude	Latitude	Altitude a.s.l (m)	Main tree species	Photographs and LQS measurements			
					2020		2021	
Managed forested stands								
Hundseck (1.1)	08°13'35'E	48°38'33'N	929	<i>Picea abies</i>	May.13/ Jun.07	Aug.10/ Aug.30	Dec.03	Feb.04
Protected forested stands								
Herrenwies (2.1)	08°16'30'E	48°39'50'N	784	<i>Picea abies</i>	May.13/ Jun.07	Aug.10/ Aug.30	Dec.03	Feb.04

Based on our manual measurements, tree density, average tree height 17 m, and average tree diameter at breast height (DBH) were approximately 0.8/100 m² and 97 cm, respectively. The climatological data for the study sites were obtained from a nearby meteorological station (<1 km away; 08°13'57" E, 48°38'37" N; 867 m a.s.l.) (Dong & Menzel, 2017). LAI was measured in 100-m² forest stands (Figure 3.2) that were representative of the structure and species composition of the Black Forest.



Data: © OpenStreetMap Contributors; © European Environment Agency (EEA), Copernicus programme; © Esri

Figure 3.2: Overview of the study sites at Hundseck and Herrenwies, Black Forest, Germany. Red-colored squares indicate the locations of the experimental plots. Data sources: BKG 2020 (gdz.bkg.bund.de) and Openstreetmap (planet.openstreetmap.org).

3.5 Data collection for LQS and HP analyses

3.5.1 LQS data collection and processing

Canopy transmittance in each stand was measured using a handheld LI-191R Line Quantum Sensor (LI-COR Biosciences, Lincoln, NE, USA) that quantifies photosynthetic photon flux density ($\mu\text{mol s}^{-1} \text{m}^{-2}$). The sensor features a light-sensitive 1-m quartz rod positioned beneath a diffuser that directs light onto a single filtered silicon photodiode, thereby integrating measurements from essentially an infinite number of surface points into one representative value. This device was coupled with a battery-powered digital data logger (model LI-250A/Light Meter, LI-COR), which provides direct digital PAR outputs by averaging ~60 readings taken over 15 s. Measurements were recorded in 2020 and 2021 (Table 3.1) on the same day of the year and under conditions identical to those used for HP, to minimize any potential bias in comparative analyses.

Diffuse light below the canopy was sampled along a systematically gridded transect initiated from a random starting point. Each transect consisted of 50 samples spaced ~14 m apart. PAR measurements were obtained by holding the quantum sensor with outstretched arms and completing a full 360° rotation, covering an effective sample area of ~6 m². Each transect was completed in under 1 h, representing 45,000 individual sampling points per stand. Total incoming PAR was measured at both the beginning and end of each transect in a nearby clear-cut or open area, with additional measurements taken in larger canopy openings (>100 m²) when possible.

To identify the most appropriate *K*-value for each stand, the LAI was estimated using Equation 2 with *K*-values ranging from 0.40 to 0.65. The LAI estimates were validated against independent HP data using Equation 3, with all analyses performed in RStudio (RStudio Team, 2015; see Section 3.5.3). Finally, provided that the assumptions underlying the Beer–Lambert law were satisfied, Equation 2 was reformulated into Equation 4 to calculate transmittance for each stand based on the measured LAI and adjusted *K* (see Section 3.5.3).

3.5.2 HP data collection and processing

Canopy photographs were acquired using a digital camera (D7000, Nikon, Tokyo, Japan) fitted with a 180° fisheye lens (EX-DC, SIGMA, Kawasaki, Japan) and mounted on a tripod equipped with manual levelers (Dörr Airpod, Neu-Ulm, Germany). Each image was meticulously evaluated for overexposure and blooming effects to ensure the highest quality photographs were selected for analysis. The selected images were then processed using Hemisfer 2.2 (Swiss Federal Institute for Forest, Snow, and Landscape Research, Birmensdorf, Switzerland) to estimate the LAI and characterize the light regime, following the methodology described by Schleppi et al. (2007). Each pixel was classified as either sky (white) or canopy (black) based on brightness threshold values derived from the red, green, and blue channels. Color frequency distributions were calculated to determine an appropriate threshold in accordance with the algorithm proposed by Schleppi et al. (2007). Subsequently, the algorithm was used to transform the photographs into binary black-and-white images, which were analyzed to identify borders—defined as regions with the steepest color gradients between adjacent pixels across any color channel (Schleppi et al., 2007; Thimonier et al., 2010). LAI was then estimated as previously described (Miller, 1967).

3.5.3 Statistical analysis

Based on the LAI estimated using LQS, the optimal K -value (0.40–0.65) for each managed and protected forest stand was calculated as follows:

$$\text{Sum of squares} = \sum_{i=1}^n (X_{LQS} - \bar{X}_{HP,i})^2, \quad (3)$$

where X_{LQS} is the LQS-based LAI and $\bar{X}_{HP,i}$ is the mean HP-based LAI. Equation 3 yields the summed difference between HP- and LQS-based LAI estimates for a given K (Allen, 1974). The range of variation was described as a percentage of the LAI to determine the error contributed by the sampling technique at any given point. Given the validity of the Beer–Lambert law, we transposed Equation 2 to predict the transmittance for each stand based on the measured LAI and adjusted K .

$$\frac{I}{I_0} = \exp(-K * LAI) \quad (4)$$

Here, I/I_0 is canopy transmittance, K is the light extinction coefficient, and LAI is the value estimated via LQS. Correlations between the measured canopy transmittance and LAI for adjusted K -values were graphically analyzed and compared between sites using the Kolmogorov–Smirnov (Marsaglia et al., 2003), Wilcoxon (Wilkinson & Rogers, 1973; Hollander & Wolfe, 1999), and linear regression tests (Chambers, 1992).

3.6 Method validation

Figure 3.3 presents the HP- and LQS-based LAI values for each site. Figures 3.4 and 3.5 show the LAI values derived from LQS at various K -values (0.40–0.65) using Equation 3 for Hundseck and Herrenwies, respectively. In both managed and protected forests, the LAI was overestimated and underestimated at K -values of 0.40–0.52 and 0.55–0.65, respectively. The changing K -value had different effects between forest types likely due to the differences in forest management regimes and, specifically, the lower number of young trees in managed compared to protected forests. $K = 0.54$ was selected for Hundseck, and $K = 0.53$ for Herrenwies. We verified the applicability of the adjusted K for temperate coniferous forests by comparing the HP- and LQS-based LAI values (Figures 3.6 and 3.7; $R^2 = 0.80$ and 0.81 at Hundseck and Herrenwies, respectively). The results indicated a strong positive relationship (Table 3.2).

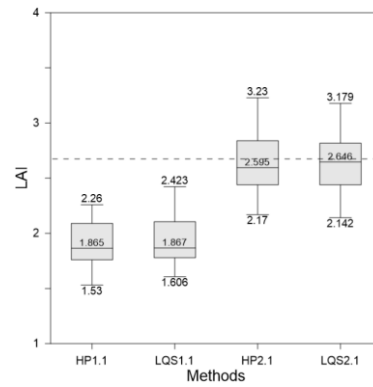


Figure 3.3: Comparison of leaf area index (LAI) values obtained from hemispherical photography (HP) and line quantum sensing (LQS) relative to the average global LAI for temperate forests (dashed line; Asner et al., 2003). Each box shows the median (line) and interquartile range (upper and lower box limits) of 50 independent measurements. The whiskers indicate the extremes. The number following each abbreviation in the x-axis represents the site code (Hundseck, 1.1; Herrenwies, 2.1; $n = 50$ per site).

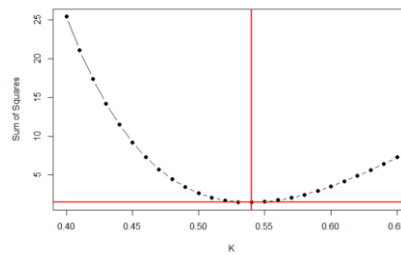


Figure 3.4: Comparison of optimal K -values (0.40–0.65) for LQS at Hundseck. Based on the optimal result ($K = 0.54$), the LAI was estimated and is compared to HP values in Figure 3.6. The red line represents the lowest sum of squares error.

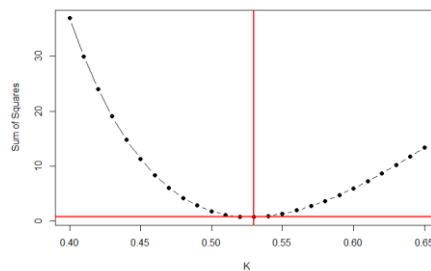


Figure 3.5: Comparison of optimal K -values (0.40–0.65) for LQS at Herrenwies. Based on the optimal result ($K = 0.53$), LAI was estimated and is compared to HP values in Figure 3.7. The red line represents the lowest sum of squares error.

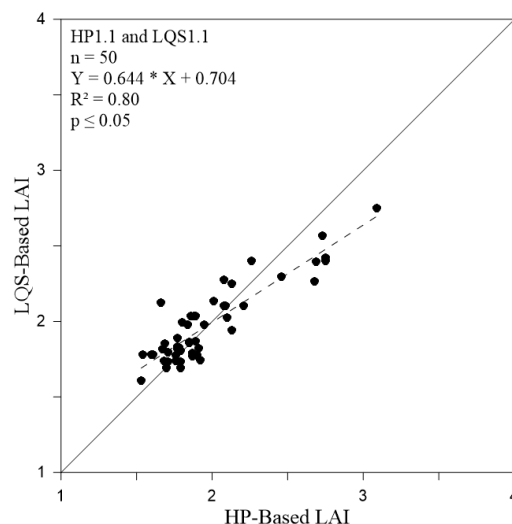


Figure 3.6: Linear regression of LAI values (Hundseck) estimated using HP and LQS with $K = 0.54$. The black line shows a 1:1 relationship; the dashed line represents the regression line.

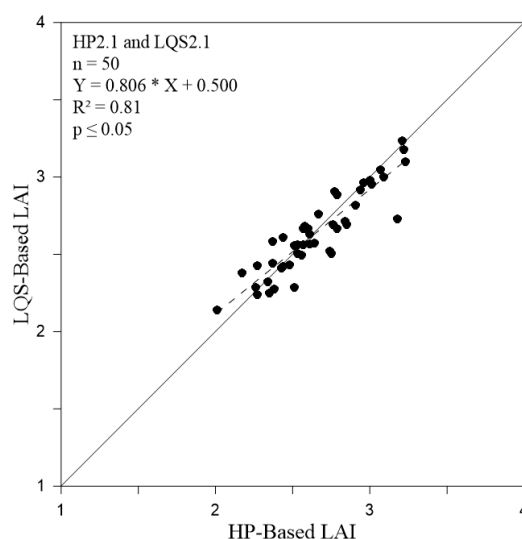


Figure 3.7: Linear regression of LAI values (Herrenwies) estimated using HP and LQS with $K = 0.53$. The black line shows a 1:1 relationship; the dashed line represents the regression line.

Table 3.2. Leaf Area Index (LAI) values obtained through two indirect survey methods, statistical methods: (KS) Kolmogorov-Smirnov test, (W) Wilcoxon test, and (Lm) Linear models.

Site code	<i>n</i>	LAI						Statistical methods		
		Hemispherical			LQS			KS	W	Lm
		Min	Max	Median	Min	Max	Median	p - value		
Managed forested area										
Hundseck (1.1)	50	1.53	2.26	1.865	1.606	2.423	1.867	0.864	0.86	≤0.05
Protected forested area										
Herrenwies (2.1)	50	2.17	3.23	2.595	2.17	3.179	2.646	0.54	0.43	≤0.05

Based on the measured LAI and adjusted K -values, the trends in transmittance values were found to be consistent between stands ($R^2 = 0.94$ and 0.91 at Hundseck and Herrenwies, respectively; $p \leq 0.05$; Figures 3.8 and 3.9).

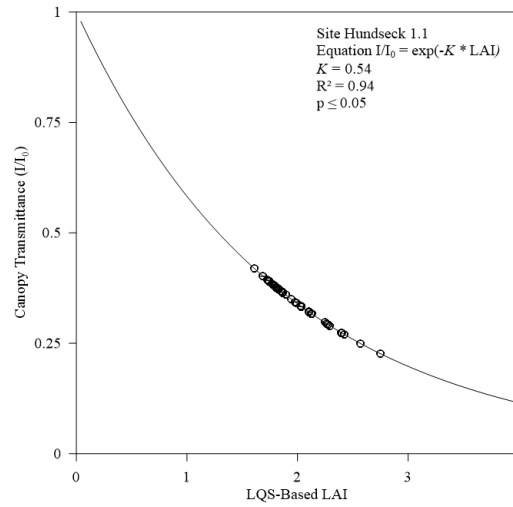


Figure 3.8: Relationship between projected LAI and canopy transmittance (I/I_0) measured at Hundseck (1.1). The Beer–Lambert law defines the curve passing through the data points ($K = 0.54$).

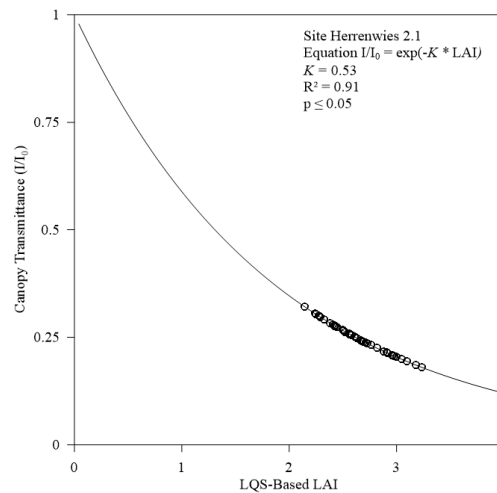


Figure 3.9: Relationship between projected LAI and canopy transmittance (I/I_0) measured at Herrenwies (2.1). The Beer–Lambert law defines the curve passing through the data points ($K = 0.53$).

3.7 Conclusion

We employed a modified Beer–Lambert law to derive site-specific K -values, thereby enhancing LAI estimation accuracy. The range of potential K -values (0.40 – 0.65) may introduce major uncertainties in the analysis of individual forest ecosystems. Given their significant impact on LAI estimates obtained via LQS, it is essential to calibrate K -values for different forest types to improve estimate accuracy. Few studies have evaluated how adjusting K -values affects LAI accuracy in differently managed forests. Our results indicate that forest management practices influence both LAI and K -values, with the protected forest exhibiting

a slightly lower K -value (0.53) compared to the managed forest (0.54). Ground-truthed HP measurements were crucial for selecting the most appropriate value. This study demonstrates that the use of adjusted K -values in LQS-based LAI measurements is applicable in temperate coniferous forests and can be extended to various environmental monitoring projects. Although LQS outperformed HP, some limitations were identified—many of which align with those discussed by Jonckheere et al. (2004) and Tan et al. (2020). Notably, our analysis focused exclusively on transmittance measurements above and below the canopy, without examining the vertical distribution of structural parameters across different canopy layers. Additionally, transmittance data from LQS were collected only in the vertical direction. We found that LQS measurements should be conducted under clear weather conditions to prevent interference from water droplets on the sensors. For maximum accuracy, the instrument should be rotated 360° at a constant speed while held at chest level with outstretched arms to avoid shading from the operator's body, which could be misclassified as vegetation cover. Averaging the readings from a full 360° rotation may enhance estimation precision. Overall, LQS-based LAI estimation proves to be more cost-effective and less time-consuming than manual or automatic methods. This study provides a valuable framework for establishing intensive monitoring networks, particularly in remote areas with complex environmental conditions. The K -value adjustment represents an innovative approach for improving LQS-based LAI estimation in various forest management contexts, facilitating a more precise evaluation of the structural relationship between the horizontal canopy and ground.

3.8 Summary

In Chapter 3, we compared the performance of LQS and HP for estimating LAI in managed and protected temperate coniferous forests and made the following conclusions:

1. Previous LQS-based methods of estimating LAI used K -value ranges, which are unsuitable for the specific conditions of Sugnugur Valley. Our findings support the reliability of using a fixed site-specific K for rapidly estimating LAI.
2. The modified method accounts for the differences between individual ecosystems by applying the optimal K -value for a given vegetation type.
3. The method accurately reflects the dynamic changes of forest canopy structure, allowing for the integration of additional environmental parameters.
4. HP provides high-resolution, spatially comprehensive information on canopy structure with helpful visualization, whereas LQS relies on gap fraction measurements that offer a generalized estimate of canopy information, without visualization.
5. HP is sensitive to direct sunlight, under which images are distorted and LAI is underestimated. In contrast, LQS can be applied in the same conditions, though its accuracy depends on prior calibration using HP.

Based on the current findings, we applied LQS in Chapter 5 for estimating LAI and investigating the changes in ecological parameters in pristine, partly burned, disturbed, and burned forests.

Chapter 4

4 Selection of optimal method for detecting leaf area index: Unmanned aerial vehicle imaging versus hemispherical photography

4.1 Study objectives

In this chapter, we assessed the suitability of unmanned aerial vehicle (UAV) imaging for determining LAI in the Black Forest (south-west Germany) for use in Sugnugur Valley (northern Mongolia). Specifically, this study considered the area, terrain, and geographical and climatological conditions of the study site, as well as the remote nature of Sugnugur valley.

4.2 Data collection prospects using UAVs

The development of high-resolution digital cameras has renewed interest in HP (Frazer et al., 2001), which allows for the immediate processing of digital images. Various studies have compared LAI estimations based on two indirect techniques, i.e., HP and UAV imagery. UAV imaging is time-efficient, though the image-processing method plays a decisive role in estimation accuracy (Danson et al., 2007). Compared to HP, UAV images are more difficult to process owing to difficulties in distinguishing the canopy and leaves from the ground (Schleppi et al., 2007; Gonsamo et al., 2018). Nevertheless, UAV imaging provides a promising technique for informing the setup and validation of various ecological models and applications related to LAI estimation. Moreover, the extensive sensing capabilities of UAVs can aid in long-term forest monitoring.

4.3 Methods

4.3.1 Field measurements

Data collection was performed in four plots split between protected and managed coniferous forest stands (Hundseck and Herrenwies) in the topographically heterogeneous Black Forest of southwest Germany, a humid and temperate climate zone of the mid-latitudes. We compared the LAI values obtained using HP (ground-truthed data) with those estimated using the UAV images taken 100 m above the canopy (Figure 4.1).

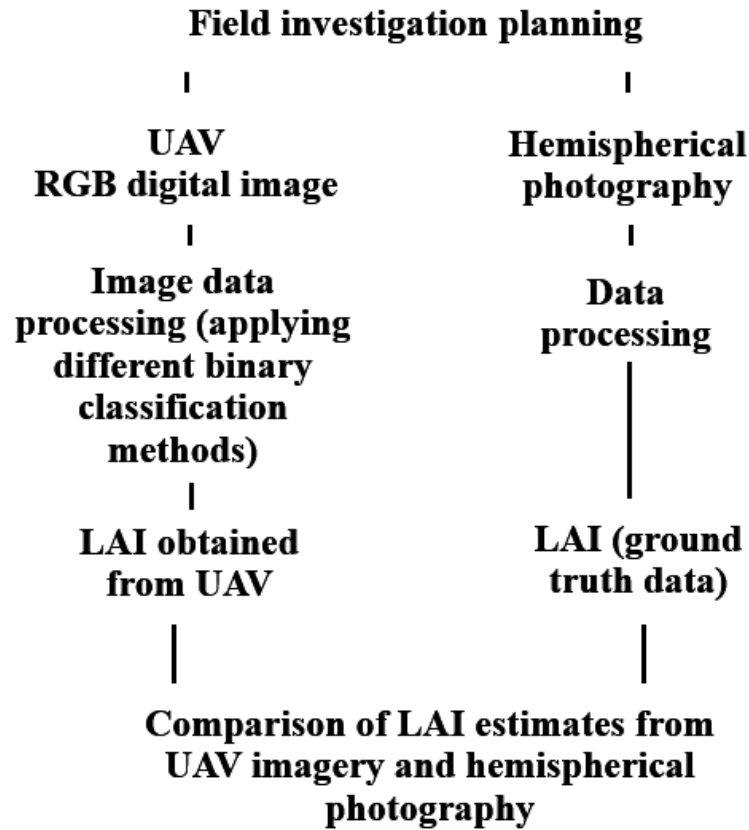


Figure 4.1: Study framework.

The study area is characterized by highly diverse ecological conditions and a large contiguous forest area of ~391 000 ha (Figure 4.2). According to the National Forest Inventory in Germany, forests in this area are ~80% coniferous (spruce, fir, and pine) and ~20% deciduous (beech, birch, and oak) and ~110 years old (Steinkamp et al., 2001; Yousefpour et al., 2010). Based on our field measurements, tree density was ~0.8/100 m² and the average TBH was 97 cm.

The Black Forest is a low mountainous region in southern Germany that rises from the Upper Rhine Graben with highly variable elevations. The mean annual air temperature is ~6 °C. Depending on the altitude, the average annual precipitation is 1700–2000 mm (Ludemann, 2010).

LAI monitoring was performed in the large-scale managed forest stand at Hundseck (953 m a.s.l.) and protected forested area of Herrenwies (875 m a.s.l.). On December 20, 2019, and from February 4 to August 30, 2020 (Table 4.1), we performed HP using the fisheye lens-fitted Nikon D7000 digital camera and UAV imaging using a Mavic-Mini (DJI, Shenzhen, China), which has four propellers, an optical camera, global positioning system (GPS) receiver, and self-calibrating gimbal. The camera can take 12 MP images and videos at 4K resolution (3,840 × 2,160) (Carter, 2019). The flight route (Figure 4.2), altitude, overlap degree, and camera parameters were manually set. The flight altitude was set to 100 m, the heading overlap to 90%, and side overlap to 80%. During flight, images were automatically captured every 5 s. Data were collected in four permanent quadrants distributed over intensively monitored subplots covering 100 × 100 m each. Measurements were usually

conducted either shortly before sunset or under overcast conditions. The UAV images were cropped to remove ineffective areas and the identical area captured by HP. Each extracted grid image was processed through binary classification to distinguish the ground and tree components.

Within each quadrant, HP was conducted from a height of 1 m above ground level using the fisheye lens-fitted Nikon D7000 digital camera mounted on the tripod (Dörr Airpod). The camera was operated in program (P) mode, wherein exposure time and aperture settings were automatically determined. To mitigate camera shake, all photographs were captured using the automatic release function. The resulting images were saved as high-resolution uncompressed files ($4,928 \times 3,264$ pixels).

UAV imagery were usually collected on the same day and under the same conditions as the HP. The inertial measurement unit and compass were always calibrated and leveled with the previous plot to obtain comparable readings.

The obtained LAI values were compared between the methods using the Kolmogorov–Smirnov (Birnbaum & Tingey, 1951; Conover, 1971; Durbin, 1973; Marsaglia et al., 2003), Wilcoxon (Bauer, 1972; Hollander & Wolfe, 1973, 1999), and linear regression tests (Wilkinson & Rogers, 1973; Chambers, 1992) in RStudio (RStudio Team, 2015). The analyses showed that the two indirect methods obtained comparable LAI values.

Table 4.1 Dates of photographs and UAV measurements

						Photographs ands UAV measurements				
Site name	Site code	Longitude	Latitude	Altitude a.s.l (m)	Main tree species					
						2019	2020			
Managed forested stands										
Hundseck.U	HU1.1	08°13'35'E	48°38'33'N	929	<i>Picea abies</i>	Dec.20	Feb.04/ Feb.09	Mar.04	May.13/ Jun.07	Aug.10/ Aug.30
Hundseck.B	HU1.2	08°13'55'E	48°38'27'N	864						
Protected forested stands										
Herrenwies.U	HE2.1	08°16'30'E	48°39'50'N	784	<i>Pciea abies</i>	Dec.20	Feb.04	Mar.04	May.13/ Jun.07	Aug.10/A ug.30
Herrenwies.B	HE2.2	08°16'26'E	48°39'37'N	866						

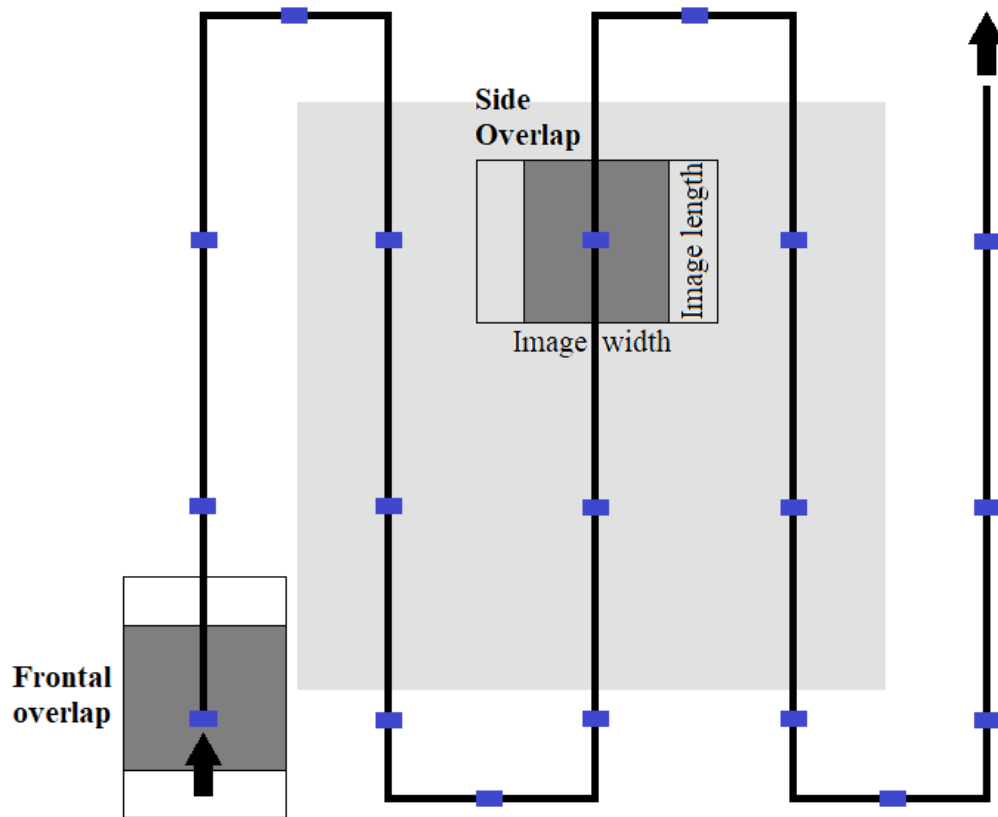


Figure 4.2: UAV flight plan over the experimental plots with 90% frontal and 80% side overlap (the rectangles represent capture-stops).

4.3.2 Processing of hemispherical photographs

Hemispherical photographs can be processed using several approaches to estimate LAI. Initially, the images were converted into binary black-and-white format utilizing the algorithm proposed by Nobis and Hunziker (2005). The optimal threshold to differentiate the sky (white) from the canopy (black) was determined based on the pixel borders with the steepest color gradients across any combination of red, green, and blue (RGB) channels. In standard file formats, physical light intensity is encoded as brightness values (of 0–255) following a power law, where the exponent (γ) is typically set to 0.45 for digital still cameras (Thimonier et al., 2010); consequently, most optical methods for LAI estimation employ this γ value for thresholding.

In Hemisfer 2.2 (Schleppi et al., 2007), several equations are available to calculate LAI, including Miller’s method, Lang’s equation, and the inversion method, which assumes an ellipsoidal leaf angle distribution. Under the inversion method, the application provides two outputs: one based on the approach of Norman and Campbell (1989) and another derived by minimizing the sum of squared errors between the measured and predicted contact frequencies—errors that are weighted by the solid angle of each concentric ring (Schleppi et al., 2007). Hemispherical photographs were partitioned into zenithal sectors using concentric

rings and, within each ring, the proportion of visible sky (or gap fraction) was calculated to determine the contact frequency.

HP distinguishes between light intercepted by foliage and other plant parts (stems and branches). The LAI estimates obtained from the photographs were corrected directly, based on the optimal threshold used to distinguish between sky and canopy, using the algorithm of Schleppi et al. (2007).

4.3.3 Processing of UAV images

Miller's method was implemented to estimate LAI from the UAV images. Selecting an appropriate classification method is important to distinguish tree pixels in the foreground and background and improve the accuracy of LAI estimation. In general, binary classification is applied because of the intense brightness of vegetation pixels compared with the background (Sold, 2010; Garvelmann et al., 2013). The binary image classification should satisfy two criteria: First, it should account for varying illumination conditions and provide stable performance for highly dynamic contrasts. Second, it should sensitively reflect the canopy leaf area dynamics. Only the foreground leaf area should be included, otherwise the superposed ground vegetation in the background will overestimate the LAI, even after light changes.

We compared the following binary thresholding classifiers used to extract targets from complex backgrounds: MaxEntropy (Kapur et al., 1985), Huang (Huang & Wang, 1995), IsoData (Ridler & Calvard, 1978), Li (Li & Tam, 1998), MinError (Kittler & Illingworth, 1986), and Otsu (Otsu, 1979). Detailed descriptions of the algorithms are provided by Sezgin and Sankur (2004). Binary processing was executed using ImageJ software (Collins, 2007). Figure 4.3 shows representative binary images obtained using the six classifications (the original images are shown for reference). The MinError classifier reflected leaf area variations more accurately than the other methods. A common disadvantage of the other methods is that they classify more leaf area pixels in situations with low LAI (Figure 4.3), failing to accurately reflect leaf area dynamics. To determine an appropriate binary classification method for the UAV images, the processed images were compared to the ground-truthed HP imagery (Figures 4.4 and 4.5). The MinError classification produced optimal thresholds for the images, indicating that the other methods overclassified the leaf area pixels. Otsu showed comparable LAI values (Figure 4.4), but the LAI was slightly decreased compared with MinError. Otsu classification has been used for single-tree LAI estimation from UAV images of *Citrus reticulata* stands (Raj et al., 2020). Therefore, this method may be more applicable for single-tree stands than for mixed coniferous stands (Figure 4.3). Accordingly, the MinError binary classification method was applied to all UAV images. We compared the LAI results between the temperate coniferous forest stands in Figures 4.4 and 4.5 (Spanner et al., 1990).

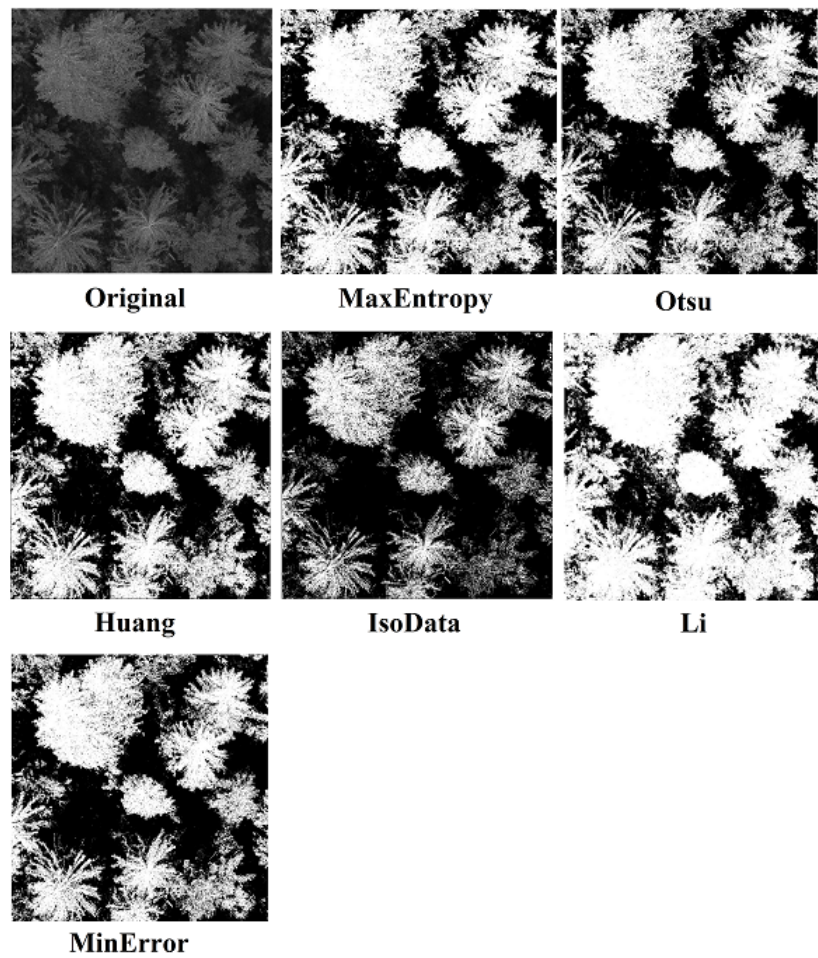


Figure 4.3: UAV and binary classified imagery derived from different methods.

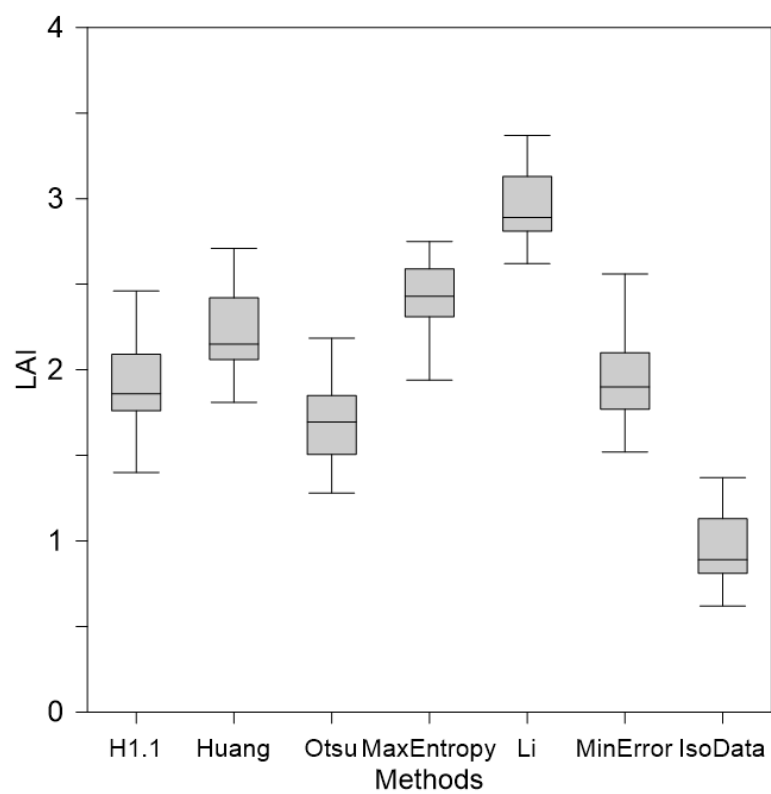


Figure 4.4: Comparison of LAI obtained from UAV images processed using various binary classified methods. The estimated LAI was compared with HP values (HU1.1) (Table 4.2).

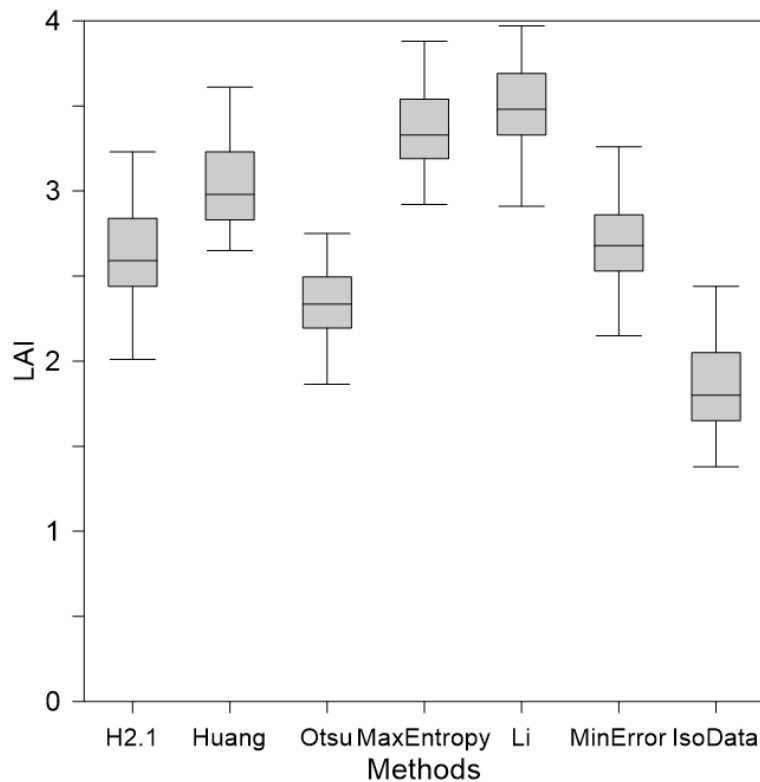


Figure 4.5: Comparison of LAI obtained from UAV images processed using various binary classified methods. The estimated LAI was compared with HP values (HE2.1) (Table 4.2).

4.4 Results

The LAI estimates for the HU1.1 and HU1.2 plots accurately reflected the managed coniferous forest stands since both indirect methods generated lower LAI estimates than those of the cross-referenced coniferous forest stands (Figure 4.6) (Spanner et al., 1990). Raj et al. (2019) noted that LAI estimates below 1.7 were representative of open-canopy or managed forest stands. The LAI values in the managed forest stands (HU1.1 and HU1.2; Table 4.2) were lower than those in the protected forested stands estimated using both indirect methods.

Figures 4.7–4.10 illustrate moderate to strong positive correlations ($R^2 = 0.75$ for Hundseck and 0.71 for Herrenwies) between the LAI values obtained using the two survey methods, indicating that the UAV-based LAI values were highly comparable to the ground-truthed HP-based values. The LAI of the managed forest stands was relatively low, consistent with previous findings in managed forests with temperate and humid climates (Hausler & Scherer-Lorenzen, 2001). The LAI values for the protected forest areas were comparatively high (Figures 4.7 and 4.8), likely owing to the numerous young trees. These trends were consistent for both indirect methods. The MinError classifier was superior to the other algorithms in determining LAI from the UAV images; therefore, this method was employed in the final image analyses.

Table 4.2 LAI values obtained through two indirect survey methods

Site code	<i>n</i>	LAI						Statistical methods		
		Hemispherical photograph (H)			UAV images (D)			K	W	Lm
		Min	Max	Median	Min	Max	Median	p - value		
Managed forested area										
HU(1.1)	51	1.4	3.09	1.86	1.52	3.19	1.9	0.41	0.72	≤0.05
HU(1.2)	27	1.87	2.46	2.13	1.81	2.39	2.11	0.88	0.74	≤0.05
Protected forested area										
HE(2.1)	51	2.01	3.23	2.59	2.15	3.26	2.68	0.38	0.40	≤0.05
HE(2.2)	51	2.06	3.48	2.94	2.015	3.41	2.91	0.11	0.07	≤0.05

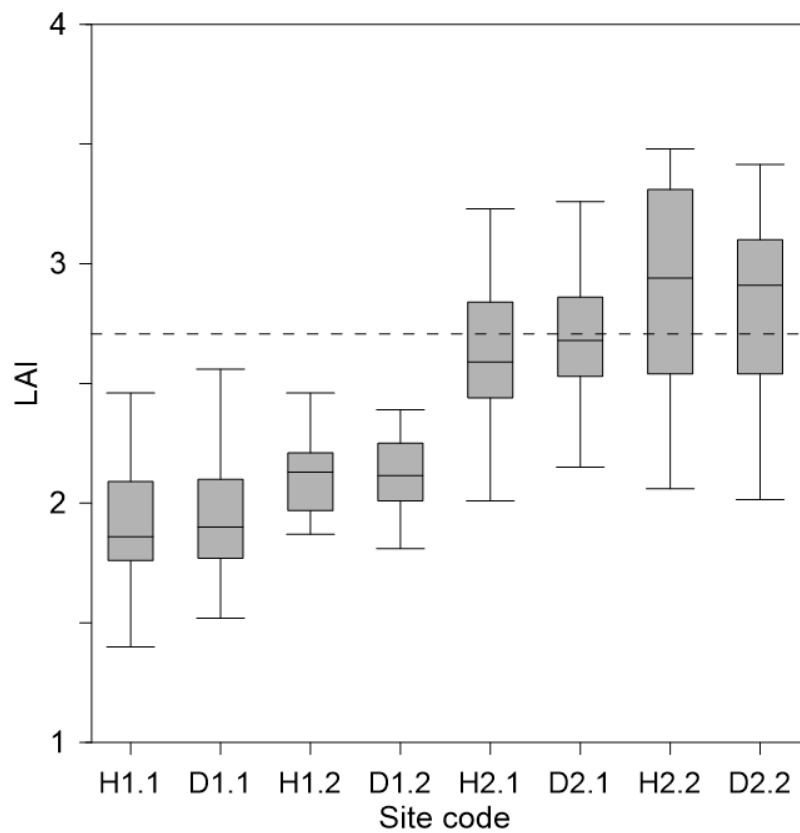


Figure 4.6: Comparison of LAI values (Hundseck: 1.1, 1.2; Herrenwies: 2.1, 2.2) from the hemispherical photographs (H), UAV images (D), and global temperate forest average (dashed line) (Asner et al., 2003). The number following each letter on the x-axis represents the site code.

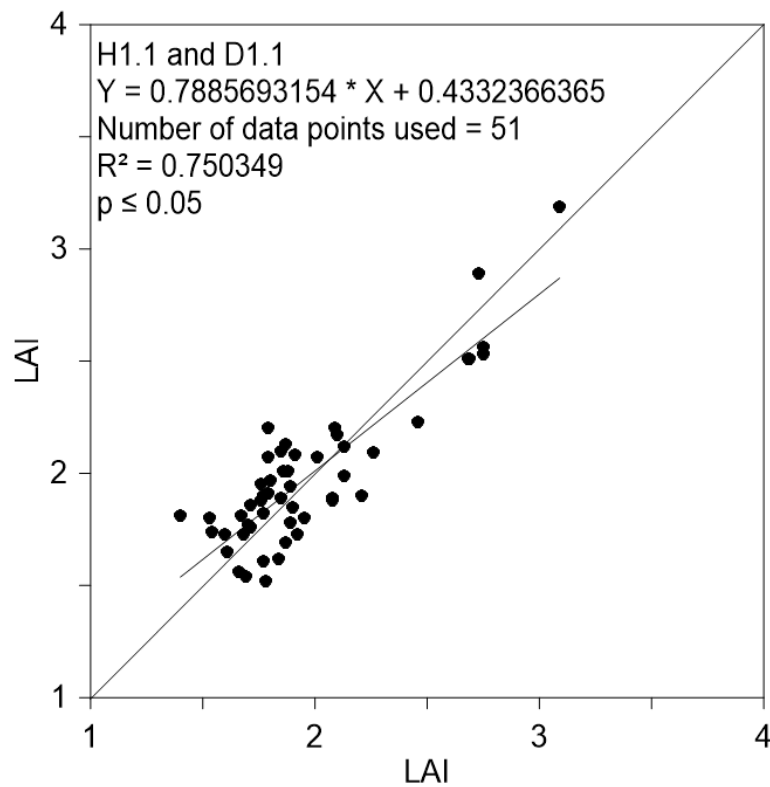


Figure 4.7: Linear regression of LAI values (site code HU1.1) from the hemispherical photographs (H1.1) and UAV images (D1.1) for Hundseck.

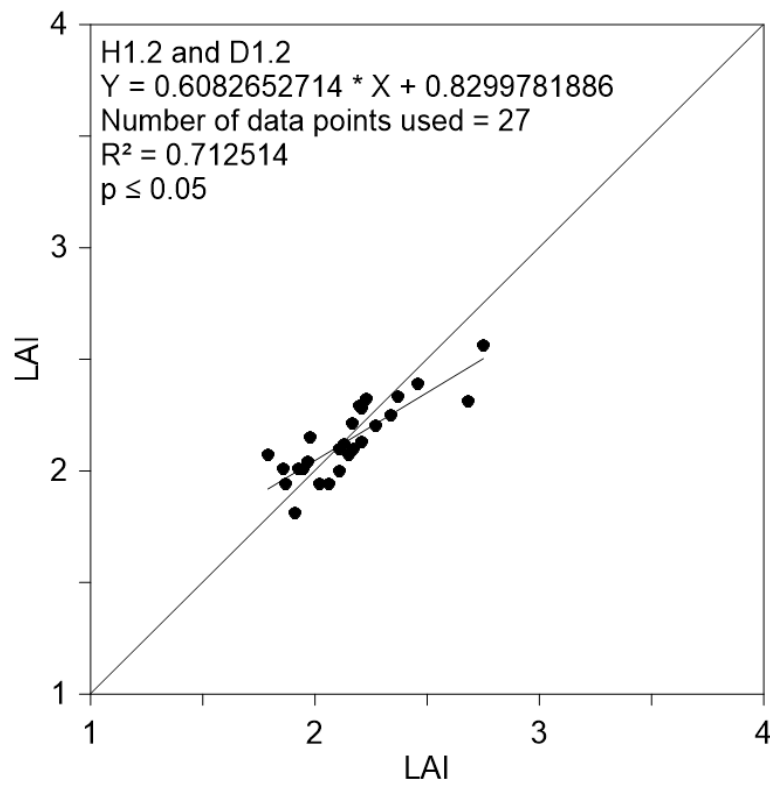


Figure 4.8: Linear regression of LAI values (site code HU1.2) from the hemispherical photographs (H1.2) and UAV images (D1.2) for Hundseck.

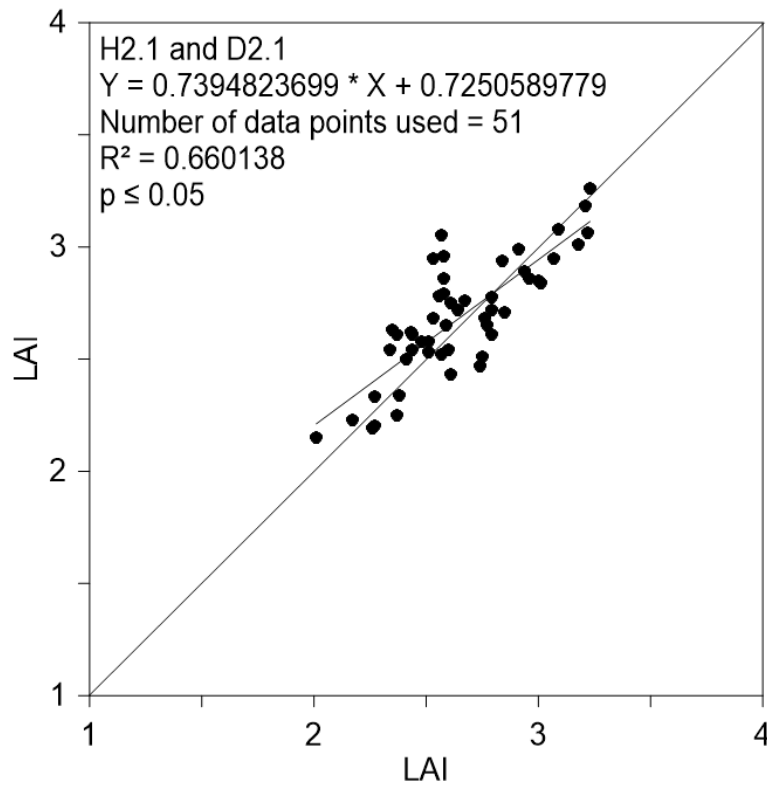


Figure 4.9: Linear regression of LAI values (site code HE2.1) from the hemispherical photographs (H2.1) and UAV images (D2.1) for Herrenwies.

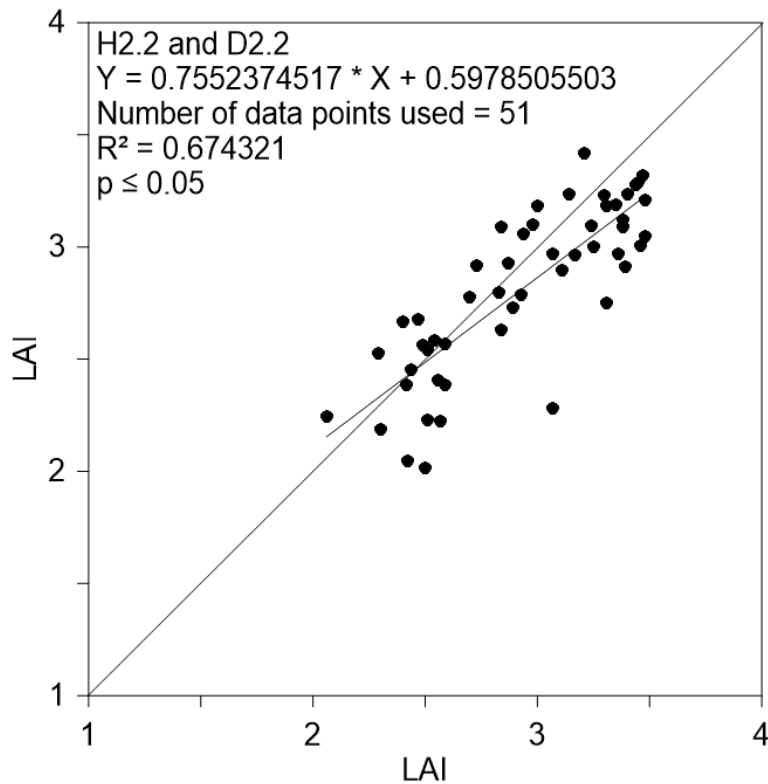


Figure 4.10: Linear regression of LAI values (site code HE2.2) from the hemispherical photographs (H2.2) and UAV images (D2.2) for Herrenwies.

4.5 Discussion

In this study, we used optical-based indirect methods to estimate LAI in managed and protected forests. The HP- and UAV-based methods both performed well, though they showed some limitations, many of which have been discussed by Olivas et al. (2013) and Chason et al. (1991). Specifically, to ensure successful monitoring and improve imaging accuracy, the UAV should be operated in stable weather conditions to reduce image blur. To calculate vegetation cover across heterogeneous terrain while accounting for the difficulties associated with flying at a constant height, speed, and angle under changing wind conditions, multiple flights are required at different speeds according to site-specific conditions (i.e., vegetation type and topography). For both indirect methods, imaging should ideally be performed during the hours just prior to sunrise or sunset to avoid misclassification of solar reflections on the leaf area as sky or ground and reduce bias in LAI estimation.

The findings suggested that UAV imaging is appropriate for measuring LAI dynamics across managed and protected coniferous forest stands. This method is also more cost- and time-efficient than both manual and automated approaches, making it particularly well-suited for establishing extensive monitoring networks in regions with complex environmental conditions. Notably, since the distance of the UAV to the canopy influences LAI estimation, a constant flight height is important for comparisons between locations. In our study, the optimal flight height was 100 m based on image quality and weather conditions. Although the analytical framework for digital photographs is similar to that for remote sensing data, this indirect measurement approach may introduce some uncertainties (Dong & Menzel, 2017). For example, the accuracy of image-based LAI is sensitive to the weather and requires stable conditions (Li et al., 2021). Nevertheless, although the study sites were highly heterogeneous, the UAV and ground-truthed HP estimates showed strong positive relationships, demonstrating the applicability of UAV imaging as a low-cost method for LAI classification in varying ecological monitoring projects.

4.6 Conclusion

Both HP and UAV imaging provide accurate estimations of LAI because, unlike other techniques, they offer a time-sensitive record of the canopy structure, enabling the visualization of the distribution and size of canopy gaps. However, scattered clouds are problematic for both methods. UAV imaging requires less time than HP owing to the development of high-resolution digital cameras, automated navigation, and obstacle-free flight as well as advanced software for digitizing time-lapse photography. In HP, automatic thresholding may reduce the sampling time and avoid the subjective bias introduced by manual thresholding in UAV images; however, automatic thresholding does not allow for the correction of errors in LAI estimation due to non-optimal exposure. Further investigations of temporal and spatial variations should help to interpret the differences in LAI estimates obtained using these methods. To ensure the accuracy of LAI estimates, measurements using UAV imaging and HP should be repeated throughout the year to confirm their temporal alignment with stand phenology. These measurements can be supplemented with concurrent radiation recordings above and below the canopy. Furthermore, the method's reproducibility should be evaluated by conducting repeated measurements at intervals of several days during periods of maximum LAI under varying light conditions (e.g., overcast skies, pre-sunrise, and post-sunset). Additionally, immediate re-measurements at the same locations following the initial series may help identify any biases related to fluctuating light conditions.

4.7 Summary

We compared the LAI estimates obtained using UAV imaging and HP in managed and protected temperate coniferous forests and made the following conclusions:

1. UAV imaging, processed using the MinError thresholding classifier, provides a rapid cost-effective approach for LAI estimation, with highly comparable performance to HP. The optimized UAV method demonstrates reliable performance across diverse forest conditions, supporting its potential for extensive ecological monitoring and the integration of additional environmental parameters.
2. The output can also be used to create high-resolution maps of forest status, such as burned, pristine, and disturbed forests.
3. UAV images require a low flying altitude (~100 m) for maximum resolution. The high energy requirement may not be optimal for remote areas with no electrical supply, such as Sugnugur Valley.
4. For Sugnugur Valley, the UAV should be operated at a higher altitude to cover large areas in short periods of time with as little energy as possible.

Based on the findings of Chapters 3 and 4, we applied the HP technique for estimating LAI and UAV technique for collecting aerial information in Chapter 5 to investigate changes in ecological parameters across pristine, partly burned, disturbed, and burned forest stands.

Chapter 5

5 Major drivers of forest cover loss and their effects on forest structure and soil properties in the Khentii Mountains, northern Mongolia

5.1 Study objectives

We systemically investigated the complex relationships between wildfires, anthropogenic damage, and forest health. This study aimed to comprehensively characterize (1) the impact of wildfires on forest structure, (2) drivers of forest cover loss, and (3) changes in soil properties following forest damage in the Khentii Mountains, northern Mongolia. Our work elucidates the ecological and geological effects of forest damage in a remote mountainous headwater area and reveals the impact of wildfire and anthropogenic damage on forest structure and soil properties. This study contributes to the data availability of an underreported mountainous region with complex geographical features and serves as a useful reference for future forest-fire monitoring studies.

5.2 Impacts of wildfire on forest structure and composition

The boreal forests of northern Mongolia play a crucial role in maintaining regional ecosystem functions and water supply. In the Khentii Mountains, between the boreal forests and dry steppes, extensive forest fires and large-scale deforestation have occurred over the last several decades. We investigated the effects of wildfires and logging on forest stand recovery along with the associated changes in forest composition, structure, and soil properties. The forests in the region were classified into four categories, natural forest (NF), partly burned forest (PBF), burned forest (BF), and disturbed forest (DF, Figure 5.1), each with unique compositions and structures. The NF site primarily comprised conifers, larches, and birches. Tree species composition was fairly similar in the NF and PBF sites, whereas that in the BF mainly comprised young Siberian birch (*B. platyphylla*), with few conifers. The diversity of forest floor vegetation was lower in the DF and BF sites than in the PBF and NF sites. We analyzed the physical and hydrological characteristics of soil samples and observed clear differences in soil temperature and texture between the BF and PBF sites. Silt generally dominated; however, the soil of the BF had lower amounts of silt and clay than that of the PBF.

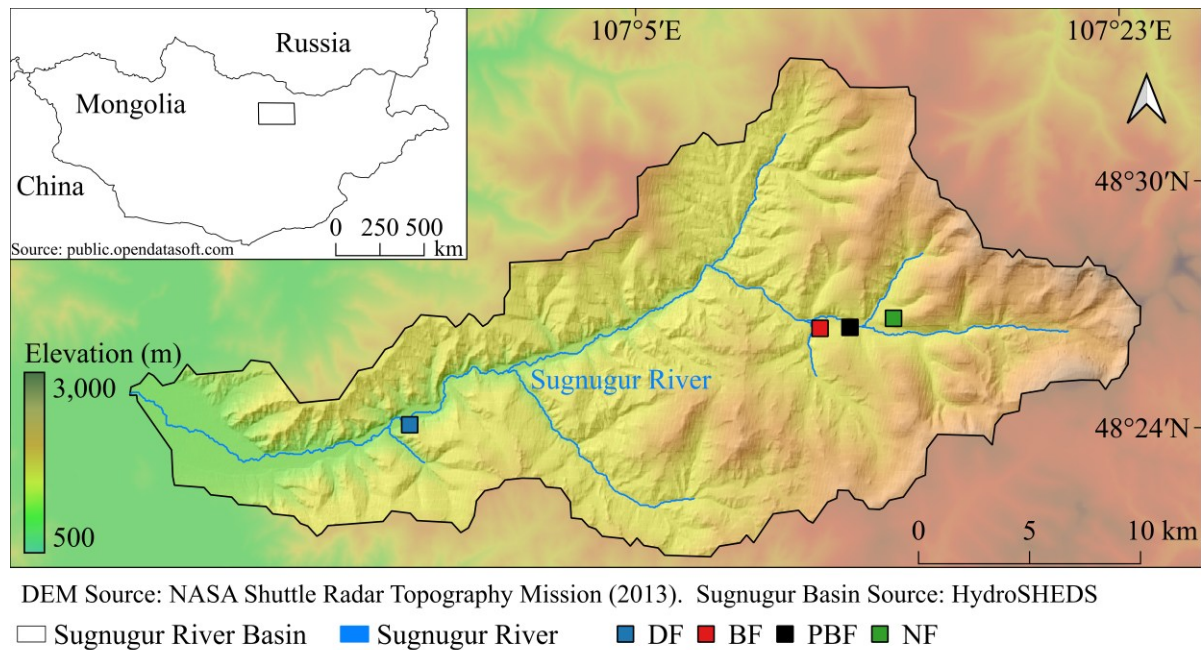


Figure 5.1: Digital elevation map (DEM) of the study area indicating the positions of the forest plots. The colors indicate the vegetation categories: disturbed forest (DF; blue), burned forest (BF; red), partly burned forest (PBF; black), and natural forest (NF; green). The top-left inset indicates the international borders of Mongolia, along with the location of the study area (black square). NASA, National Aeronautics and Space Administration.

5.3 Methods

5.3.1 Study sites and fieldwork

The DF site was adjacent to a forest-based settlement and subjected to selective logging and livestock grazing. The BF site was completely destroyed by a fire. The PBF site was partially destroyed by a fire. The NF site was relatively undamaged. Soil samples were taken from the NF bottom (NFB), PBF bottom (PBB), BF bottom (BFB), DF bottom (DFB), unburned valley (UBV), and south-sided slope bottom (SB). Site details are shown in Table 5.1.

Table 5.1: Site locations and information.

Site name	Site code	Elevation (m)	Longitude	Latitude	Vegetation	Slope °
Natural forest	NF	1,733	48°26'89.9" N	107°14'20.9" E	Forest area	30
Natural forest bottom	NFB	1,638	48°26'84.6" N	107°13'84.4" E	Forest area	11
Partly burned forest	PBF	1,552	48°26'72.2" N	107°12'61.7" E	Forest area	27
Partly burned forest bottom	PBB	1,518	48°26'80.6" N	107°12'55.6" E	Forest area	16
Burned forest	BF	1,509	48°26'70.7" N	107°11'49.9" E	Forest area	24
Burned forest bottom	BFB	1,500	48°26'75.1" N	107°11'47.6" E	Forest area	19
Disturbed forest	DF	1,199	48°24'63.3" N	106°56'44.5" E	Forest area	25
Disturbed forest bottom	DFB	1,184	48°24'65.0" N	106°56'44.2" E	Forest area	8
Unburned valley	UBV	1,477	48°26'99.4" N	107°11'59.1" E	Non forest-type	36
South-sided slope	SB	1,530	48°26'66.0" N	107°13'33.2" E	Non forest-type	5

In each forest stand, we measured and demarcated four plots, each with an area of 2500 m² (50 × 50 m, total area of 10 000 m²). The geographic coordinates and elevations of each plot

were recorded using a Garmin GPS (Olathe, KS, USA). The corners of each plot were marked with white paper sheets for clear visibility and accurate measurement. Approximately 6,000 UAV images were captured over 70 000 m² to create a high-resolution orthomosaic map, used for comparisons with field survey results (Figure 5.2).

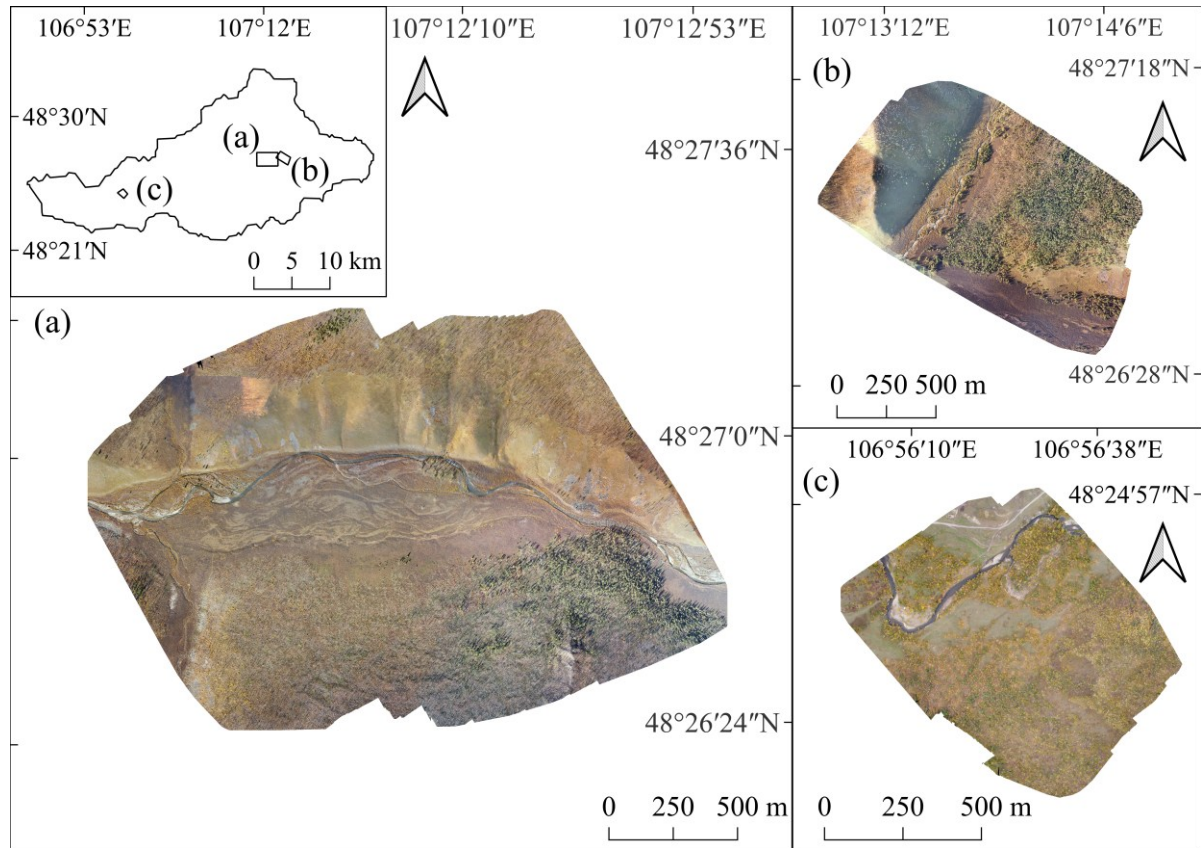
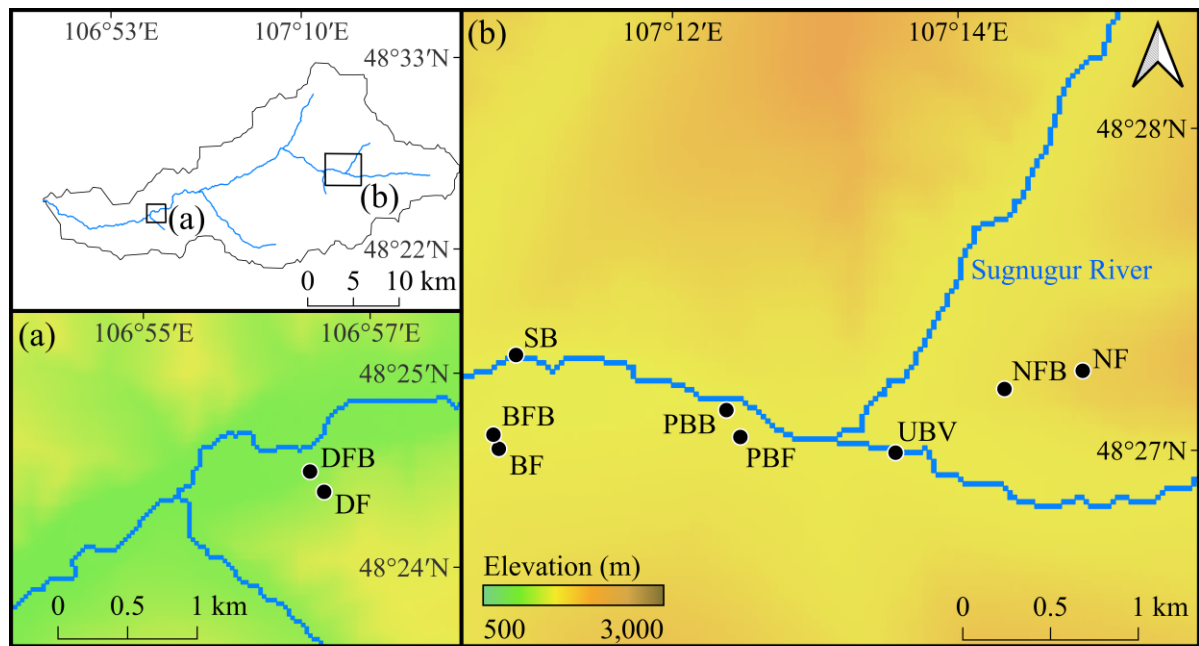


Figure 5.2: Orthomosaic map of Sugnugur Valley developed using UAV imaging, portraying the topography of the study area. (A) Main valley, which includes both BF and PBF; (B) NF; (C) DF (see appendices for details).

The high-resolution orthomosaic map clearly reveals the boundaries of forests and vegetation cover, valley slopes, and wildfire-affected areas (Figure 5.2).

The soil sampling sites are shown in Figure 5.3. To investigate soil properties, soil samples were collected using 100-cm³ sampling rings (Eijkelkamp, Giesbeek, Netherlands). A total of 26 boreholes were created up to a depth of 100–150 cm (Figure 5.4), and the presence of the water table was documented. Three soil samples were taken from the DF and DFB sites, two from the BF and BFB sites, four from the PBF site and three from the PBB site, and two from the NF and NFB sites (above a depth of 40 cm due to rock formations). Two samples each were collected from the UBV and SB sites. All samples were collected within 1 week as each borehole took 4–7 h to dig, depending on soil structure. The soil profiles were sampled horizontally, with thick horizons subdivided for further sampling. Soil temperature was measured in situ at 5-cm intervals using a thermometer (GHM Messtechnik GmbH Standort Greisinger, Remscheid, Germany).



DEM Source: NASA Shuttle Radar Topography Mission (2013). Sugnugur Basin Source: HydroSHEDS

□ Sugnugur River Basin ■ Sugnugur River ● Locations of soil samples

Figure 5.3: Topography of study area and locations of soil sampling sites. The black dots with abbreviations indicate the soil sampling locations: disturbed forest (DF) and DF bottom (DFB), burned forest (BF) and BF bottom (BFB), partly burned forest (PBF) and PBF bottom (PBB), natural forest (NF) and NF bottom (NFB), along with unburned valley (UBV) and south-sided slope bottom (SB). The top-left inset portrays the Sugnugur Valley basin and location of the study area. The soil profiles are shown in Figure 5.7. DEM, digital elevation map; NASA, National Aeronautics and Space Administration.

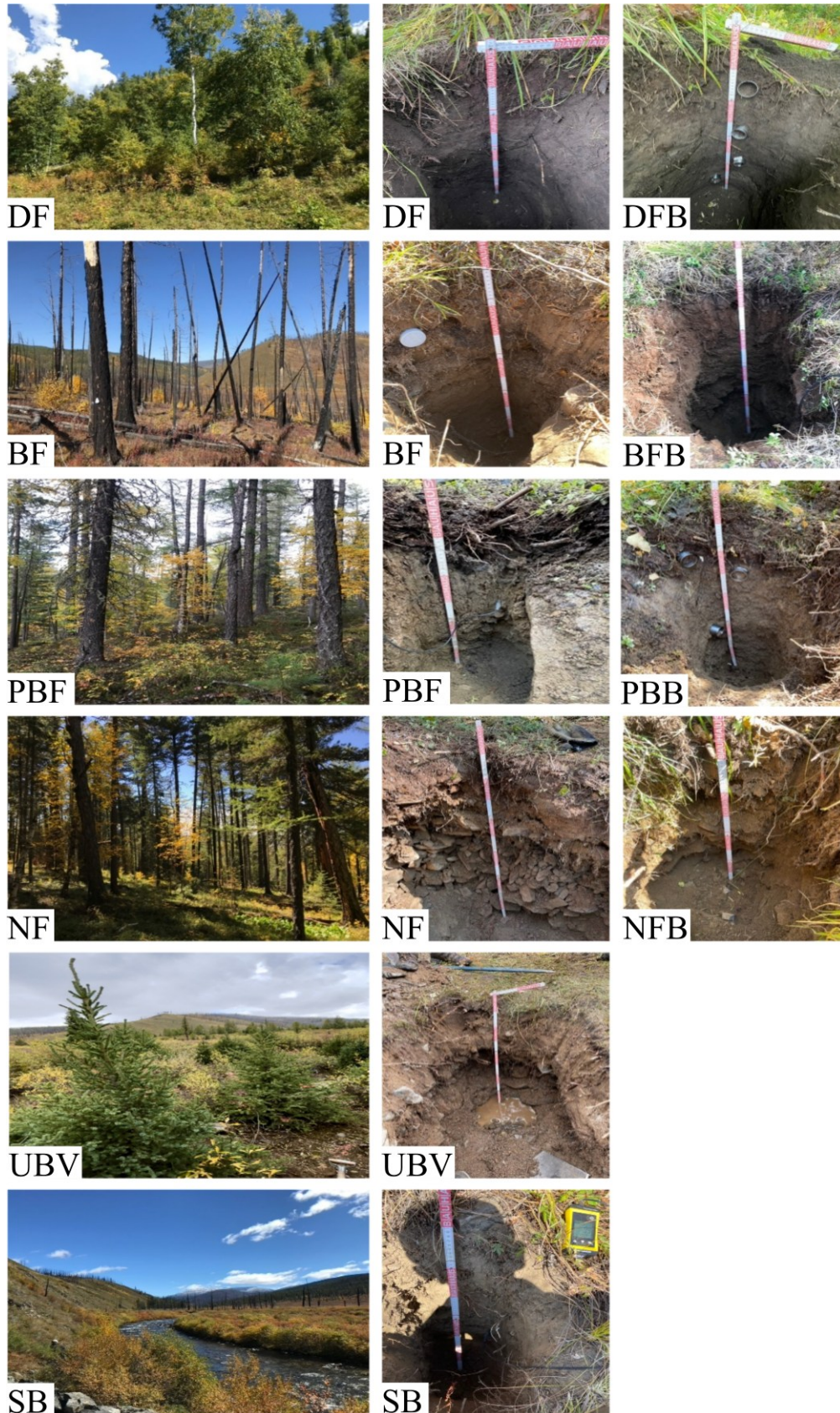


Figure 5.4: Forest conditions in six study locations. Images on the left indicate conditions for disturbed forest (DF), burned forest (BF), partly burned forest (PBF), and natural forest (NF), along with the locations of the transitional zones between the burned and unburned forest areas. The unburned valley (UBV) was located between the PBF and NF. The south-sided slope bottom (SB) was located between the NF and BF (see Appendices for details, Figure

4.A). The middle and right images depict the boreholes corresponding to each site. The images to the right depict the boreholes for the DF bottom (DFB), BF bottom (BFB), PBF bottom (PBB), and NF bottom (NFB).

5.3.2 Tree census and classification

5.3.2.1 Tree inventory and characterization

At each study site, we conducted a systematic survey of the living and dead trees reaching at least 140 cm in height. Only standing trees were considered (fallen trees were excluded). The species was recorded on site if immediately identifiable; in general, it was easy to identify living trees, unlike dead trees. If a species of living tree was not identifiable, photographs were captured for later identification in literature resources (Sharkhuu & Anarmaa, 2012). We also recorded the living/dead status and DBH of each tree.

5.3.2.2 Measurement of DBH

The DBH of the trees was determined by measuring the circumference of each tree at breast height (140 cm) using a measuring tape held horizontally and tightly around the tree trunk. The measurement was conducted while standing on the slope above the tree. For multi-stemmed trees, each stem was considered an individual entity, and the circumference of each stem was recorded separately.

5.3.2.3 Determining tree height

The height of 9–16 randomly selected living trees from each site was measured using a clinometer (PM-5; Suunto, Vantaa, Finland). We pinned one end of a measuring tape to the ground at a distance of 20 m from the tree (along the same elevation) and viewed the peak of the tree through the clinometer while recording the degree of inclination. The height of each tree was calculated using Equation 1:

$$\text{Tree height} = (\tan(Di) \times Ds) - Bh, \quad (1)$$

where Di represents the degree of inclination, Ds represents the distance between the tree and measurer, and Bh represents the height of the individual who measured the tree height.

5.3.2.4 Estimating LAI using HP

The LAI at each site was determined from HP data (described in Chapter 3). We captured 67–70 photos at each site except the BF site, where only 50 images were captured due to poor light conditions (see Section 3.4.2).

5.3.3 UAV-assisted data collection

The Mavic-Mini UAV (DJI) was used for data collection as described in Chapter 4. We captured approximately 300 and 900 images at the DF and NF sites, respectively. The UAV is equipped with a four-propeller system, 12 MP camera with 4 K (3,840 × 2,160) video capabilities, GPS receiver, and self-calibrating gimbal. Flight parameters, including flight route, altitude, overlap degree, and camera settings, were set manually to ensure that the data

were of high quality. The heading overlap was set to 90% and side overlap to 80%. The camera was programmed to automatically capture images every 5 s. The BF and PBF sites were located near each other; therefore, we combined these sites and collected ~4800 images. The UAV was set to fly at an altitude of 300 m to obtain a comprehensive overview of the study area. However, owing to heavy winds, the flight altitude for the DF site was set to 150 m. To obtain more detailed images, the flight altitude was reduced to 150 m. All flights were conducted during daylight hours to promote image quality.

5.3.4 Drivers of forest cover loss

To identify the drivers of forest cover loss in Mongolia, we used datasets from the National Statistics Office (2023) and Global Forest Watch (2023). We analyzed forest fire frequency (National Statistics Office, 2023) on monthly and seasonal scales.

5.3.5 Measurement of soil properties

5.3.5.1 Determining organic and carbonate contents

We determined the contents of organic matter and carbonates in all soil samples using the loss-on-ignition (LOI) method (Heiri et al., 2001). The samples were first dried overnight at 40 °C to eliminate moisture and then passed through a 2-mm sieve to remove large particles.

For accurate and precise measurements, we weighed each soil sample to ~16 g using a high-performance scale (AX205, Mettler Toledo, Columbus, OH, USA), which provides a controlled and enclosed environment, mitigating errors caused by wind and contaminants. The samples were placed in pre-weighed crucibles and dried again at 105 °C overnight to determine the remaining water content.

Thereafter, the organic matter was burned at 550 °C for 6 h, and the carbonates were burned at 950 °C for 2 h. The samples were cooled to room temperature in a desiccator to ensure accurate measurement. LOI analyses were performed using a muffle furnace equipped with a digital temperature display and thermostatically regulated temperature control. The LOI was calculated as follows:

$$LOI_{550} = \left(\frac{DW_{105} - DW_{550}}{DW_{105}} \right) \times 100, \quad (2)$$

where LOI_{550} represents the percentage weight loss of a sample upon heating to 550 °C, DW_{105} represents the initial dry weight of the sample prior to combustion, and DW_{550} represents the final dry weight of the sample after heating.

In the second step, carbon dioxide was liberated from the carbonates, resulting in the formation of oxides, and the LOI was determined as follows:

$$LOI_{950} = \left(\frac{DW_{550} - DW_{950}}{DW_{105}} \right) \times 100, \quad (3)$$

where LOI_{950} represents the percentage LOI at 950 °C, DW_{550} is the dry weight of the sample after the combustion of organic matter at 550 °C, DW_{950} is the dry weight of the sample after

heating to 950 °C, and DW_{105} is the initial dry weight of the sample prior to the combustion of organic material.

5.3.5.2 Grain size distribution analysis

An ANALYSETTE 22 NeXT (Fritsch GmbH, Idar-Oberstein, Germany) particle size analyzer was used to determine the grain size distribution of the soil samples. Prior to the analysis, the soil samples were dried at 40 °C to remove moisture. A 2-mm sieve was used to remove larger particles other than sand, silt, and clay. Approximately 0.4 g of each sample was placed in Falcon tubes and treated with 1 mL of 12% hydrochloric acid to dissolve the carbonates. Two-thirds of the tubes were filled with distilled water, and the chemical reaction was allowed to proceed for ~48 h. To stop the reaction, each sample was rinsed twice with distilled water and centrifuged for 5 min at 2600 g.

The soil organic matter was dissolved by adding 0.7 mL of 15% hydrogen peroxide to the samples, which were placed in a water bath at a constant temperature of 50 °C for ~72 h. The samples were then washed three times. To disperse and prevent the particles from reaggregating, the samples were treated with 1 mL sodium pyrophosphate 12 h prior to measurement using an overhead shaker. The grain size distribution analysis was performed three times to increase the accuracy of the analysis and reduce errors.

5.3.5.3 Determination of soil properties

Solid density, bulk density, and pore volume were calculated as described by Topp et al. (1992) and Radcliffe and Simunek (2018). Based on our laboratory analysis of grain size distribution, we further analyzed soil hydraulic conductivity (K), infiltration, and drainage as described by Groenendyk et al. (2015).

The density of the solid matter in the samples was determined using a pycnometer (Boeco, Hamburg, Germany). First, we determined the total mass of the solids. The pycnometer was filled with methanol and the liquid displacement was measured to determine the volume of the solids. The density of solids was calculated as follows:

$$\rho = m / v, \quad (4)$$

where ρ denotes the density of the solids, m denotes their mass, and v denotes the volume of the liquid.

The bulk densities of the soil samples were determined using the sand replacement method. Each soil sample was weighed and the volume of the container and quartz sand were determined using graduated cylinders. The bulk density was calculated as follows:

$$\rho_b = m / (V_c - V_q), \quad (5)$$

where ρ_b denotes the bulk density of the sample, m denotes the mass of the sample, V_c is the volume of the container, and V_q is the volume of quartz sand.

The total pore volume was calculated from the density of the solid matter and bulk density as follows:

$$\text{Total pore volume} = (1 - \rho_b / \rho). \quad (6)$$

5.3.5.4 Determining species diversity

To determine tree species diversity, we analyzed the Shannon index as previously described (Peet, 1974). We calculated Pielou's index to determine the evenness of distribution (Pielou, 1975) and Simpson's index to determine species richness and diversity (Singh, 2020).

5.3.6 Remote sensing data processing

5.3.6.1 Processing of images captured by the UAV

The images were processed using Pix4Dmapper (Pix4D SA, Prilly, Switzerland) on a computer with 64 GB RAM, 24 CPU cores, and a NVIDIA GeForce RTX 2080 SUPER graphics card to create the orthomosaic map used for interpreting the data. Images were uploaded and automatically assigned to the World Geodetic System 1984/Universal Transverse Mercator zone 48 [WGS 84/UTM zone 48N; Earth Gravitational Model of 1996 (EGM 96)] Geoid CRS. The images captured by the UAV were automatically stored, along with the camera model, GPS points, time and date, and flight altitude. We configured the technical parameters, selecting the standard three-dimension (3D) option for high-quality mapping. The output generated a full keypoint image scale, minimizing the resolution loss and maintaining a point cloud densification factor of 1 (original image size). Each map required ~72 h to develop, and we processed more than 6,000 images.

5.3.6.2 DEM generation

To create the DEM, the rectangular area enclosing Sugnugur Valley was downloaded, and the resulting data were duplicated three times.

In addition to the DEM, a shapefile of Sugnugur Valley was generated from a water basin layer (obtained from www.hydrosheds.org). We used a global dataset comprising water basins of varying sizes (Lehner et al., 2008), from which we selected the data for Sugnugur Valley while discarding all other data. The SRTM image and Sugnugur Valley shapefile were projected onto the UTM zone 48N using the WGS 84 datum (EPSG:32648) as the CRS.

Three DEM layers were integrated to produce the final map. One DEM served as the background layer and was colored using an elevation color ramp sourced from the cpt-city color ramp catalog. The other two DEMs were clipped to the dimensions of Sugnugur Valley, using the Sugnugur Valley shapefile as a mask. The hillshade layer was generated by applying the hillshade function to one of the two DEMs, and the relief information was used to simulate the shadows created by the terrain. The elevation layer was generated by coloring and categorizing the final DEM, using the same process for simulating the background layer.

The river network, simulated using DEM data, was included in the map using the Strahler Order tool from the System for Automated Geoscientific Analyses geographic information system. All minor rivers were manually removed using a raster calculator, and the remaining river network was vectorized and colored blue to enhance map legibility.

5.3.6.3 Normalized difference vegetation index (NDVI)

A total of 23 NDVI maps were generated using Landsat 8, 7, and 5 satellite images obtained from the United States Geological Survey (USGS) EarthExplorer (www.earthexplorer.usgs.gov). The images were captured at the same location (path 131 and row 026) over 2000–2022, with one image selected per year.

We considered only the images that were captured during the summer months. Notably, in the winter, the NDVI values were considerably low, making it difficult to identify the differences in vegetation cover caused by wildfires. We selected cloud cover-free images captured in June–September of each year.

The Landsat images were projected to the UTM zone 48N using the WGS 84 datum (EPSG:32648) as the CRS. The NDVI maps were created based on the NDVI values calculated as the ratio between the red and near-infrared values, i.e., $(\text{NIR} - \text{R}) / (\text{NIR} + \text{R})$. The calculation of NDVI values differed for each type of satellite: $(\text{Band 4} - \text{Band 3}) / (\text{Band 4} + \text{Band 3})$ for Landsat 5 and 7, and $(\text{Band 5} - \text{Band 4}) / (\text{Band 5} + \text{Band 4})$ for Landsat 8. NDVI values over 0–0.06 were determined through raster calculation. These values were classified into six equal interval classes and colored using a green color ramp, wherein the low NDVI values are represented by light-green hues and high NDVI values are denoted by dark-green hues.

5.3.6.4 Forest cover loss map

The forest cover loss maps were created using Hansen Global Forest Change version 1.9 (Hansen et al., 2013), a global dataset representing the area of tree cover loss (resolution of $\sim 30 \times 30$ m). This dataset was generated using multispectral satellite imagery from Landsat 5, 7, and 8. Tree cover was defined as vegetation having a height of ≥ 5 m. In general, tree cover loss was defined as the stand replacement disturbance or complete removal of the tree canopy at the Landsat pixel scale (Hansen et al., 2013).

The dataset includes a raster depicting the global annual forest loss, as well as other layers, such as `treecover2000` and `lossyear`, which we used to create the forest cover loss maps (downloaded from www.globalforestwatch.org). Both layers were projected onto UTM zone 48N using the WGS 84 datum (EPSG:32648) as the CRS.

We created two sets of 22 small maps and one large map. The large map provided an overview of the forest loss in Sugnugur Valley for 2001–2021, depicted on a time scale as yellow (early 2000s) to red (recent years), providing an approximate representation of the time of forest loss. The 22 small maps indicated the exact areas of annual forest loss for 2000–2021. To create the maps, we applied the Hansen `lossyear` and `treecover2000` layers, which were both clipped to the Sugnugur Valley shapefile as a mask. The large map was created by classifying the Hansen `lossyear` layer into 22 paletted/unique values using the equal interval mode; the layer was colored using the YlOrRd color ramp. The background of the map, along with all other forest loss maps, was composed of the Hansen `treecover2000` layer, which depicted the tree-cover density in 2000. This layer was classified into five classes according to tree cover density using the equal interval mode, and further colored using a green color ramp, with the darker and lighter hues symbolizing high and low tree-cover densities, respectively.

We generated one set of maps indicating the accumulated forest loss from 2000 to 2021, and another portraying the forest loss for each year (without accumulation). For the two sets of small maps, the Hansen `lossyear` layer was polygonized and duplicated 22 times. For each

small map, all values except those depicting the forest loss of the concerned year were removed manually (using the attribute table).

5.3.7 Statistical analysis

We investigated the relationship between forest cover loss and NDVI using Pearson's (r) (Puth et al., 2014) and Spearman's correlation coefficients (r_s) (Yang et al., 2021).

5.4 Results

We analyzed the major drivers and trends of forest loss over time. Notably, the total protected forest area was reduced in 2000 by the transformation of formerly protected forest areas into national parks (Figure 5.5a) (Oyungerel, 2004). From 1999 to 2021, the total amount of legally harvested timber in Mongolia varied greatly, with a minimum of $4.644 \times 10^5 \text{ m}^3$ in 1999 and maximum of $9.557 \times 10^5 \text{ m}^3$ in 2020 (Figure 5.5b). Notably, the Khentii Mountain region represented only 12–33% of the total legally harvested timber.

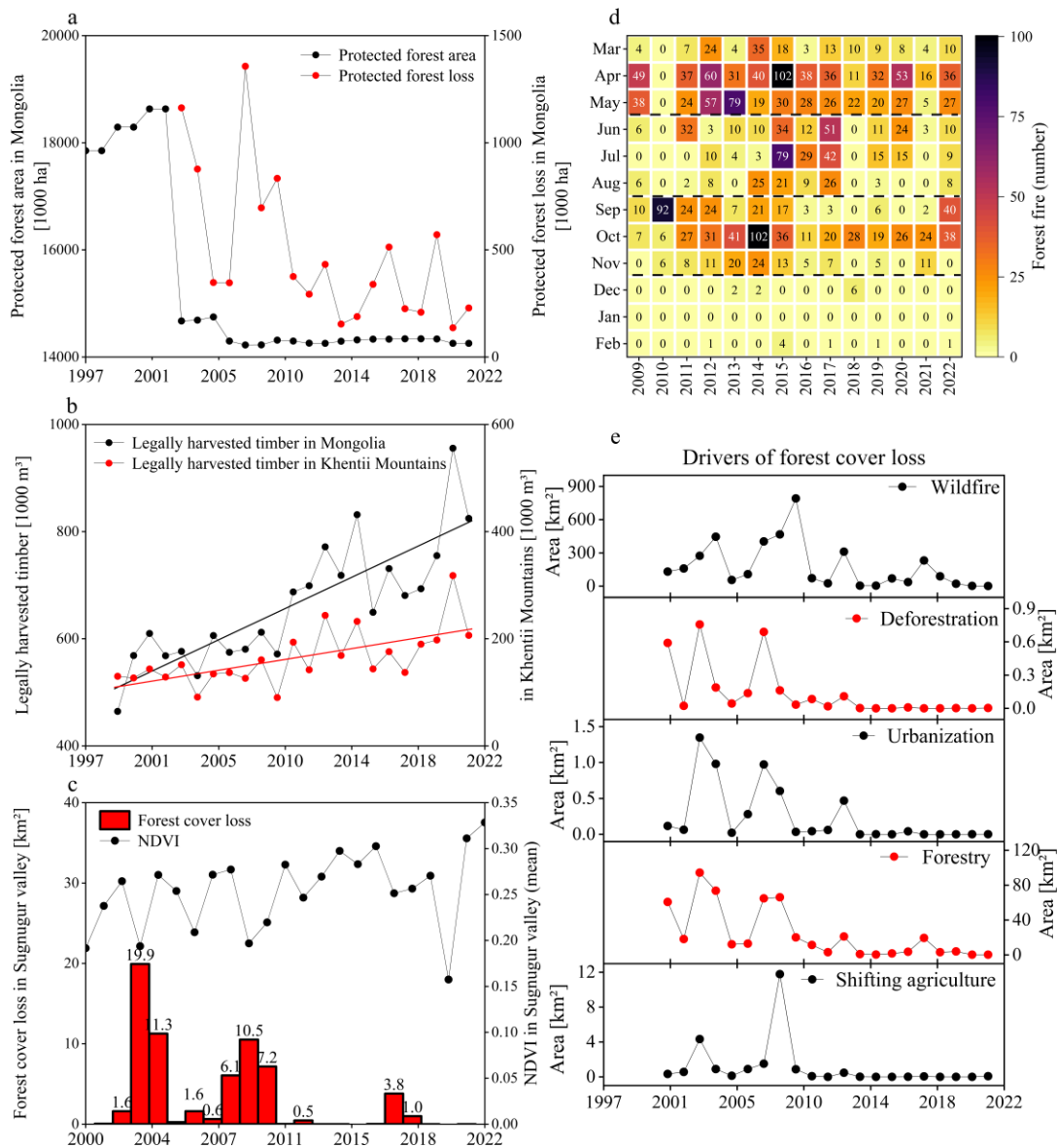


Figure 5.5: Major drivers of forest cover loss. (a) Total area of protected forests in Mongolia, along with the loss of protected forest area. (b) Volumes of legally harvested timber in Mongolia and the Khentii Mountain region. (c) Annual difference in forest cover loss and normalized difference vegetation index (NDVI) in Sugnugur Valley. (d) Monthly wildfire occurrence in Mongolia, highlighting the months with the highest fire incidence. (e) Main drivers of forest cover loss in Mongolia, including wildfires, commodity-driven deforestation, urbanization, forestry, and shifting agriculture.

Sugnugur Valley experienced considerable forest cover loss since 2002 (Figure 5.5c): forest cover was reduced by 1.6 km² in 2002, and has continued to decline since. The highest forest cover loss was observed in 2003, with a reduction of 19.9 km². In some years, the forest cover loss was minimal (e.g., in 2000 and 2015). The NDVI values fluctuated over time but showed an overall upward trend. The highest NDVI value of 0.32 was observed in 2022, indicating an increase in the density of green vegetation from earlier years. The lowest NDVI value of 0.15 was observed in 2020. We observed a moderate negative relationship between

forest cover loss and NDVI ($r = -0.37$, $r_s = -0.32$); thus, NDVI decreased with increasing forest cover loss.

The forest fire data from 2009–2022 indicated varied and sporadic patterns across different months and years (Figure 5.5d). We categorized the data by season: spring (March–May), summer (June–August), autumn (September–November), and winter (December–February). The number of forest fires showed strong seasonal variation. The majority of forest fires occurred in spring and fall, with the highest number of fires occurring in April and October.

We analyzed the major drivers of forest cover loss in Mongolia, including wildfires, commodity-driven deforestation, urbanization, forestry, and shifting agriculture during 2001–2021. Commodity-driven deforestation and wildfire were the dominant drivers (Figure 5.5e). The frequency of wildfires (i.e., the uncontrolled burning of forests) varied greatly across years. For instance, the most damage was recorded in 2009 (~800 km²), while the least damage was recorded in 2013 and 2014 (4.11 and 4.28 km², respectively). Commodity-driven deforestation (i.e., the clearing of forests for agricultural purposes) had a relatively consistent contribution over time. The maximum damage was recorded in 2003 (0.75 km²), while the least damage was recorded in 2014. The data of Hansen et al. (2013) indicated considerable variation in the contribution of forestry (i.e., the management, conservation, and development of forests) across years, with the maximum damage recorded in 2003 (60.74 km²) and least damage recorded in 2020 (0.22 km², Figure 5.5e). Shifting agriculture (i.e., in which the location of cultivation is changed periodically) showed relatively consistent contributions over time, with the maximum recorded in 2008 (11.79 km²).

We assessed the LAI of the four vegetation types (Figure 5.6a). The NF site had LAI values of 1.59–1.86; PBF site, 1.51–1.73; BF site, 0.09–0.17; and DF site, 1.4–1.27.

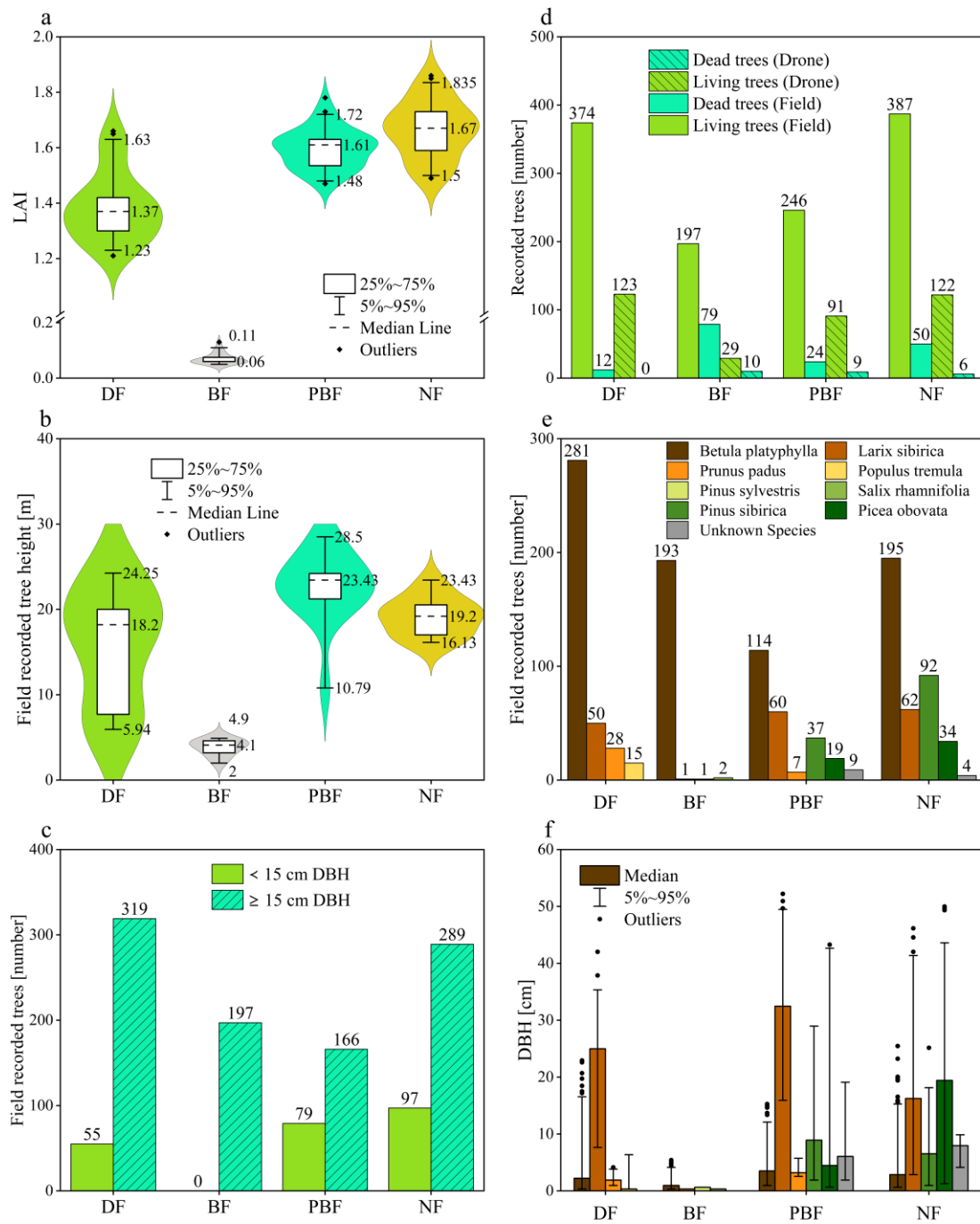


Figure 5.6: Field and UAV-based measurements in natural forest (NF), partly burned forest (PBF), burned forest (BF), and disturbed forest (DF). (a) Leaf area index (LAI) and boxplot along with distribution. (b) Tree height and boxplot along with distribution. (c) Number of trees in two categories [diameter at breast height (DBH) of ≥ 15 cm and ≤ 15 cm]. (d) Comparison between field and UAV (drone)-based measurements. (e) Tree species (colors indicate different species). (f) DBH for all tree species.

The average tree height at the DF site (18.53 m) was considerably higher than that at the BF and PBF sites. The BF site had an average tree height of 3.44 m, whereas the PBF site had an average of 22.26 m, higher than that at the BF site but lower than that at the DF site. The

average tree height at the NF site was 19.95 m, which was lower than that at the DF site (Figure 5.6b).

At the DF site, we recorded 55 thick ($\text{DBH} \geq 15 \text{ cm}$) and 319 thin ($\text{DBH} \leq 15 \text{ cm}$) trees. The BF site had no thick trees but 197 thin trees. The PBF site contained 79 thick and 166 thin trees, indicating a comparatively balanced composition. The NF site contained 97 thick and 289 thin trees (Figure 5.6c).

Field and drone surveys yielded discrepant tree counts in different forest types (Figure 5.6d). At all sites, the drone surveys indicated lower values than the field surveys, both for living and dead trees.

We identified and quantified the most prevalent species at each site to determine the abundance and composition of living tree species (Figure 5.6e). The Shannon–Wiener index ranged from 0.12 to 1.4. The BF (0.12) and DF (0.8) sites exhibited lower values than the PBF (1.4) and NF (1.24) sites. Pielou’s index ranged from 0.05 to 0.58. The BF (0.05) and DF (0.31) sites exhibited higher values than the PBF (0.58) and NF (0.47) sites. Simpson’s diversity index was used to measure the population size of each species, with higher values indicating more diversity and evenness: 0 implies the dominance of one species, whereas 0–1 indicates some degree of species diversity. The Simpson’s diversity index was higher in the NF (0.65) and PBF (0.69) sites than in the DF (0.41) and BF (0.04) sites.

At the DF site, DBH was measured for *B. platyphylla*, *L. sibirica*, *Prunus padus*, and *Populus tremula* (Figure 5.6f). The DBH range was quite different for each species, with *B. platyphylla* exhibiting the smallest range (0.31–18.46 cm) and *L. sibirica* exhibiting the largest (7.32–42.01 cm). At the BF site, DBH was measured for *B. platyphylla*, *L. sibirica*, *Pinus sylvestris*, and *Salix rhamnifolia*. The DBH range was relatively small (maximum of 5.5 cm). The PBF site contained the greatest diversity of species, including *B. platyphylla*, *L. sibirica*, *Picea obovata*, *P. sibirica*, *P. padus*, and an unknown species. Among these, *L. sibirica* had the highest mean DBH, whereas the unknown species had the highest maximum DBH. The NF site comprised *B. platyphylla*, *L. sibirica*, *P. obovata*, *P. sibirica*, and an unknown species. The DBH range was quite wide, with the unknown species and *B. platyphylla* having the largest and smallest DBH values of 61.11 cm and 0.31 cm, respectively.

Figure 5.7a shows the soil profiles for all sampling sites based on field observations and laboratory analysis. The active vegetation layer was 2–8 cm thick, with the thickest layers observed in the PBB (20 cm) and thinnest layers in the SB and UBV (2 cm) sites. The organic layers mostly ranged from 6 to 20 cm, except for the PBF and PBB sites, where it ranged from 4 to 6 cm. The thickest organic layer was observed in the PB site, while the thinnest layers were observed in the SB and UBV sites. The vegetation root depths of the BF, PBF, and DFB sites were 35–45 cm, while those of the NF, NFB, and PBB sites were 8–34 cm. Notably, the vegetation at the UBV site had the deepest roots (average of 44 cm). The depth of the water table was 85 cm at the UBV site. In terms of soil texture, the samples from all boreholes were categorized as silt loam, except those from the UBV site, which were categorized as sand (95% sand content). The organic matter content in all the samples ranged from 1% to 28%, and the carbon content from 0.3% to 1.3%. The highest organic content was observed in the BF and PBF sites, including the BFB and PBB sites, where it ranged from 15% to 28%. The lowest contents were recorded in the NF and UBV sites (1–3%). The density of solid matter at all sites ranged from 1.7 to 2.5 g/cm³. The samples from the burned areas (BF, BFB, PBF, and PBB sites) had the lowest values, while the NF site had the highest value (2.35 g/cm³). The bulk density at all sites ranged from 0.89 to 1.07 g/cm³, and the pore volume ranged from 0.55% to 0.63%. The hydraulic conductivities (*K*) at all sites ranged from 25 to 829 cm/d. The highest *K*-value was observed at the UBV site (829 cm/d). The SB site also had a high *K* of 103 cm/d. In contrast, the PBF site had the lowest *K* of 25 cm/d. The highest infiltration value

of 8.48 cm was observed at the UBV site. The SB site had the second-highest infiltration value (5.95 cm), while the BFB site had the lowest (4.04 cm). The highest drainage value was observed at the UBV site (8.32 cm), while the lowest was observed at the PBF site (2.16 cm).

The temperature measurements were recorded at depths of 5–100 cm; however, at the NF site, we recorded the soil profile up to a depth of 150 cm (Figure 5.7b). The temperature was generally higher at the BF site than at the NF site. At a depth of 5 cm, the soil temperature at the BF site was 6.3 °C while that at the NF site was 4.8 °C. The temperature difference gradually decreased with increasing depth: At 5 cm, the temperature at the PBF site was 4.7 °C while that at the NF site was 4.8 °C. The temperature at the DF site was 5.7 °C while that at the NF site was 4.8 °C. At 100 cm, the temperature at both the BF and NF sites was ~3 °C. The PBF site also exhibited a higher temperature than the NF site, but not as high as that of the BF site. The temperatures in the PBF and NF sites were 2.3 °C and 2.8 °C, respectively. At the DF site, the soil temperature was lower than that at the NF site at all depths. The temperatures at the DF and NF sites were 1.5 °C and 2.8 °C, respectively. At 150 cm, the temperature at the NF site was 2.5 °C.

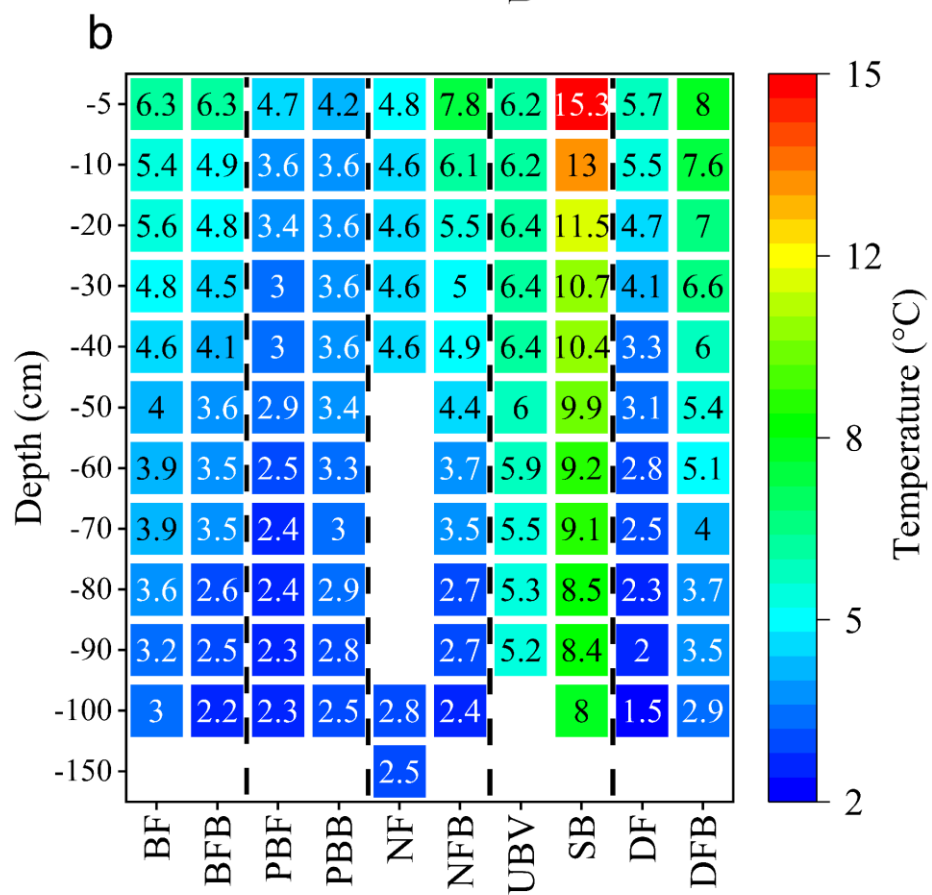
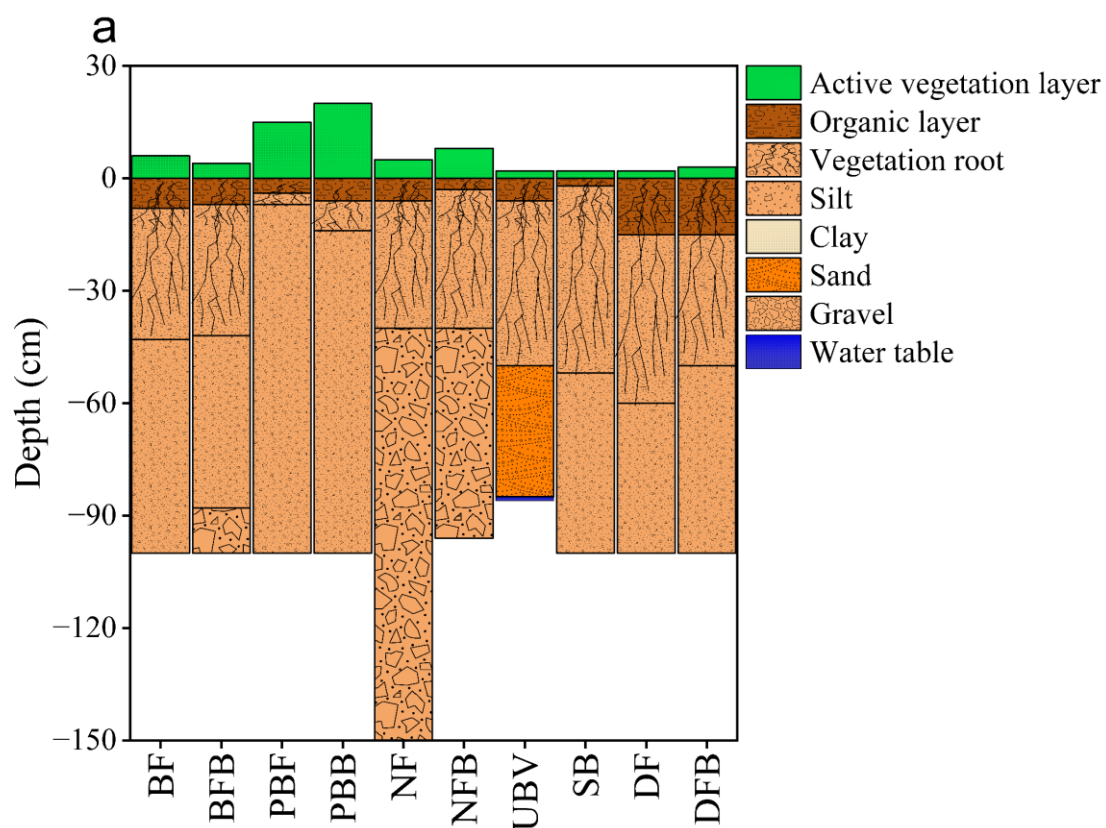


Figure 5.7: Soil characteristics across vegetation types in Sugnugur Valley. (a) Soil profiles and (b) temperatures at different depths (cm) at the 10 sampling locations in the burned forest (BF), partly burned forest (PBF), disturbed forest (DF), natural forest (NF), BF bottom (BFB), PBF bottom (PBB), NF bottom (NFB), DF bottom (DFB), south-sided slope bottom (SB), and unburned valley (UBV).

Figure 5.8 highlights the forest cover loss and NDVI changes after wildfires. In 2009, NDVI declined to 0.1 and forest cover decreased to 0% in the wildfire-affected area.

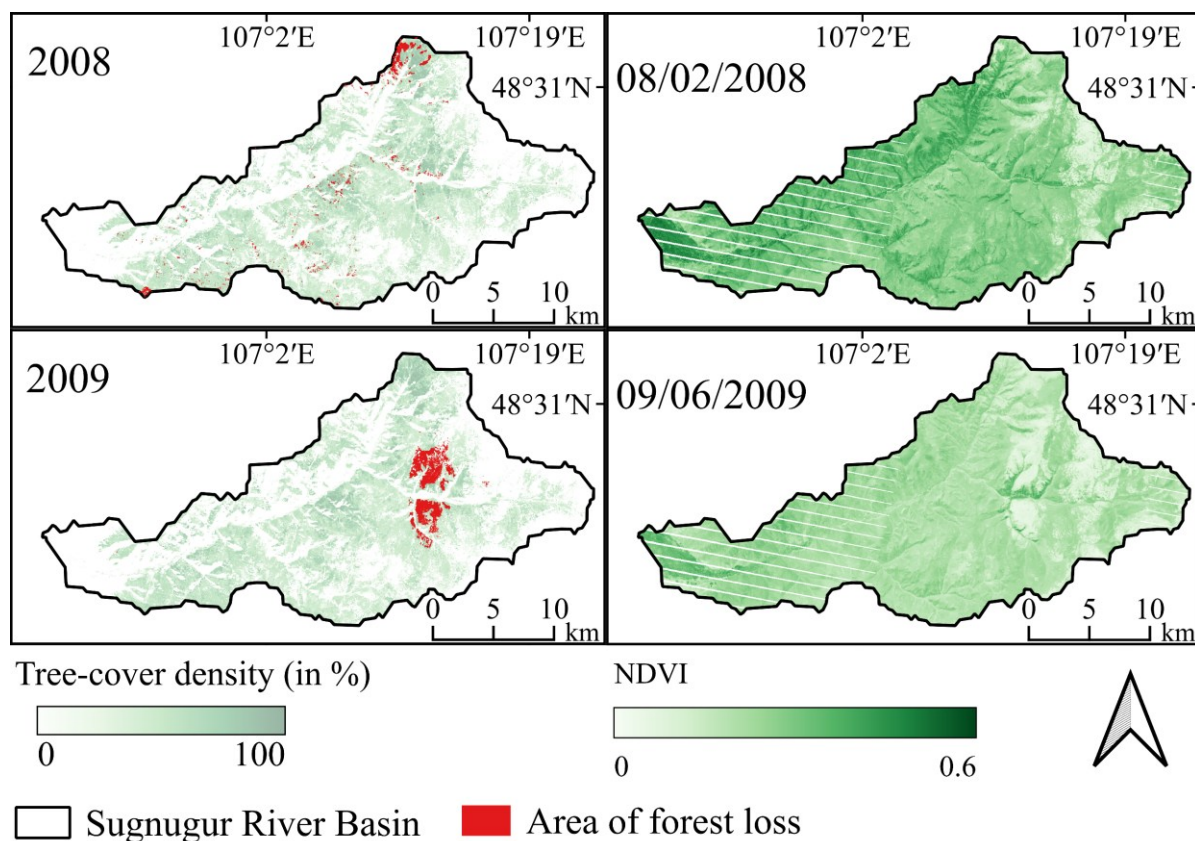
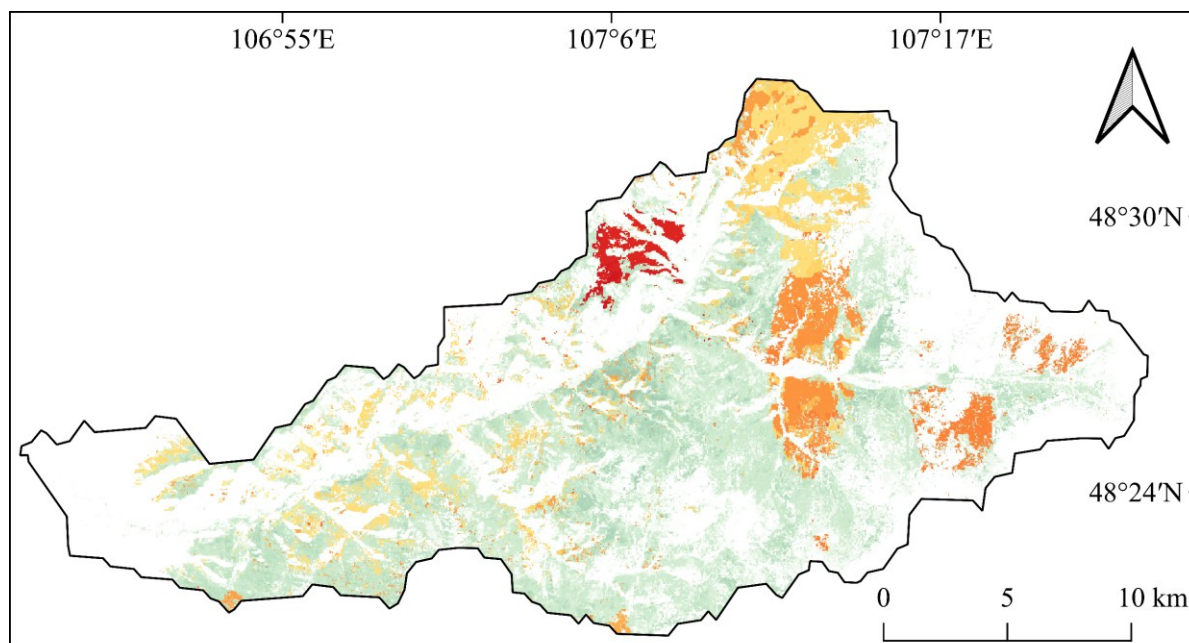


Figure 5.8: Regional trends in tree cover and normalized difference vegetation index (NDVI). Impact of wildfires on forest cover loss over 2008–2009 in Sugnugur Valley (Right). NDVI trends for 2008–2009 (Left). See Figure 5.9 for the accumulated forest cover loss over 2001–2021, and Figures 4.10 and 4.11 for accumulated and non-accumulated yearly forest cover loss, respectively.

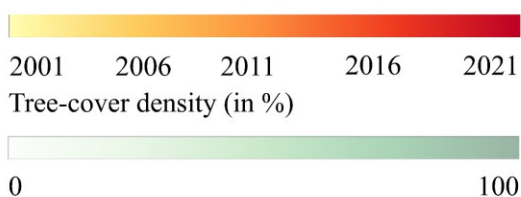
In 2001, 0.05 km² of forest cover was lost due to wildfires (Figures 5.9–5.11). In 2002, the area increased dramatically to 1.6 km². Notably, in 2003, the forest cover loss was 19.9 km². The following years exhibited varying levels of loss; for some years, there was no recorded loss (e.g., 2015 and 2020), while notable losses were recorded in other years (e.g., 10.5 km² in 2009 and 3.8 km² in 2017). Mean NDVI was relatively stable during 2000–2003 (0.19–0.26, Figure 5.12); however, in 2004, there was a sudden increase (to 0.27) that continued until peaking in 2011 (at 0.28). For 2011–2015, the mean NDVI remained relatively stable (0.28–0.30), after which it gradually decreased, reaching a minimum (0.16) in 2020. However,

there was a considerable increase in mean NDVI (0.31) in 2021. The highest mean NDVI was recorded in 2022 (0.33).



Forest loss data source: Hansen/UMD/Google/USGS/NASA. Sugnugur basin source: HydroSHEDS

Forest loss in the Sugnugur Valley from 2001 to 2021



□ Sugnugur River Basin

Figure 5.9: Accumulated forest cover loss over 2001–2021 in Sugnugur Valley. Different colors indicate forest cover loss in different years. The basemap is based on the tree-cover density in 2000. The darker and lighter green hues indicate denser and more sparse forest cover, respectively. USGS, United States Geological Survey; NASA, National Aeronautics and Space Administration; UMD, University of Maryland.

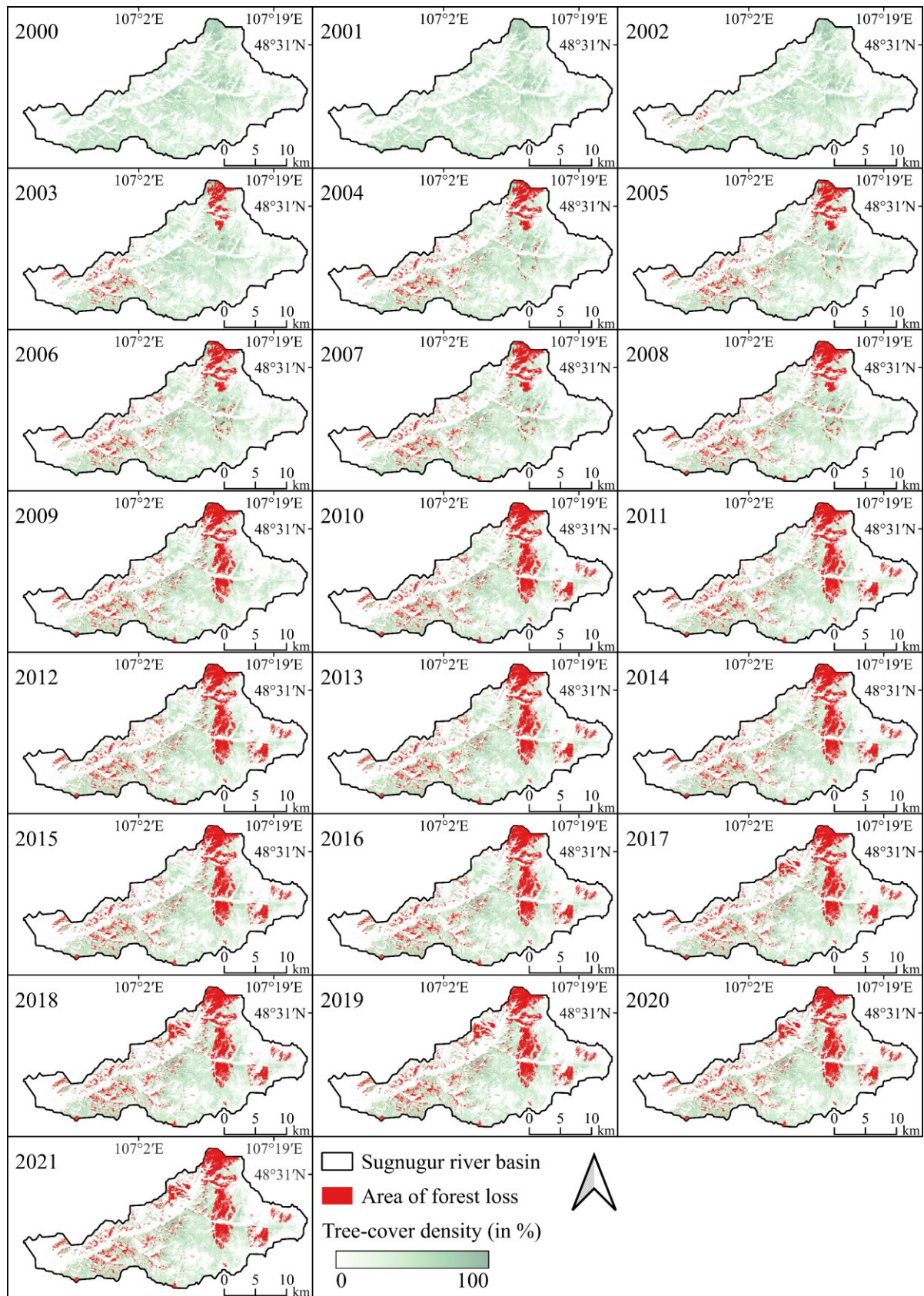


Figure 5.10: Accumulated yearly forest cover loss in Sugnugur Valley.

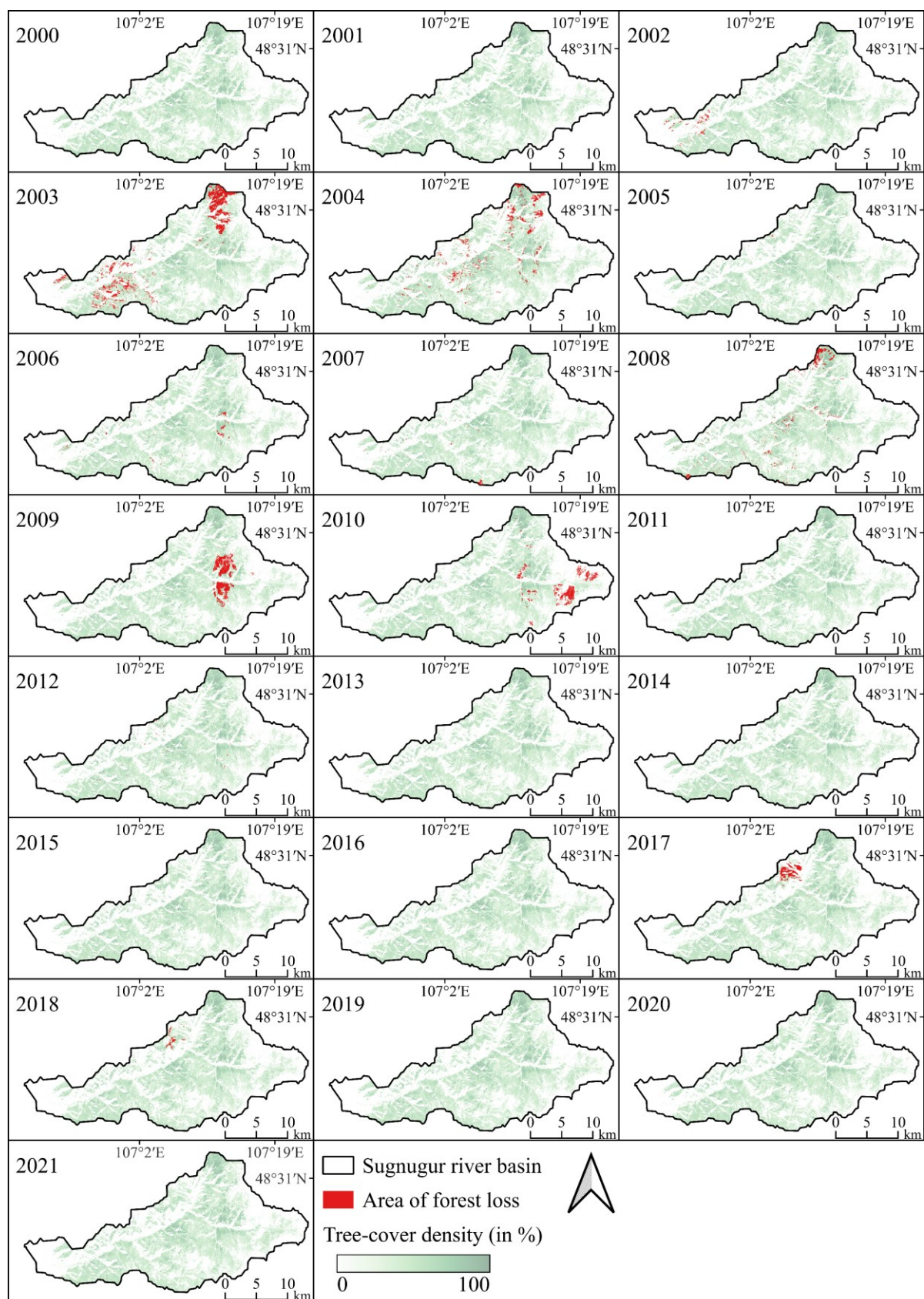


Figure 5.11: Impact of wildfire on accumulated forest cover loss for 2000–2021 in Sugnugur Valley.

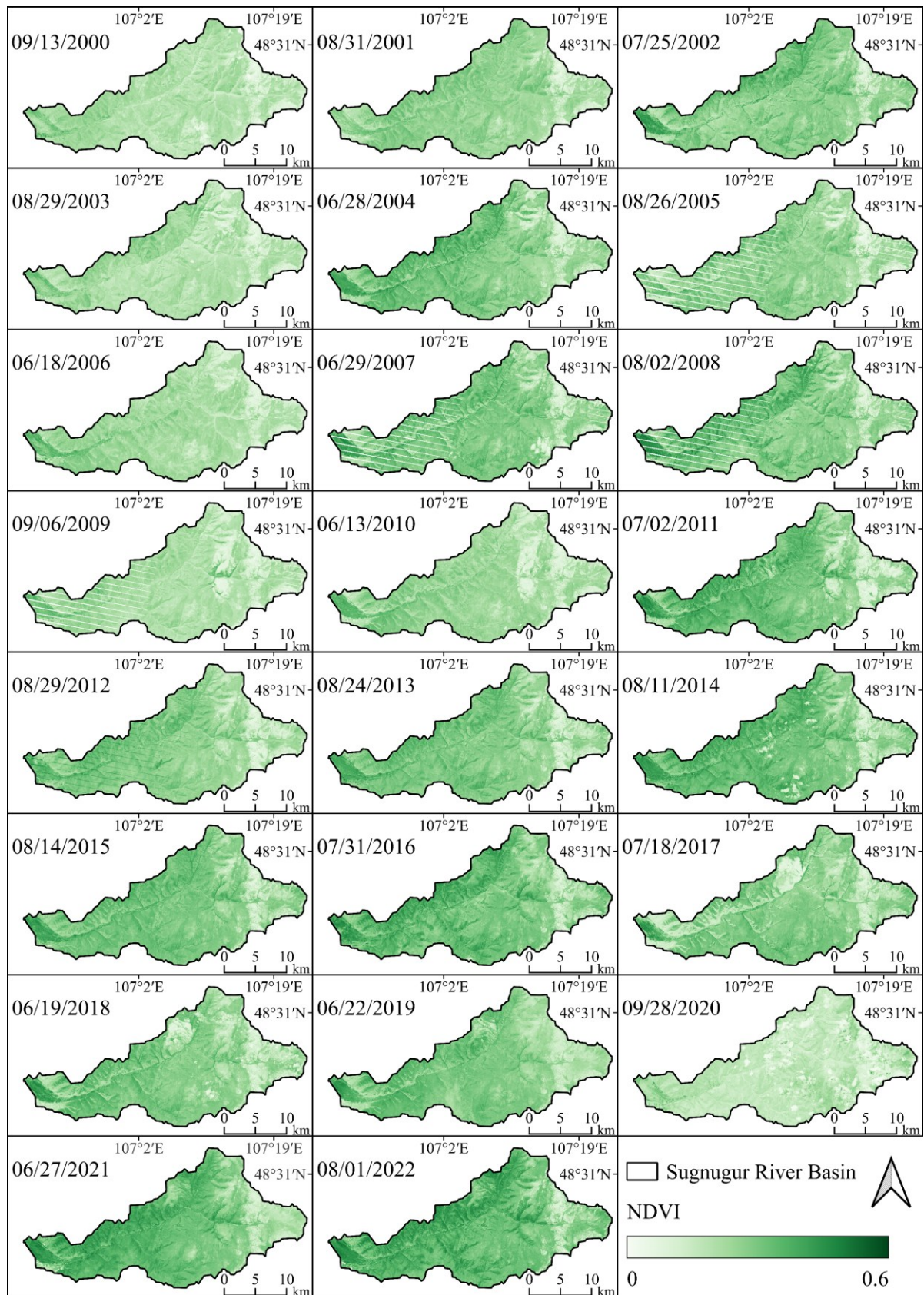


Figure 5.12: Normalized difference vegetation index (NDVI) for 2000–2022 in Sugnugur Valley.

5.5 Discussion

5.5.1 Impact of wildfire

In the Khentii Mountains of northern Mongolia, the impact of wildfires on forest cover and soil properties is a critical concern. The region is characterized by discontinuous permafrost, with the southerly exposed steppe slopes being permafrost-free. Based on the trends in forest cover loss (Figure 5.5), we concluded that wildfire was a major driver of forest loss. Forest fires showed seasonal patterns (Figure 5.5d), with higher frequencies during warmer months, specifically from April to October. In spring, precipitation may be lower than that in summer, promoting the spread of wildfire. Notably, the area was intensely harvested for *P. sibirica* nuts by locals from late summer until the beginning of spring (Figure 5.13). The camps set up by the nut harvesters were maintained for 2–4 months, which may provide a long-term fire source. In Mongolia, up to 80% of wildfire incidents may be human-induced (Goldammer, 2007). Owing to the fire events in 2009 (Figures 5.8, 5.10, and 5.11), the forest cover in the BF decreased significantly; thus, reforestation, canopy cover, permafrost, and organic layer thickness were lower than those in the PBF site, promoting the soil absorption of shortwave radiation (Kopp et al., 2014). Our findings suggested that wildfires could increase the temperature of the upper soil layers owing to the fuel provided by the abundance of forest and vegetation cover. Dashtseren et al. (2014) found that forest cover is an important determinant of vegetation cover, soil properties, and permafrost degradation. At the BF site, the forest species richness was 0.04, species diversity was 0.12, and evenness distribution was 0.05. These low values may be attributed to the dominance of *B. platyphylla*. The low tree height at the BF site could be attributed to the severe impact of wildfires on forest cover. Notably, in the other study sites, forest-floor vegetation growth was extremely low. Forest cover is crucial not only for forest regeneration but also improving soil-based processes (e.g., permafrost and evaporation) (Ishikawa et al., 2018). The canopy dominance of *B. platyphylla* promotes the development of a moist humus layer that has a low flammability and protects the stand against reburns. In the taiga forest, *B. platyphylla* is one of the first tree species to regenerate after stand-replacing fires (Gradel & Mühlenberg, 2011). This explains the predominance of young *B. platyphylla* at the BF site after fire disturbances (Figure 5.6e); however, its dominance at the burned forest sites could be temporary. Gradel and Mühlenberg (2011) found that, 40 years after a fire in the taiga, the density of *B. platyphylla* decreased while the total stand density continued to increase due to the contribution of conifers. At the PBF site, the forest species richness, diversity, and evenness distribution indexes were 0.69, 1.4, and 0.58, respectively. However, at the NF site, these indexes were slightly lower, probably due to the influence of the tree species.

The maximum LAI was 3, consistent with the findings of a previous study in the Khentii Mountains (Mandakh et al., 2016). The highest LAI values were observed in the NF and PBF sites (Figure 5.6a), which had denser vegetation cover than the BF and DF sites. The BF site exhibited the lowest LAI values, likely owing to the abundance of heavily burned trees. The LAI values of the DF site were also lower than those of the NF and PBF sites. The NDVI analysis indicated some recovery of vegetation growth and productivity, as the highest mean NDVI value was recorded in 2022 (0.33).

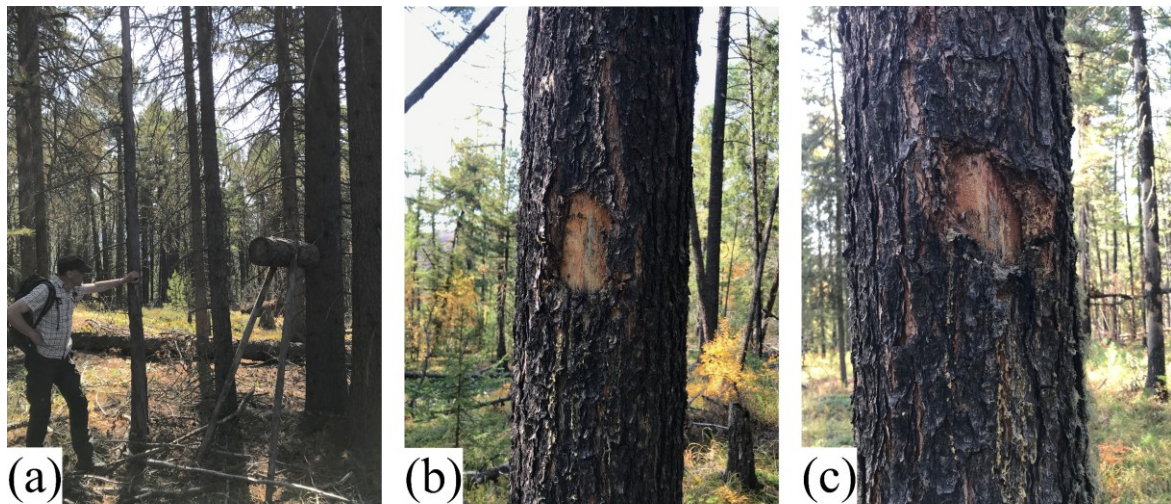


Figure 5.13: Impacts of pine-nut harvesting on *P. sibirica*. (a) Wooden hammer used to harvest nuts. (b, c) Damage after collecting nuts.

5.5.2 Other relevant environmental factors

Various anthropogenic factors other than wildfire contribute to forest cover loss. One direct driver of protected forest loss is the alteration of environmental regulations to establish tourism destinations and logging sites (Mookhor et al., 2013). Approximately 82% of Mongolia's land area is natural pasture, which is the main source of grazing (Yembuu, 2021). However, the presence of domestic livestock promotes forest disturbance, thereby impairing regeneration and degrading the forest floor vegetation (Vallentine, 2001; Mookhor et al., 2013). Livestock are known for their bark-stripping and selective feeding on the most nutritious plant parts, such as the leaves, shoots, and roots (Vallentine, 2001). Additionally, livestock prefer feeding on the seedlings and saplings of plants that grow above the surrounding vegetation, specifically damaging young trees of up to 2 m in height (Vallentine, 2001). At the DF site, we observed heavy livestock grazing, which not only decreased the forest-floor vegetation but also the number of saplings. Currently, 36–80% of Mongolia's total timber harvest is illegal (Gompil et al., 2022). Between 2009 and 2019, an average of 2.3 million m³ of forest was affected by illegal logging, resulting in a significant decrease in protected forest cover. Illegal timber harvesting was an important driver of post-disturbance tree regrowth (Figure 5.5b). The patterns of timber harvesting in Mongolia are attributed to several factors, including government regulation and enforcement. Shur and Jorgenson (2007) found that selective logging and non-lethal forest fires reduce the level of the permafrost table, whereas clear-cutting and severe forest fires lead to permafrost degradation. Gradel and Mühlenberg (2011) found that heavy disturbances, such as forest fires, promoted the replacement of the previously dark taiga forests by light taiga forests. The dark taiga may be the final stage of succession, though light taiga forests may experience a reverse or interruption in succession. Therefore, frequent disturbances in boreal forests may be necessary for a shift from dark to light taiga.

5.5.3 Vegetation cover and soil properties

In addition to forest cover, vegetation cover and soil properties are important regional parameters. Forest cover plays a vital role in maintaining the microclimate and soil properties. A decrease in the shade offered by the forest canopy, insulation offered by the organic layer, and changes in microclimate can promote permafrost degradation and reduce forest-floor

diversity (Schulze et al., 2005; Klinge et al., 2021). The meltwater from the active layer above the permafrost table can support forest and vegetation cover regeneration, whereas permafrost degradation promotes forest and vegetation cover loss (Sharkhuu & Anarmaa, 2012; Munkhjargal et al., 2020b). Dashtseren et al. (2014) investigated the influence of vegetation cover on soil temperature in the Khentii Mountains and suggested that thick organic soil layers insulated the soils from high summer air temperatures.

Among the four study sites, soil temperatures were highest in the BF and SB sites at all depths. This may be due to the relatively low levels of forest and active vegetation covers in the BF and SB sites (Figure 5.7a). The relatively high soil temperatures at the DFB site may be attributed to livestock grazing and selective timber harvesting. The differences in the soil temperatures of the burned and unburned forests may be attributed to the different thicknesses of the organic layers (Ishikawa et al., 2018). The loss of forest and vegetation covers can increase permafrost degradation (Kopp et al., 2014), especially since the thermal conductivity of soil increases with a reduction in organic layer thickness after fires (Kopp et al., 2014), and thereby increase soil temperatures.

Our study area was mostly dominated by silt-loam soil. In this area, soil texture and hydrology play a decisive role in both forest regrowth and permafrost re-establishment. Kopp et al. (2014) compared the SM and water fluxes in the pristine forests, burned forests, and steppes on the south-facing slopes of the Khentii Mountains and observed higher infiltration rates in intact than in burned forests. Similarly, we found that soil infiltration rates were lower in the BF and PBF sites than those in the intact NF and UBV sites. In the UBV site, which had a sand-dominated soil texture (Figure 5.7a), hydraulic conductivity, infiltration, and drainage levels were the highest among all sites. Water can easily infiltrate sandy soil; however, sand has a low water-holding capacity (Klinge et al., 2021). Thus, the upper 10 cm of dry sandy soil warms quickly, partly explaining the higher temperatures in the upper soil layers of the UBV site than those at other sites. The SM levels at the PBF and BF sites were similar to those at the NF site. Klinge et al. (2021) reported that moderate thinning of forests may improve growing conditions for the remaining vegetation by reducing competition for water and increasing nutrient supply from ash. Furthermore, melting permafrost leads to a temporary increase in SM and allows for deeper rooting. We observed that the active layer may influence root depth. In the BF and BFB sites, the active layer was thinner than that at the PBF site, whereas the roots were ~45 cm deeper in these sites (Figure 5.7a). At the PBF site, the active vegetation layer was 15–20 cm thick, and the depth of the roots was 5–10 cm.

5.5.4 UAV-based forest survey

We employed UAV remote sensing to map the forests in the Khentii Mountains (Figure 5.6). The UAV was equipped with high-tech sensors that provide a fast and comprehensive view of the forest area, including the boundaries of forest cover and burned areas. However, this method did not accurately measure the number of trees because of limitations related to the classification of tree species and height (Figure 5.6d).

In general, the UAV-based method tended to record lower tree numbers than field surveys, which may be due to difficulties in detecting separate trees in aerial data, particularly for dense forests. This was especially noticeable at the BF site, where there was a difference of 168 living trees between the field and drone surveys. This variation may be attributed to different factors, such as the presence of dead trees and differences in forest composition and structure. For example, the BF site was dominated by *B. platyphylla*, which grows from one core root and then separates into several main stems, making it difficult to distinguish individual trees. Tree height was another factor that contributed to the underestimation of tree numbers: The canopy of large trees tends to cover younger trees, hiding them from UAV-based detection.

Owing to these limitations, we relied on field measurements to obtain accurate tree counts. However, UAV-based mapping was still useful in providing accurate high-resolution data and identifying the boundaries of forest cover, which would have been difficult to determine through field-based measurements alone. In conclusion, UAV remote sensing is a valuable tool for forest mapping and surveying; however, its limitations should be carefully considered when interpreting the results.

5.6 Conclusion

The integration of remote sensing, field measurements, and statistical analyses allowed us to determine the degree of forest regeneration after wildfires along with the changes in soil properties and permafrost distribution in the Khentii Mountains. Short-lived repeated wildfires strongly inhibited forest recovery, possibly increasing soil erosion. In this region, forest cover, vegetation cover, and permafrost form an interconnected ecological network. Decreasing LAI values with increasing fires may reflect the decline in forest-floor vegetation, which is critical for maintaining SM availability. The reduction in vegetation cover by intensive timber harvesting and grazing can diminish forest cover, thereby promoting soil warming and drying and increasing reburn risk. In sites with unfavorable soil conditions, anthropogenic disturbances can lead to irreversible environmental changes, e.g., permafrost loss. Indeed, permafrost has largely vanished from our study area following widespread forest fires. Tree regrowth and vegetation recovery seemed to be retarded by heavy wildfires. We believe that forest-floor vegetation such as moss is unlikely to regrow until the study area has fully recovered, contributing to repeat-fire risk. Moreover, the sensitivity of some species during the sapling stage may require dense forest-floor vegetation for protection against direct radiation and SM evaporation. Therefore, the ongoing climate crisis and upsurge in human-induced forest fires may promote the replacement of local plant species with faster-growing resilient species, causing rapid environmental changes that may lead to ecosystem collapse without proper mitigation.

5.7 Summary

In Chapter 5, we comprehensively investigated the forest dynamics associated with wildfires and other disturbances in northern Mongolia, and made the following conclusions:

1. The combined use of remote sensing (UAV imagery and satellite data) and detailed field measurements provides a comprehensive methodology for interpreting environmental changes in data-scarce regions impacted by repeated wildfires and human disturbances.
2. Wildfire and anthropogenic disturbances have important impacts on forest structure, and field measurements are crucial for ground-truthing and elucidating the direct effects.
3. This study contributes greatly to the limited data for the semi-arid Khentii Mountains, providing important reference data and a useful analytical framework for future studies.

We employed the findings of Chapter 5 to simulate the regional water-balance using the TRAIN model in Chapter 6.

Chapter 6

6 TRAIN modeling of hydrological regimes and effects of repeated wildfire on runoff response in the forest–steppe ecotone and discontinuous permafrost zone of the data-scarce northern Mongolia

6.1 Study objectives

Climate change has greatly promoted the occurrence and distribution of wildfires in the Siberian region in recent decades. However, little is known of the spatiotemporal patterns of wildfires and their relationship with regional hydro-climatology. Frequent wildfires not only damage the area but inhibit new growth (Kukavskaya et al., 2016). Chapter 5 demonstrated that the study area was frequently affected by wildfires since 2000. This chapter investigated the long-term relationships between the changes in hydrology (ET and RZSM) and wildfires in Sugnugur Valley from 1980 to 2022 according to TRAIN simulations and the GLEAM, SMAP, and ERA5-Land global reanalysis products. We also compared long-term simulations of snow events with MODIS product data. The hydrological responses were simulated to represent the different states of a forest following wildfires (Figure 6.1). Because the wildfire dataset is only available for 2000–2022, the effects of repeated wildfires on the hydrological regimes could not be directly compared; thus, the simulation was performed based on the findings of Chapter 5.

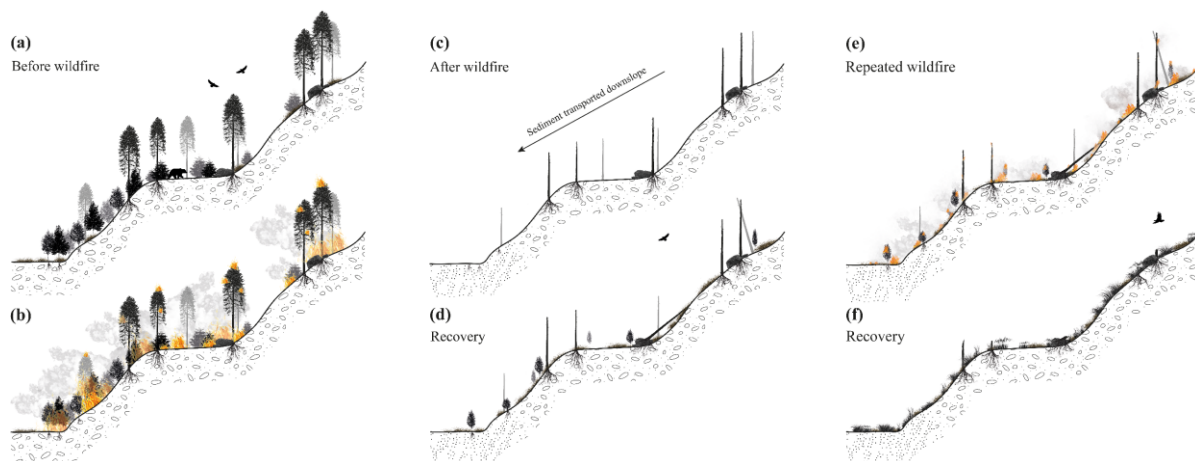


Figure 6.1: Schematic of forest structure following different events. (a) Before wildfire, (b) disturbances such as wildfire, (c) after wildfire, (d) regeneration, (e) repeated wildfire, and (f) recovery.

6.2 Evaluation of ERA5-Land temperature, precipitation, and radiation data with respect to observed meteorological data

First, we interpolated the ERA5-Land dataset to a 1×1 km resolution. Some of the global datasets had a coarser resolution than the size of the study area: in some cases, the study area only covered a few grid cells. To promote data resolution and quality, we obtained data for a larger region comprising the Sugnugur basin. We selected four grid points covered by the hydroclimatic Xoxoo station (see Section 2.3.2), which was located nearly in between the four grid cells comprising Sugnugur Valley. Data for these points were averaged and aggregated to a monthly scale to evaluate the ERA5-Land temperature, precipitation, and radiation (Figure 6.2). Because data for the hydroclimatic station is available for 2012–2020, we compared ERA5-Land variables for this period.

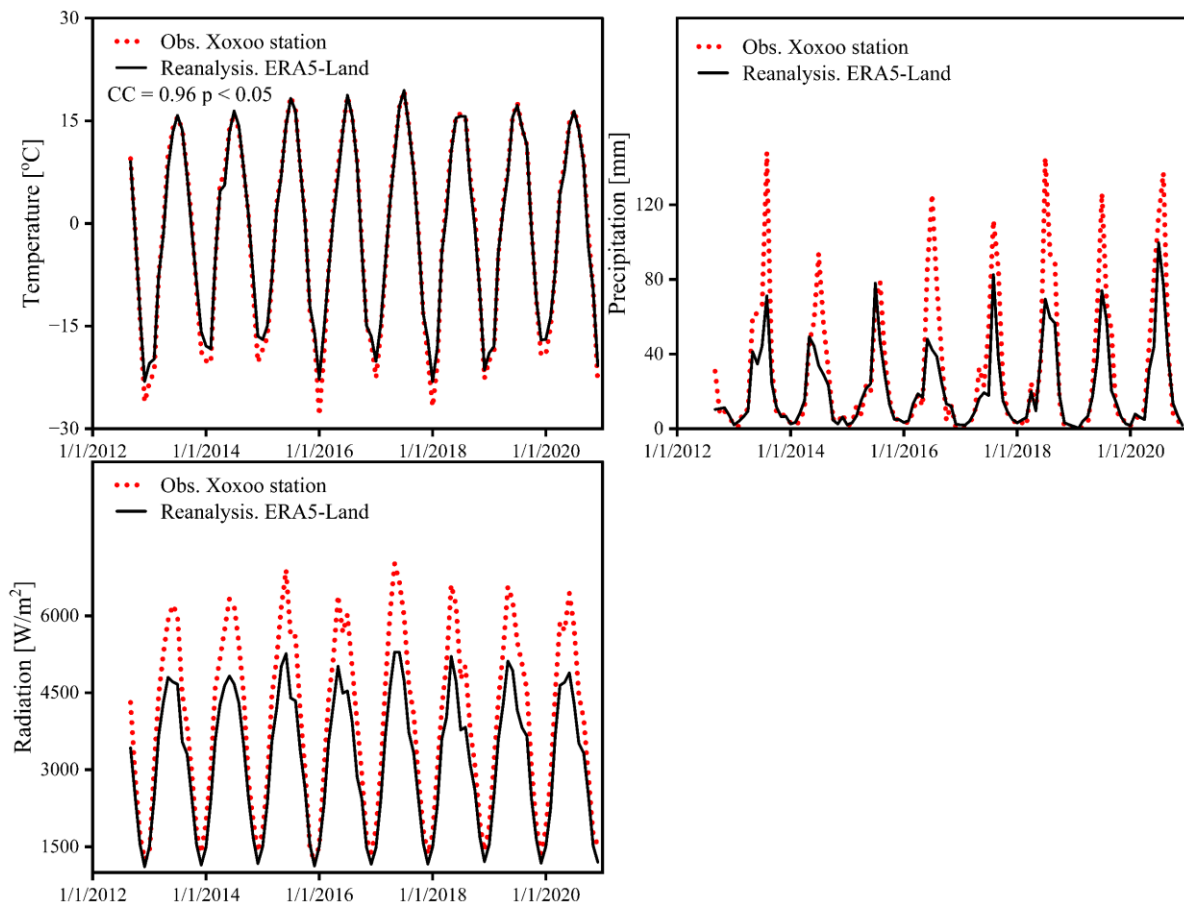


Figure 6.2: Long-term monthly point-analysis of data from the hydroclimatic station (Hydrology and Climatology Group, Heidelberg University) versus ERA5-Land temperature (°C), precipitation (mm), and radiation (W/m^2) data for 2012–2020.

We observed a strong correlation between the ERA5-Land and observed local temperature ($r = 0.96$, $p < 0.05$), precipitation, and radiation data. However, the ERA5-Land precipitation data were underestimated in July and August for some years compared to the observed data, likely owing to thick cloud cover, heterogeneous terrain, or rapidly changing landcover due to wildfires. September to June of each year showed strong variation in both datasets. The observed radiation tended to be higher than the ERA5-Land radiation data during July and August, but showed little variation during the rest of the year.

Figure 6.3 compares the ERA5-Land and observed (hydroclimatic station) data over 2018–2020. The station has not been affected by wildfires or any human/animal disturbances since its first operation. Its position on the south-sided slope gains more sunlight than the valley bottom and north-sided slopes. We observed large differences between the observed and reanalysis precipitation data (Figure 6.3a). These differences occurred mostly during the summer and over 1 d. We highlighted five dates with 1-d spikes in precipitation that could not be captured by ERA5-Land data. The reanalysis data largely underestimated accumulated precipitation compared to the observed data (Figure 6.3b). The simulated ET and RZSM were largely similar between ERA5-Land and the observed data (Figure 6.3c and d). The observed ET data were slightly higher in the summer than the reanalysis simulation. The increase in runoff (Figure 6.3e and f) could be due to increased precipitation. SWE and RZSM were relatively similar between the observed and reanalysis datasets (Figure 6.3g and h).

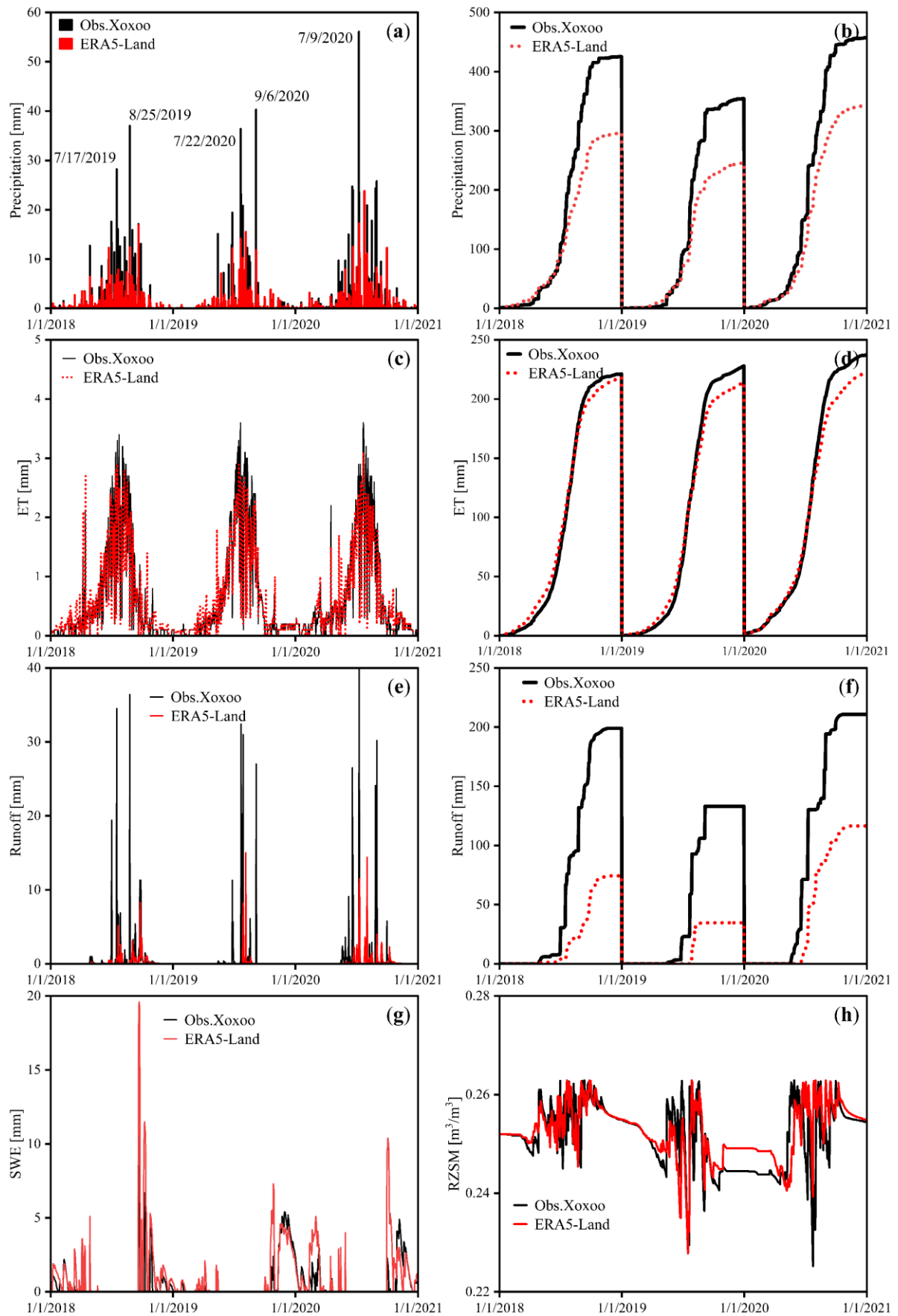


Figure 6.3: Single-site TRAIN simulation using the observed hydroclimatic (Xoxoo) station and ERA5-Land datasets for evapotranspiration (ET), snow water equivalent (SWE), and root zone soil moisture (RZSM) over 2018–2021. (a) Precipitation frequency, (b) accumulated

precipitation, (c) ET frequency, (d) accumulated ET, (e) runoff frequency, (f) accumulated runoff, (g) SWE, (h) RZSM.

6.3 Evaluation of TRAIN-simulated ET and RZSM

The simulated ET showed the strongest correlation with the GLEAM and ERA5-Land ET (basin-averaged correlation coefficient: 0.75 and 0.8, respectively; Figure 6.4). The simulated RZSM showed the strongest correlation with SMAP, followed by ERA5-Land and GLEAM RZSM (basin-averaged correlation coefficient: 0.75, 0.64, and 0.41, respectively). For the GLEAM and ERA5-Land datasets, the areas with the lowest correlations were concentrated in the north, corresponding to mountainous terrain mainly covered with steppe and shrubs. This area was mostly affected by wildfire and/or repeated wildfire. Unique topography, vegetation cover, and disturbances such as wildfire may promote uncertainties and errors in the model simulations and satellite observations of RZSM, resulting in low correlations. Otherwise, the correlation coefficients for ET and RZSM were high between the TRAIN simulation and other three datasets for most of the study area.

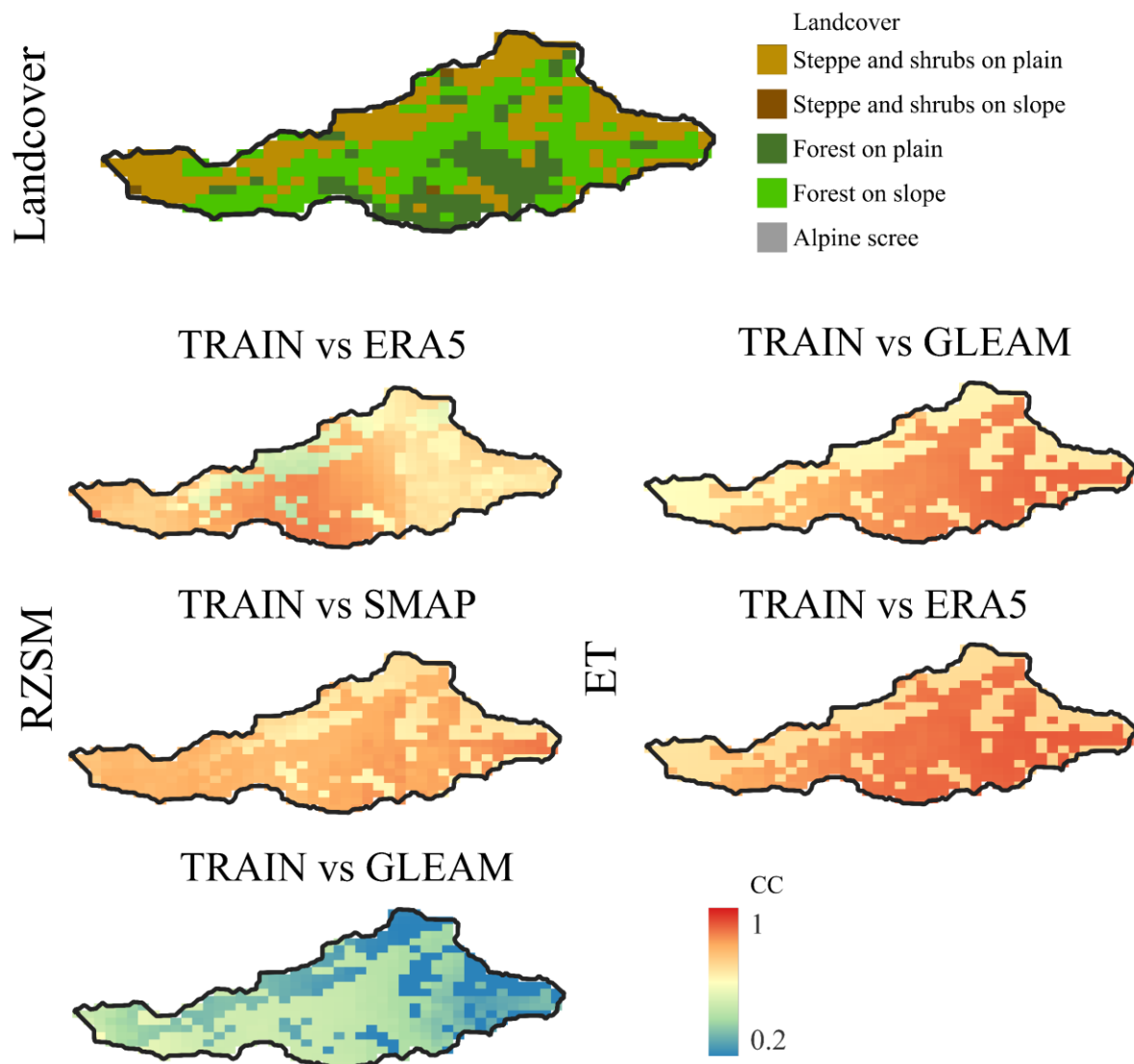


Figure 6.4: Spatial evaluation of correlations for root zone soil moisture (RZSM) and evapotranspiration (ET) between TRAIN simulations and the ERA5-Land and GLEAM datasets for 1980–2022, and SMAP dataset for 2016–2022.

We selected five sample points (Figure 6.5) to further validate the performance of the ET and RZSM simulations using the TRAIN model on a point scale. The TRAIN-simulated ET (left column in Figure 6.5) exhibited the same seasonality as the ERA5-Land and GLEAM ET (correlation coefficient: 0.79–0.89 and 0.74–0.84, respectively). The TRAIN-simulated RZSM showed good correspondence with the GLEAM, SMAP, and ERA5-Land RZSM (correlation coefficient: 0.07–0.38, 0.42–0.75, and 0.64–0.79, respectively). These results indicated that the TRAIN model provides reasonable estimates of ET and RZSM across the study area, and is suitable for further modeling the influence of wildfire on regional water balance.

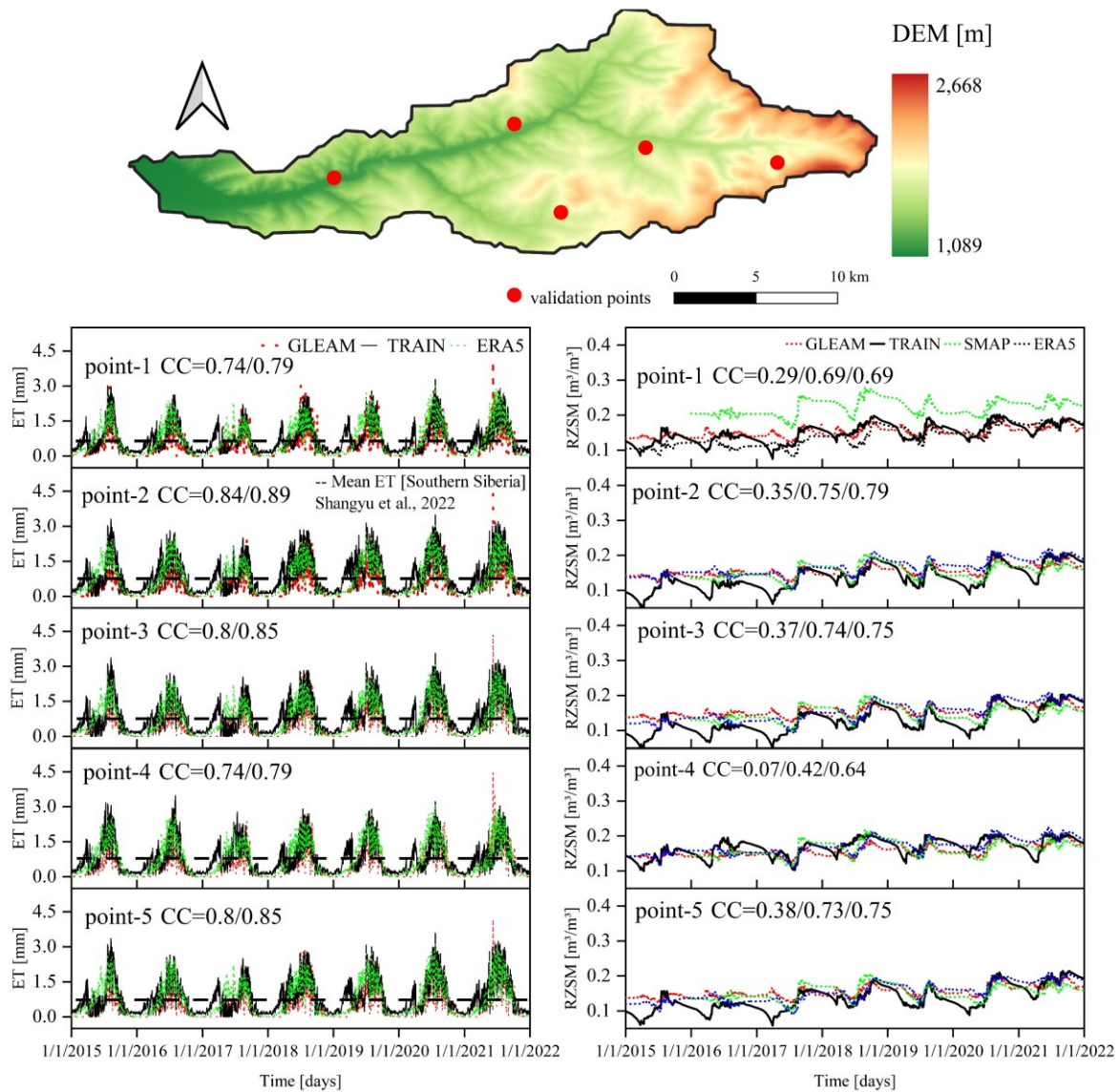


Figure 6.5: Point evaluation of the TRAIN-simulated ET and RZSM. The spatial distribution of the sample points (point-1 to point-5) is shown at the top. Coefficients on the left indicate the correlations between the simulated and GLEAM/ERA5-Land evapotranspiration (ET) data for 2015–2022. Coefficients on the right indicate the correlations between simulated and

GLEAM/ERA5-Land/SMAP root zone soil moisture (RZSM). Comparisons with GLEAM and ERA5-Land are for 2015–2022, and that for SMAP is for 2016–2022.

6.4 Evaluation of TRAIN-simulated snow events

We investigated snow development over 1980–2022 in terms of onset, cover, and melt associated with climate change (i.e., rising temperatures and changing precipitation behavior). Snow onset refers to the trend in snow events, snow cover relates to the duration of snow persistence (in days), and snow melt relates to the melting time in the study area. Figure 6.6 shows the MODIS Terra and Aqua snow products for Sugnugur Valley, which were combined to improve spatial accuracy (Dong & Menzel, 2016). We found that snow persistence was dependent on elevation, consistent with the findings of Munkhjargal et al. (2019), who also reported that snow persisted for >6 d in higher areas than lower areas. However, we avoid drawing a direct comparison since Munkhjargal et al. (2019) only considered 2001–2017, as opposed to 1980–2022 in the current study.

We selected one sample point to validate the performance of the TRAIN simulation for snow events on a point scale. Only one point was selected to correspond with the hydroclimatic Xoxoo station. The observed data provides a useful reference against the simulated and MODIS product estimates.

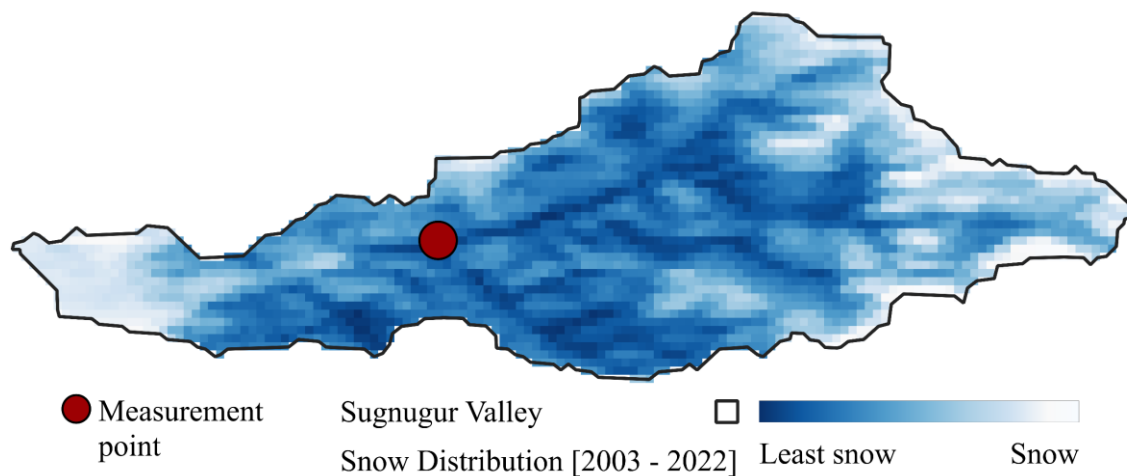


Figure 6.6: MODIS Terra and Aqua snow distribution over 2003–2022 at Sugnugur Valley. White represents areas with the most persistent snow. The red dot represents the location of the hydroclimatic (Xoxoo) station.

Figure 6.7 compares the TRAIN-simulated, observed, and MODIS snow data for 2012–2021, which was selected due to the limited availability of the observed data. The simulated snow water equivalent (SWE) was comparable with the observed data; the MODIS dataset confirmed the presence of snow. We generated a confusion matrix for the snow data based on the potential true positive, false positive, false negative, and true negative outcomes (Rittger et al., 2013; Luo et al., 2022), from which we calculated precision, recall, accuracy, F-score, and Cohen’s Kappa (Zhang et al., 2019; Luo et al., 2022) to compare the various snow datasets (Tables 6.1–6.3). Precision indicates the probability that a grid represents snow (Rittger et al., 2013); recall, also referred to as probability of detection (Zhou et al., 2013; Dong et al., 2014), measures the ratio of correct snow predictions to the total true snow cases; accuracy refers to

the proportion of all correctly predicted cases out of all cases; the F-score combines both precision and recall into a single representative measure (Rittger et al., 2013; Luo et al., 2022); and Cohen's Kappa is a statistical measure of interrater agreement, i.e., how well a classifier performs compared to chance (Cohen, 1960; Powers, 2020).

Precision and recall are particularly important for evaluating the model performance for detecting snow (Luo et al., 2020). The F-score and Cohen's Kappa accounts for categorical imbalances, providing an overall evaluation of both the negative and positive predicting capacities; thus, they are relatively reliable for determining prediction performance in terms of binary snow cover (Luo et al., 2020).

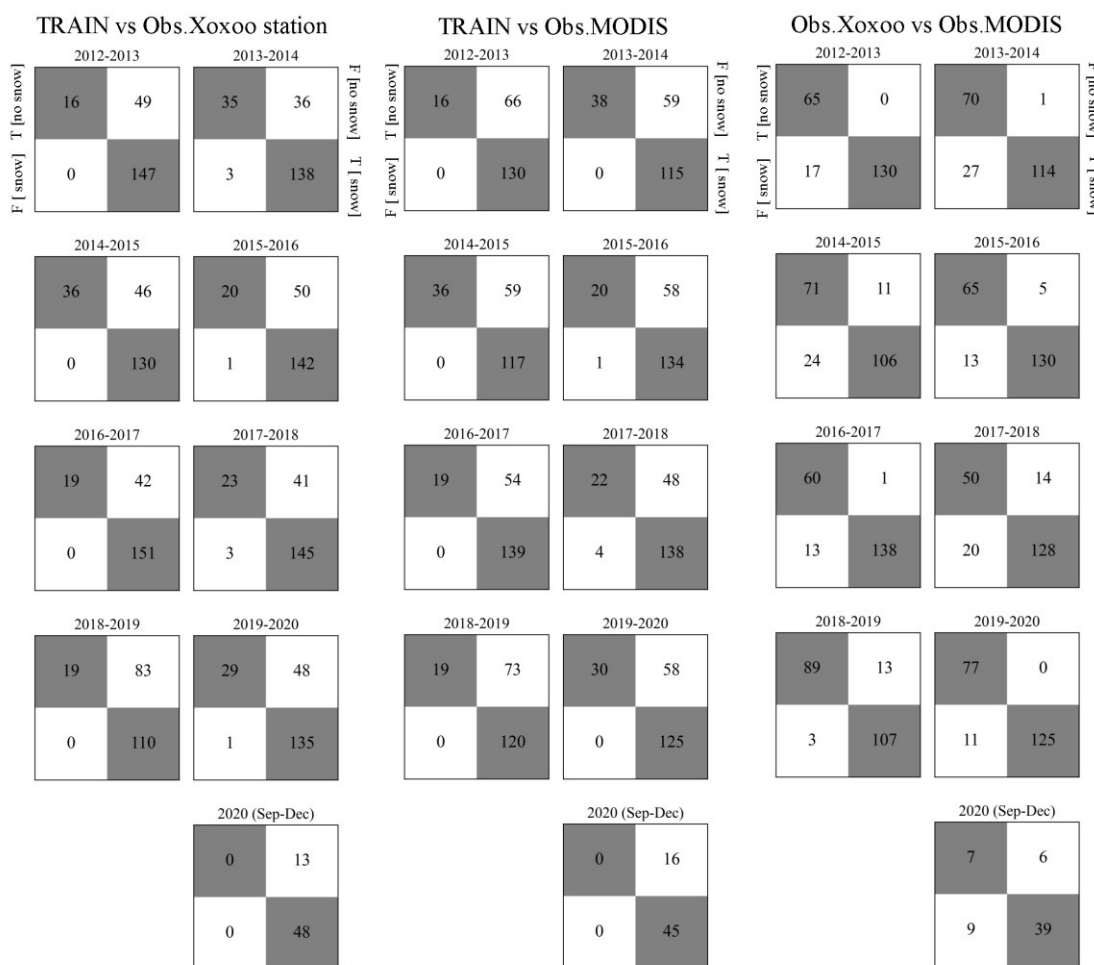


Figure 6.7: Confusion matrices of the TRAIN, observed, and MODIS snow data.

The recall (0.95, Table 6.1) for the TRAIN-simulated versus observed snow data suggested that the model effectively predicts most snow events. The confusion matrices (Figure 6.7) compare the actual labels of the dataset to the predicted labels from the classification model, showing counts for true positives, false positives, true negatives, and false negatives. The

variability in precision and Cohen’s Kappa for September–December 2020 indicates a decline in the model’s reliability, likely owing to the limited data availability for that period. These results indicated that the TRAIN model exhibits robust detection capabilities.

Table 6.1: Summary of evaluation metrics for the TRAIN-simulated and observed snow data for 2012–2020.

Year	Precision	Recall	Accuracy	F-score	Cohen's Kappa
2012–2013	0.75	1.00	0.77	0.86	0.31
2013–2014	0.79	0.98	0.82	0.88	0.53
2014–2015	0.74	1.00	0.78	0.85	0.49
2015–2016	0.99	0.74	0.76	0.85	0.34
2016–2017	0.78	1.00	0.80	0.88	0.39
2017–2018	0.78	0.98	0.79	0.87	0.41
2018–2019	0.57	1.00	0.61	0.73	0.19
2019–2020	0.74	0.99	0.77	0.85	0.43
2020 (Sep–Dec)	0.30	1.00	0.30	0.46	0.00
2012–2020	0.74	0.95	0.75	0.83	0.34

Compared to the MODIS estimations, the model consistently achieved near-perfect recall (Table 6.2), indicating that nearly all true snow events were detected. However, precision was moderate (0.62–0.74). Overall accuracy was ~0.72, the F-score was ~0.81, and Cohen’s Kappa, a measure of agreement beyond chance, averaged 0.33. Therefore, the TRAIN simulations reliably capture true snow occurrences.

Table 6.2: Summary of evaluation metrics for the TRAIN-simulated and MODIS snow data for 2012–2020.

Year	Precision	Recall	Accuracy	F-score	Cohen's Kappa
2012–2013	0.66	1.00	0.69	0.80	0.23
2013–2014	0.66	1.00	0.72	0.80	0.41
2014–2015	0.67	1.00	0.72	0.80	0.40
2015–2016	0.70	0.99	0.72	0.82	0.30
2016–2017	0.72	1.00	0.75	0.84	0.31
2017–2018	0.74	0.97	0.76	0.84	0.34
2018–2019	0.62	1.00	0.66	0.77	0.23
2019–2020	0.68	1.00	0.73	0.81	0.38
2020 (Sep–Dec)	0.74	1.00	0.74	0.85	0.00
2012–2020	0.69	0.99	0.72	0.81	0.33

The MODIS data showed robust performance in distinguishing snow from non-snow events (Table 6.3). The high precision indicated that nearly all predicted snow events were correct, while the recall showed that ~88% of the actual snow events were detected. The high F-Score (0.91) signified a strong balance between precision and recall (Rittger et al., 2013; Luo et al., 2022), with a relatively low false alarm rate (0.08). The high Cohen's Kappa (0.77) indicated a strong agreement with the observed datasets, well above random chance (Cohen, 1960). Overall, these results support the reliability of MODIS in detecting binary snow cover, with moderate variability among years. As noted by Luo et al. (2020) and Zhang et al. (2019), the F-score and Cohen's Kappa are particularly useful for data exhibiting class imbalances (e.g., relatively few true snow or non-snow events in certain months). The consistently high Kappa values in most years confirm the model's robust performance across a range of climatic conditions and observation periods.

Table 6.3: Summary of evaluation metrics for the observed and MODIS snow data for 2012–2020.

Year	Precision	Recall	Accuracy	F-score	Cohen's Kappa
2012–2013	1.00	0.88	0.92	0.94	0.83
2013–2014	0.99	0.81	0.87	0.89	0.73
2014–2015	0.91	0.82	0.84	0.86	0.66
2015–2016	0.96	0.91	0.92	0.94	0.82
2016–2017	0.99	0.91	0.93	0.95	0.85
2017–2018	0.90	0.87	0.84	0.88	0.63
2018–2019	0.89	0.97	0.92	0.93	0.85
2019–2020	1.00	0.92	0.95	0.96	0.89
2020 (Sep–Dec)	0.87	0.81	0.75	0.84	0.32
2012–2020	0.95	0.88	0.89	0.91	0.77

We assessed the model performance for predicting the long-term SWE (Figure 6.8a–c). The TRAIN-simulated SWE was highly comparable with the observed and MODIS data (Figure 6.8a). It reliably captured the onset and duration of snow accumulation, as evidenced by its alignment with ground observations from the Xoxoo station. The TRAIN model also mirrored the timing of snowfall, as independently confirmed by the MODIS satellite data, supporting its reliability. The minor quantitative differences during transitional periods do not detract from its robust overall performance. Figure 6.8b shows a comparison between the observed data at the Baruun Kharaa and Kharaa stations. Figure 6.8c shows the full-length datasets for 1980–2022 according to overall SWE and snow presence in Sugnugur Valley compared with the Baruun Kharaa and Kharaa stations.

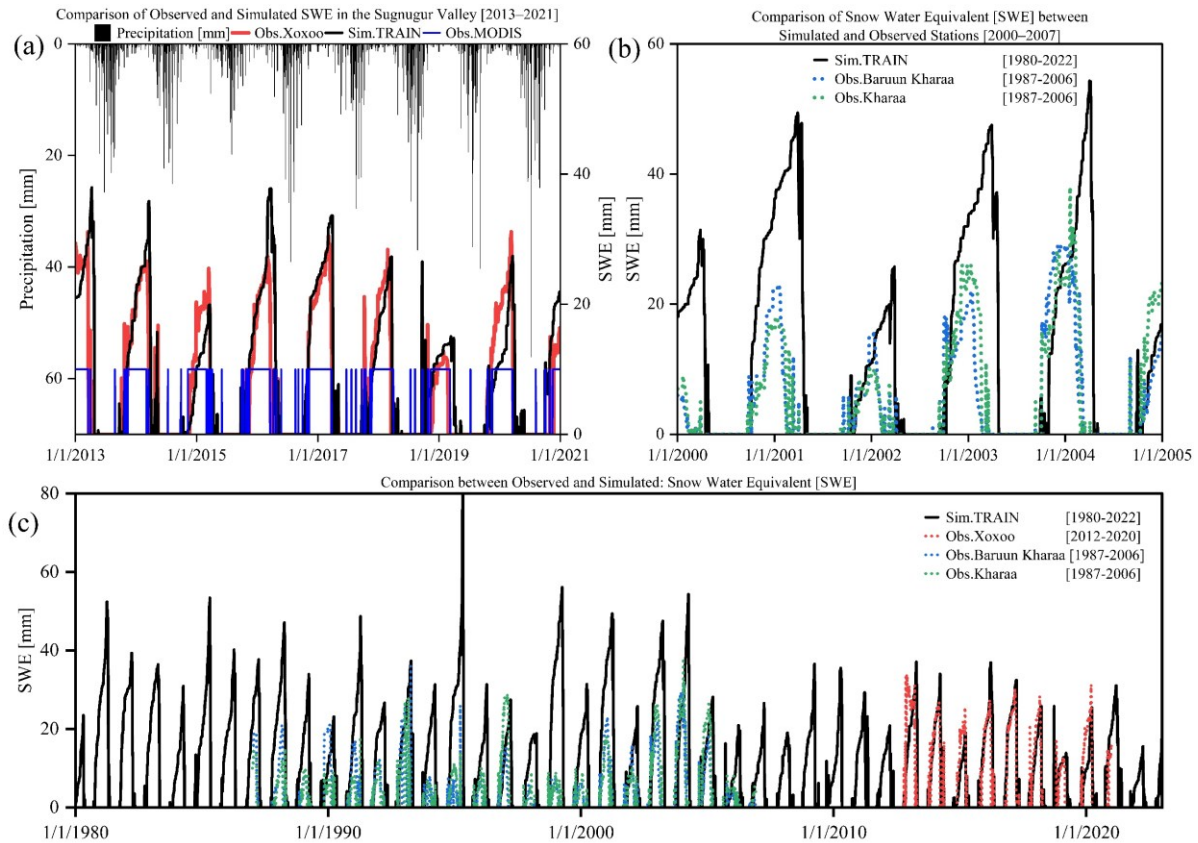


Figure 6.8: Long-term daily snow water equivalent (SWE) analysis in Sugnugur Valley. (a) Point comparison between SWE and snow presence together with precipitation for 2013–2021. (b) TRAIN-simulated SWE compared with observed data at Baruun Kharaa (2000–2006) and Kharaa (2000–2006). (c) SWE for maximum available datasets for the simulated TRAIN and observed data (Sugnugur Valley as well as Baruun Kharaa and Kharaa stations at nearby locations).

We analyzed the snow cover, onset, and melt (Figure 6.9). In Figure 6.9a, we compare the annual snow cover days for 1980–2022 along with the winter temperatures. We defined the winter months based on the snow onset days, and averaged the winter temperature in each year for October to March. For 1980–2022, the trendline showed that snow cover days were reduced from ~173 to ~140. This could suggest decreased snow cover persistence or late precipitation. The Sen’s slope showed that temperature increased annually at 0.05 °C, and snow cover declined by 0.7 d per year. We divided the dataset into a 1980–2000 and 2001–2022 period.

In the first period, the TRAIN model indicated an annual decrease in snow cover of 0.17. In the second period, snow cover decreased by 1.4 d/year for the observed and MODIS data (–1 for both datasets). For snow onset days over the whole period, the TRAIN model showed a Sen’s slope of 0.46 (Figure 6.9b), suggesting that the snow onset may be shifting towards December. Interestingly, the observed data indicated earlier snow onset over time, likely because more data is available for 2012–2020, though this window may be too short to reflect the true trend. The TRAIN model showed that snow melt days declined by 0.11 d/year (Figure 6.9c), suggesting that snow melt occurs earlier over time. The trend line suggested that, for 1980–2022, the snow melt shifted by ~25 d from April to the beginning of March. In the second period, snow melt occurred very close to the beginning of March; the observed and MODIS data showed snow melt even in late February.

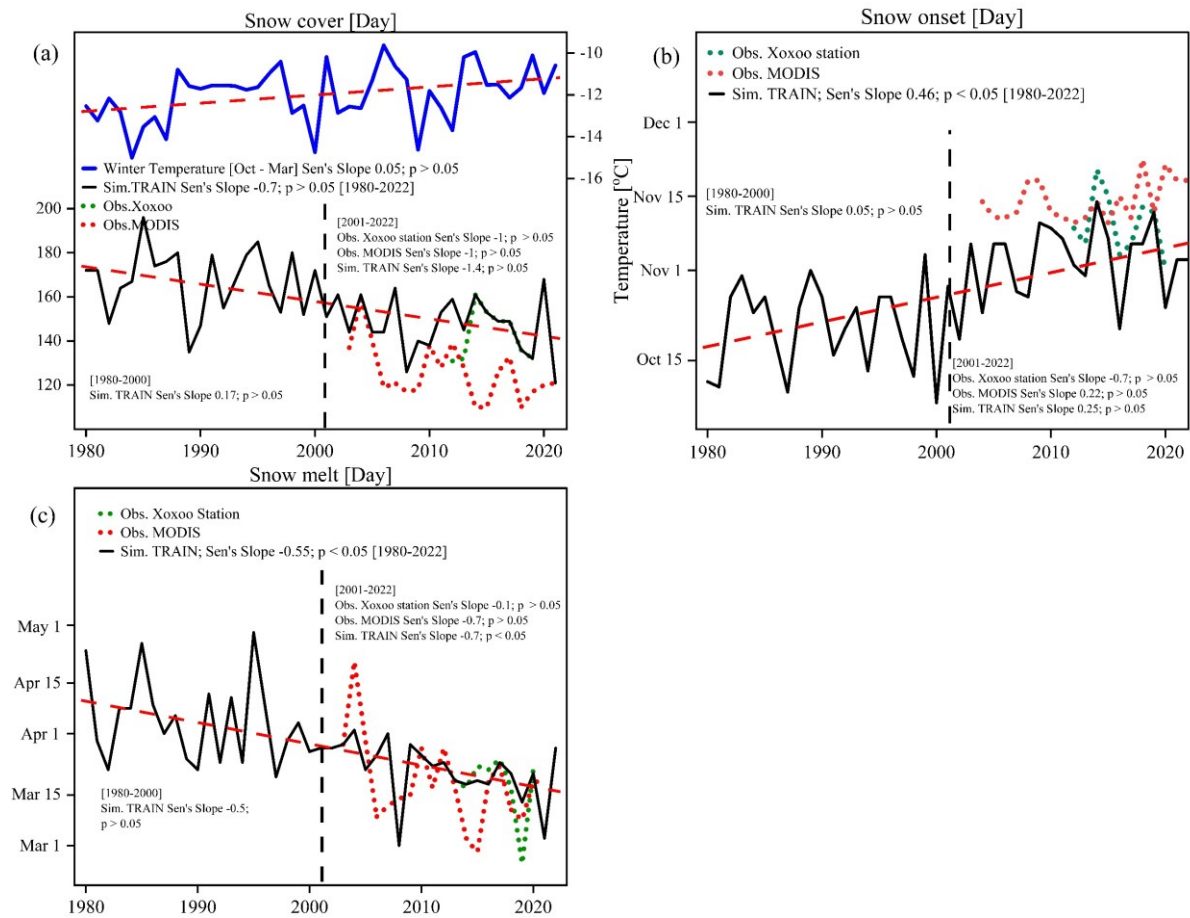


Figure 6.9: TRAIN simulation of snow events compared to observed and MODIS data. Snow cover (a), onset (b), and melt (c) days in Sugnugur Valley for 1980–2022 (the vertical dashed line separates the data into two equal periods).

6.5 Inter-annual hydroclimatic variability

We analyzed the long-term inter-annual variability of hydroclimatic variables, such as river runoff, precipitation, snow cover, temperature, RZSM, and ET (Figure 6.10) for the Sugnugur basin. (For clearer interpretation, related variables are presented in the same plot.) Due to the limited data availability for the region, we compared the TRAIN-simulated runoff with the observed data for the Sugnugur, Kharaa, Baruun Kharaa, and Tuul river basins, which were selected based on their proximity, availability of data, and time series coverage.

For 1980–2022, the runoff in the Sugnugur (-0.03 L/s km^2 , $p < 0.05$), Kharaa (-0.06 L/s km^2 , $p < 0.05$), and Tuul basins declined (-0.1 L/s km^2 , $p < 0.05$), whereas it increased in the Baruun Kharaa basin (0.04 L/s km^2 , $p < 0.05$; Figure 6.10a). The available data varied between the basins for different periods; therefore, we performed the comparison for 1980–2000 and 2001–2022 to gain a clearer view of the runoff trends. For 1980–2000, runoff declined in the Sugnugur (-0.05 L/s km^2), Kharaa (-0.08 L/s km^2 , $p < 0.05$), and Tuul basins (-0.01 L/s km^2). For 2001–2022, runoff increased slightly in the Sugnugur (0.005 L/s km^2) and Kharaa basins (0.04 L/s km^2 , $p < 0.05$). However, the observed datasets did not fully cover the study period. Runoff in the Tuul basin declined (-0.02 L/s km^2). For 2001–2022, precipitation declined compared to 1980–2000, which may explain the decreased runoff in the second period.

For 1980–2022, snow cover declined (-0.1 mm , $p > 0.05$) whereas temperatures increased ($0.04 \text{ }^{\circ}\text{C}$, $p < 0.05$; Figure 6.10b). For 1980–2000, snow cover declined (-0.06 mm , $p > 0.05$) and temperature increased ($0.06 \text{ }^{\circ}\text{C}$, $p < 0.05$). For 2001–2022, snow cover declined more rapidly compared to the previous period (-0.11 mm , $p > 0.05$) and temperature increased but not as clearly ($0.01 \text{ }^{\circ}\text{C}$, $p > 0.05$). Nevertheless, the mean annual air temperature in the Sugnugur basin increased to $\sim 2.6 \text{ }^{\circ}\text{C}$ ($p < 0.05$) from 1980 to 2022. Therefore, snow cover may decline because of increasing temperatures. We analyzed the temperature in winter periods (October–March) and found that it increased over 1980–2022 ($0.06 \text{ }^{\circ}\text{C}$, $p < 0.05$), which may contribute to declining snow cover. Both periods showed increasing temperatures ($0.08 \text{ }^{\circ}\text{C}$ and $0.06 \text{ }^{\circ}\text{C}$ for 1980–2000 and 2001–2022, respectively).

For 1980–2022, RZSM declined ($-0.001 \text{ m}^3/\text{m}^3$, $p < 0.5$; Figure 6.10d). The mean annual RZSM was higher in 1980–2000 ($0.17 \text{ m}^3/\text{m}^3$) than that in 2001–2022 ($0.14 \text{ m}^3/\text{m}^3$). Therefore, the second period was drier than the earlier period. For 2001–2022, we observed an increasing trend ($0.001 \text{ m}^3/\text{m}^3$, $p > 0.05$).

For 1980–2022, both precipitation (-1.95 mm/year , $p < 0.05$) and ET declined (-0.28 mm/year , $p > 0.05$; Figure 6.10e).

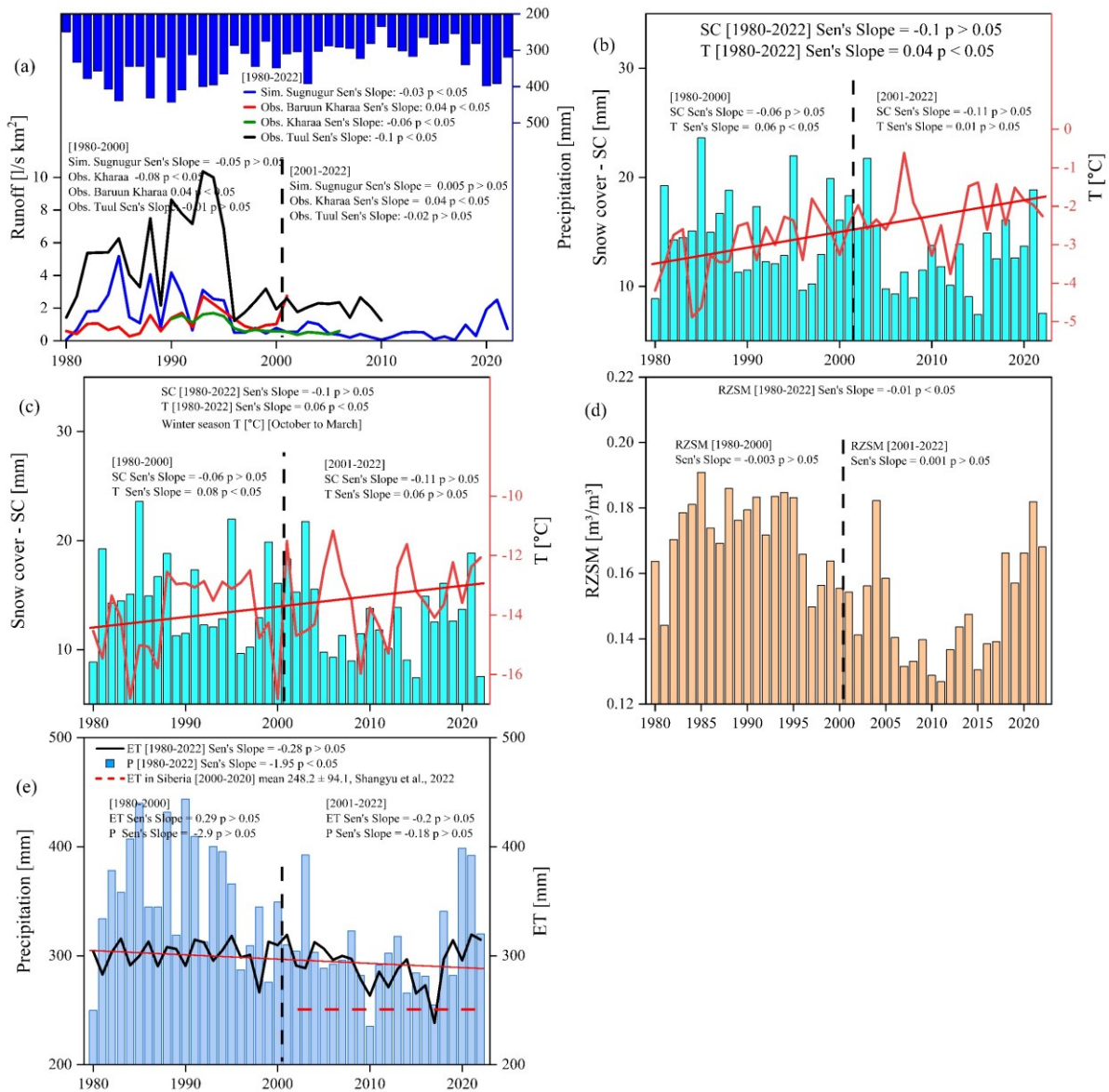


Figure 6.10: Annual time series of hydroclimatic variables, including runoff (L/s km^2), precipitation (mm), snow cover (mm), temperature ($^{\circ}\text{C}$), root zone soil moisture (RZSM, m^3/m^3), and evapotranspiration (ET, mm) for 1980–2022. The dashed black line divides the dataset into equal periods. The red dashed line in (e) represents mean ET in Siberia (Shangyu et al., 2022).

6.6 Hydroclimatic regime shifts

We investigated the shifts in intra-annual river runoff, precipitation, and ET. Due to the limited availability of data, not all datasets correspond to the same period, thus we divided the datasets into 1980–2000 and 2001–2022.

In the Sugnugur basin, minor variations were observed in precipitation and ET between the two periods, unlike for river runoff (Figures 6.11 and 6.12). During the first period, the peak differences in runoff were minimal, creating an evenly distributed intra-annual pattern (Figure 6.12). The absolute precipitation level differed between the periods, with a marked decline from July to October in 2001–2022 compared to 1980–2000, which was primarily attributed to oscillations in large-scale atmospheric circulation (Iwao & Takahashi, 2006; Han & Menzel, 2022). Because of this substantial reduction in warm-season precipitation after 2000, both runoff and ET decreased greatly during 2001–2022. The concurrent decline in these three hydroclimatic variables underscores the dominant influence of summer precipitation on surface hydrological processes in the Sugnugur basin.

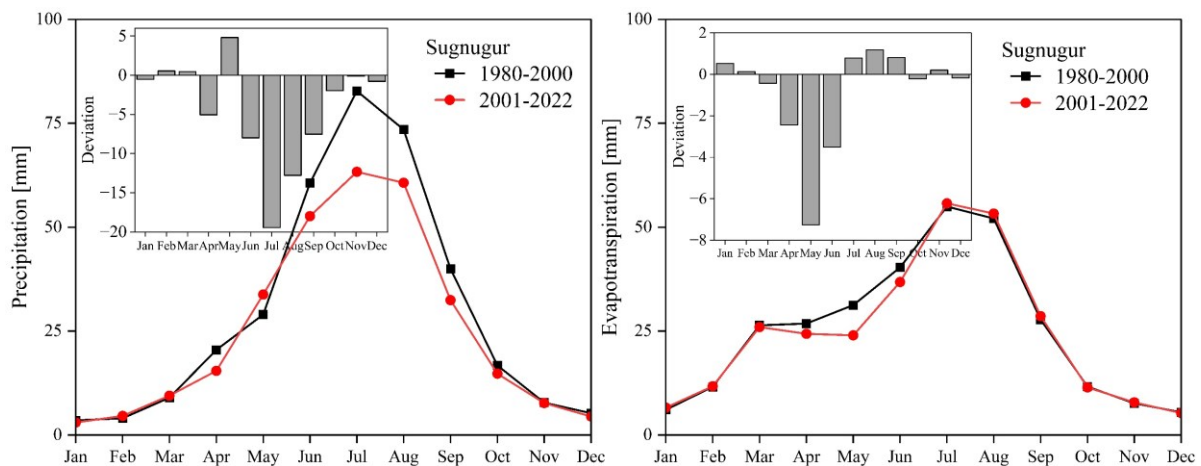


Figure 6.11: Intra-annual patterns of precipitation and evapotranspiration during 1980–2000 and 2001–2022 in the Sugnugur basin.

For 1980–2022, the peak runoff, precipitation, and ET occurred during July (Figures 6.11 and 6.12). The deviation was greatest in July and August between the two periods. In August and September, precipitation, ET, and runoff declined faster than in the spring months up to November.

We compared the findings for the Sugnugur basin to those for the Kharaa, Baruun Kharaa, and Tuul catchments (Figure 6.12), each of which are regenerated from the Khentii Mountains. In the Kharaa basin, the data were available for 1990–2006; for consistency, we divided the dataset into 1990–2000 and 2001–2006. In the first period, clear changes were observed starting from May–June, with the runoff declining towards early summer and then gradually increasing into early autumn. In 2001–2006, the runoff gradually decreased in the

beginning of June towards winter, unlike the trend in the first period. Törnros and Menzel (2010) found that, in the Kharaa basin after the 1990s, decreased runoff could be caused by hydrological changes specific to the study site or climatic variations. The variation was highest between July–October in both periods. Runoff tended to increase in the first period and decrease in the second period. In the Baruun Kharaa basin, the data were available for 1951–2000, thus we divided the dataset into 1951–1979 and 1980–2000. The runoff regime was comparable between the periods. Although the first period showed slightly higher runoff than the second period, the deviation was lowest among the basins. In the Tuul basin, the data were available for 1990–2006, thus we divided the dataset into 1990–2000 and 2001–2010. This basin showed the highest variation between the first and second periods. The highest runoff occurred starting from April to October. Peak deviations occurred in July, August, and September.

Based on our field observations for 2022 (Figure 6.13), ice slowly formed on the river edges from mid-October (Figure 6.13e) towards the end of October (Figure 6.13g). By mid-November, the river could be fully covered by ice (Figure 6.13h-i). Munkhjargal (2020) reported that this region is characterized by discontinuous permafrost, and reduced surface water availability is likely affected by warming-induced permafrost degradation (Han and Menzel, 2022). In 2001–2022, ET declined in March–May and increased towards July, which could be related to the changing precipitation regime and anthropogenic disturbances such as wildfire. The low precipitation in early Spring and increased windspeed lead to dry conditions that are favorable for ignition. The removal of vegetation cover by wildfire promotes desiccation of the topsoil and reburn risk. This could degrade the permafrost and limit water availability for surface hydrologic processes, i.e., ET and runoff, in spring and early summer, further impeding forest growth and recovery.

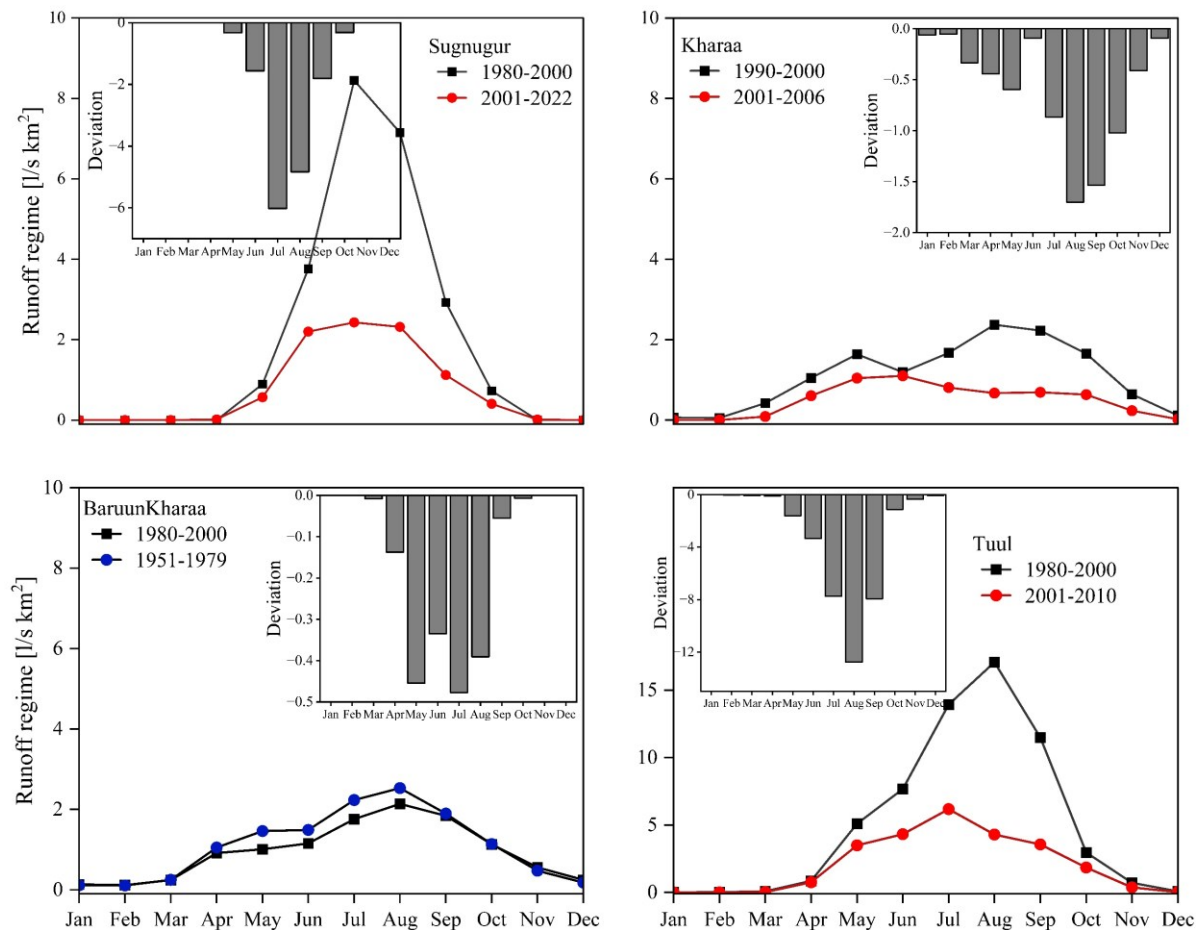


Figure 6.12: Periodical regimes of river runoff during 1980–2000 and 2001–2022. Due to limited data availability, some datasets start earlier or later than the desired timeline. The inset bar plot shows the deviations in the corresponding dataset.

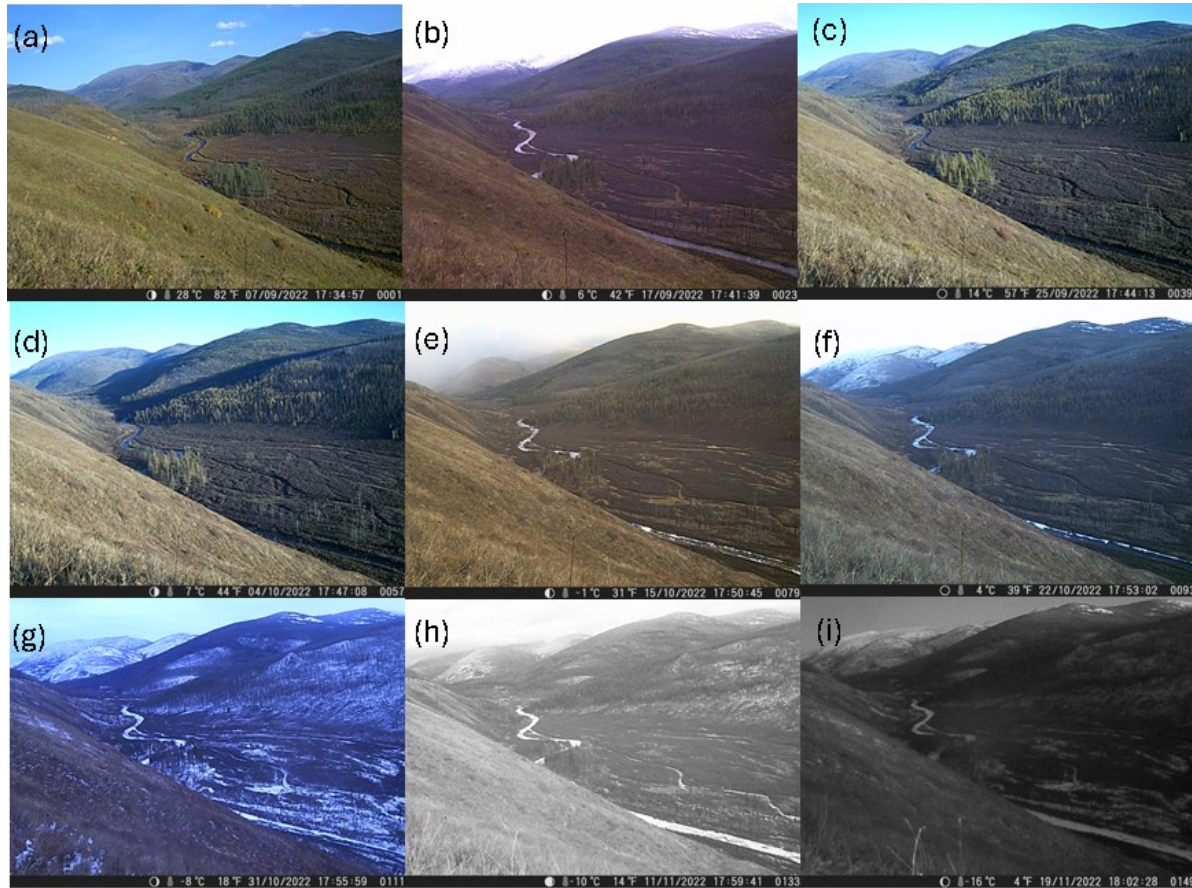


Figure 6.13: Time-lapse images of river and snow development captured by the wildlife camera at Sugnugur Valley in 2022. The camera was directed in a south-easterly direction. (a) 7 September, (b) 17 September, (c) 25 September, (d) 4 October, (e) 15 October, (f) 22 October, (g) 31 October, (h) 11 November, and (i) 19 November.

6.7 Hydrological changes due to climate change and repeated wildfire

We performed a comprehensive investigation on the effects of repeated wildfire in Sugnugur Valley. Based on the findings in Chapter 5, we incorporated the effects of repeated wildfire on landcover, starting from 2001 to 2012 (12 years) and from 2016 to 2018 (3 years). Ruggirello et al. (2023) found that higher latitude forests may require recovery times of more than 16 years after wildfire, while complete recovery can take several decades in many cases (30–50 years or even longer). Therefore, our simulation incorporated accumulated burned areas in the landcover classification.

We investigated the temporal changes in RZSM with and without fire (Figure 6.14). In 1980–2000, precipitation and RZSM levels were higher than those in 2001–2022. Interestingly, RZSM increased with fire compared to that without fire even in low-precipitation periods (Figure 6.14a). Similar trends were observed at the seasonal scale (Figure 6.14b). RZSM was lower during the second period, likely due to lower precipitation during these years (Figure 6.14c). The fluctuations across years suggest RZSM is not uniformly

affected by wildfire likely owing to interactions with other factors such as annual precipitation and seasonal variability.

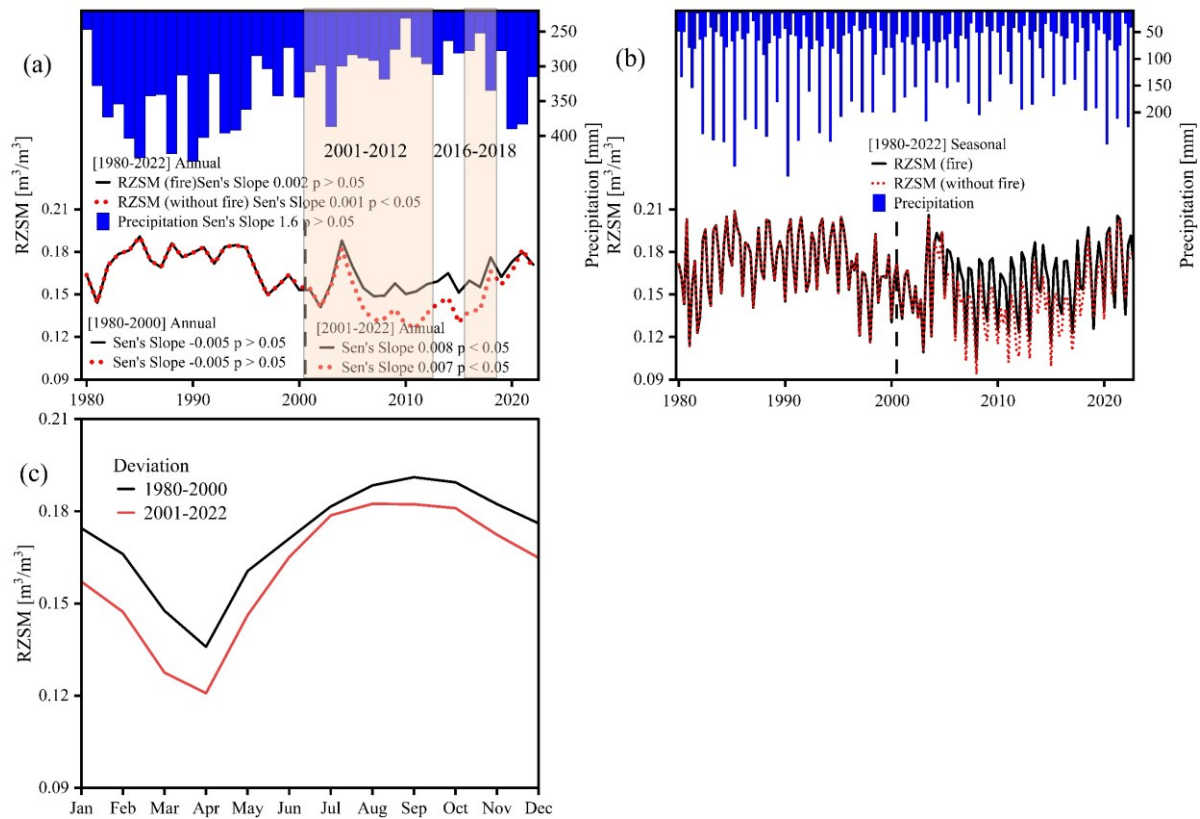


Figure 6.14: Simulated effects of wildfire on RZSM (m^3/m^3) in Sugnugur Valley. (a) Mean annual RZSM from 1980 to 2022, with and without fires; the yellow shaded area shows stages of repeated wildfire (2001–2012 and 2016–2018). (b) Mean seasonal RZSM and cumulative precipitation (mm). (c) RZSM regimes of two time periods. The black dotted line in (a) and (b) separates two periods of equal duration.

We further analyzed mean seasonal RZSM across years (Figure 6.15) with and without wildfire. Precipitation was an important contributor of RZSM fluctuations. RZSM declined rapidly during low-precipitation seasons and increased during the moderate- to high-precipitation seasons. The summer season is the major rainfall period in this area. From 1980 to 2022, summer precipitation ranged from ~120 mm to above ~300 mm; few precipitation events above 300 mm were recorded. RZSM increased in autumn of 2016–2018 during repeated wildfires likely because of an increase in precipitation.

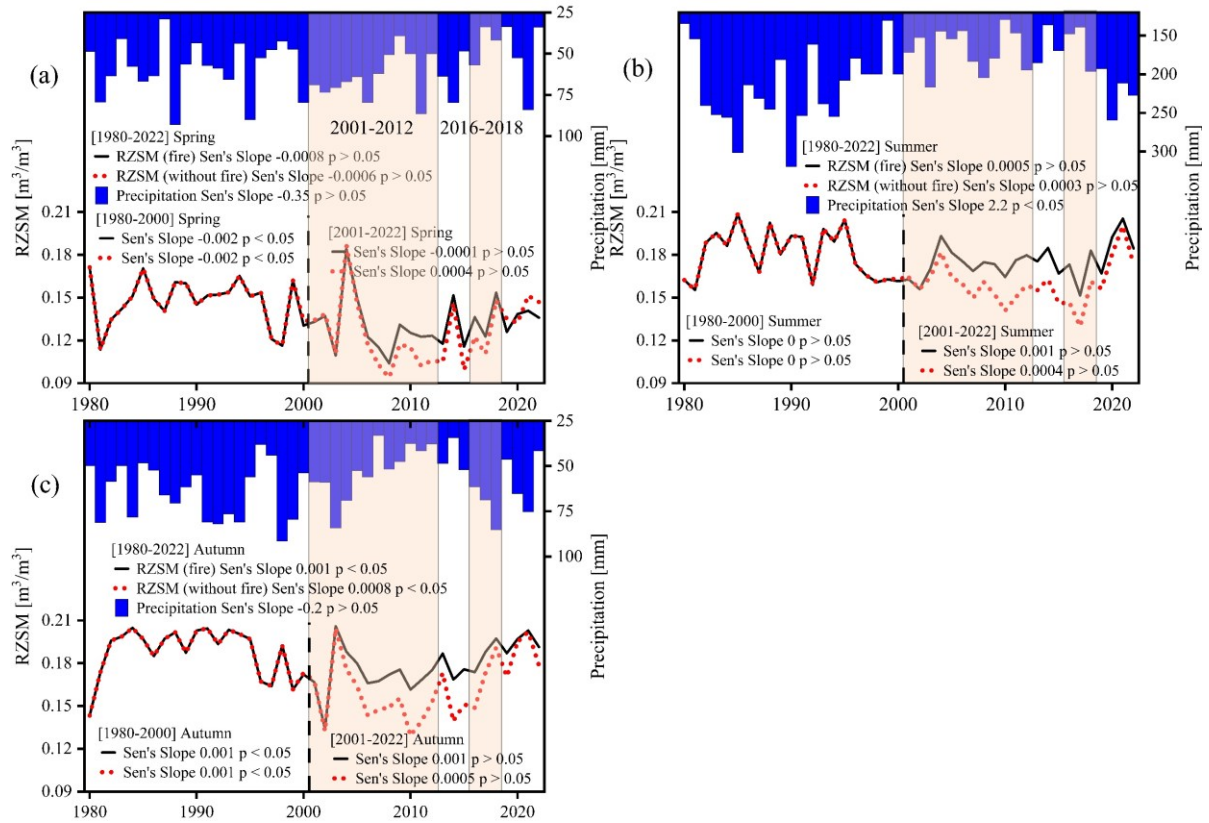


Figure 6.15: Mean seasonal RZSM during 1980–2022 with precipitation. The yellow-shaded areas represent stages of repeated wildfires. (a) Spring, (b) Summer, and (c) Autumn. The black dotted line separates two periods of equal duration.

We investigated the simulated runoff in Sugnugur Valley at the annual and seasonal scales for 1980–2022 (Figure 6.16). With fire, runoff increased slightly during the first period (0.05 mm/year, $p > 0.05$) and even more so during the second period (0.08 mm/year, $p < 0.05$; Figure 6.16a). In contrast, without fire, runoff increased slightly in the first period and decreased slightly in the second period, though not significantly so. At the seasonal scale (Figure 6.16b), runoff increased during wildfire periods, likely due to seasonal changes in many other factors such as precipitation, snow melt, and temperature. Runoff varied during the two periods and seemed to shift towards late summer.

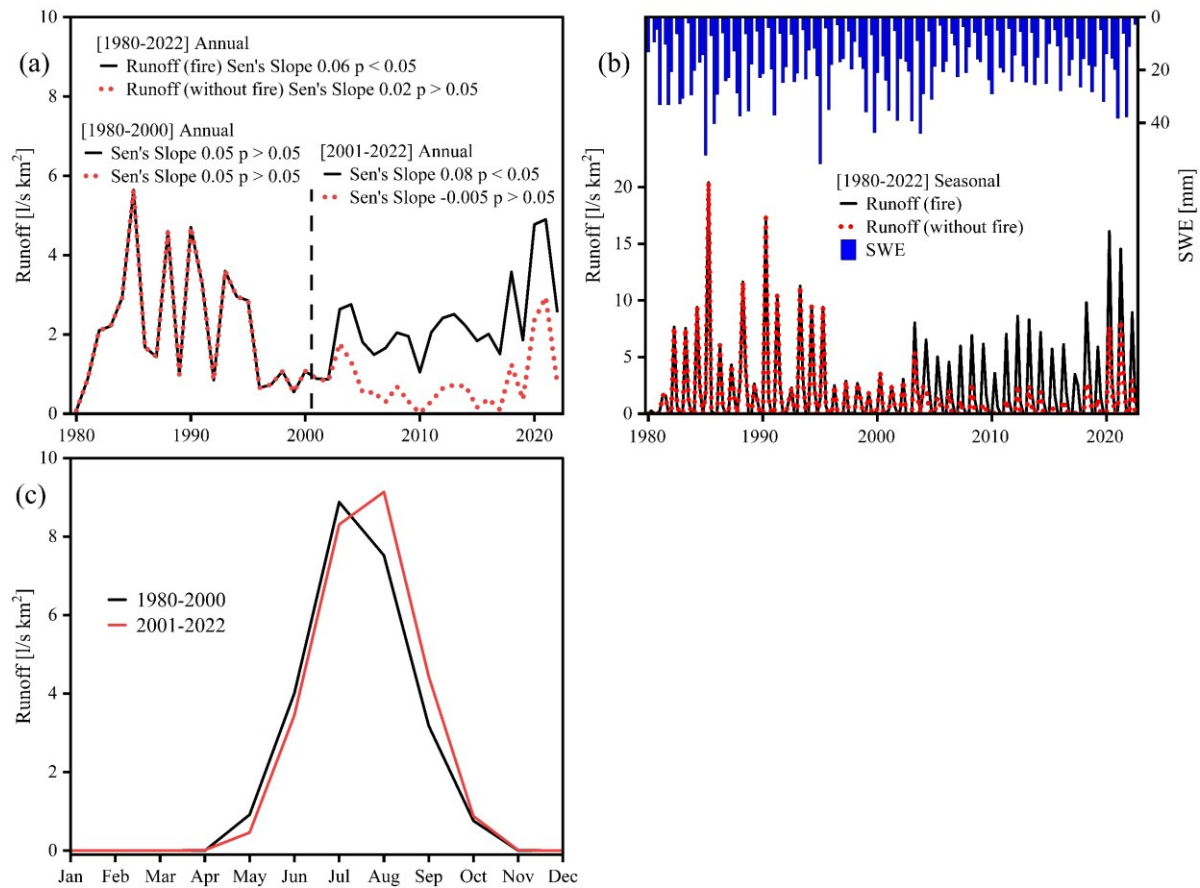


Figure 6.16: Simulated runoff (L/s km²) in Sugnugur Valley. (a) Mean annual runoff from 1980 to 2022. (b) Mean seasonal runoff and snow water equivalent (SWE, mm). (c) Runoff regimes of the two periods. The black dotted line in (a) separates two periods of equal duration.

We investigated the seasonal trends in runoff and SWE over 1980–2022 (Figure 6.17). Snow was a major contributor to runoff in spring and autumn, likely owing to accelerated snow melt under increasing regional temperatures. During summer, both runoff and precipitation were higher during the first than second period.

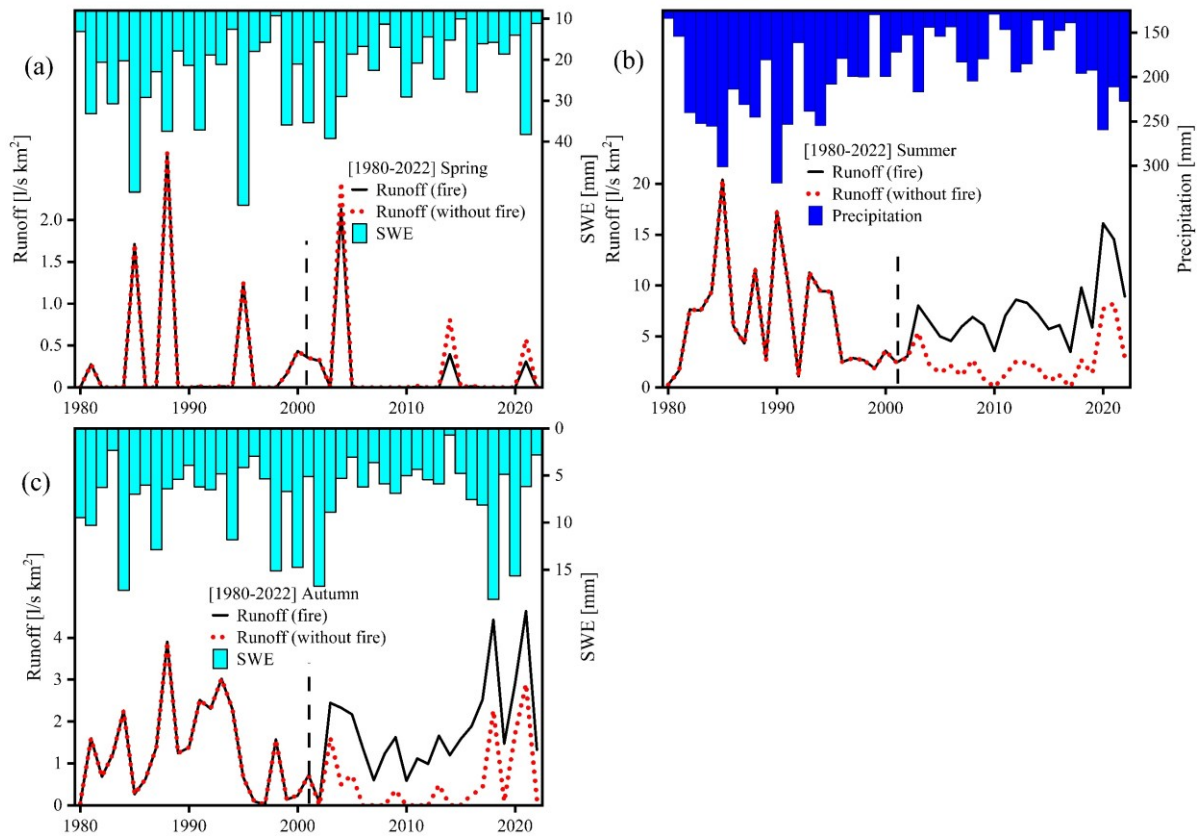


Figure 6.17: Mean seasonal runoff and SWE during 1980–2022. (a) Spring, (b) Summer, and (c) Autumn. The black dotted line separates two periods of equal duration.

Since ET is a critical component of both the water and energy cycles in the hydroclimatic system, its variations provide valuable insights into terrestrial water availability. We investigated the spatial distribution and temporal variations in ET simulated using the TRAIN model (Figure 6.18). During the wildfire period of 2001–2012, mean annual ET declined, similar to some years without fire, likely due to low precipitation during these years. Overall, ET declined from 1980 to 2022 (-2.2 mm/year , $p < 0.05$); however, a slight increase was observed in 1980–2000 both with and without fire. During 2001–2022, ET declined with and without fire, though more so during periods of fire. Similar trends were observed for mean seasonal ET. ET varied during the two periods, especially during late spring to late autumn (Figure 6.18c).

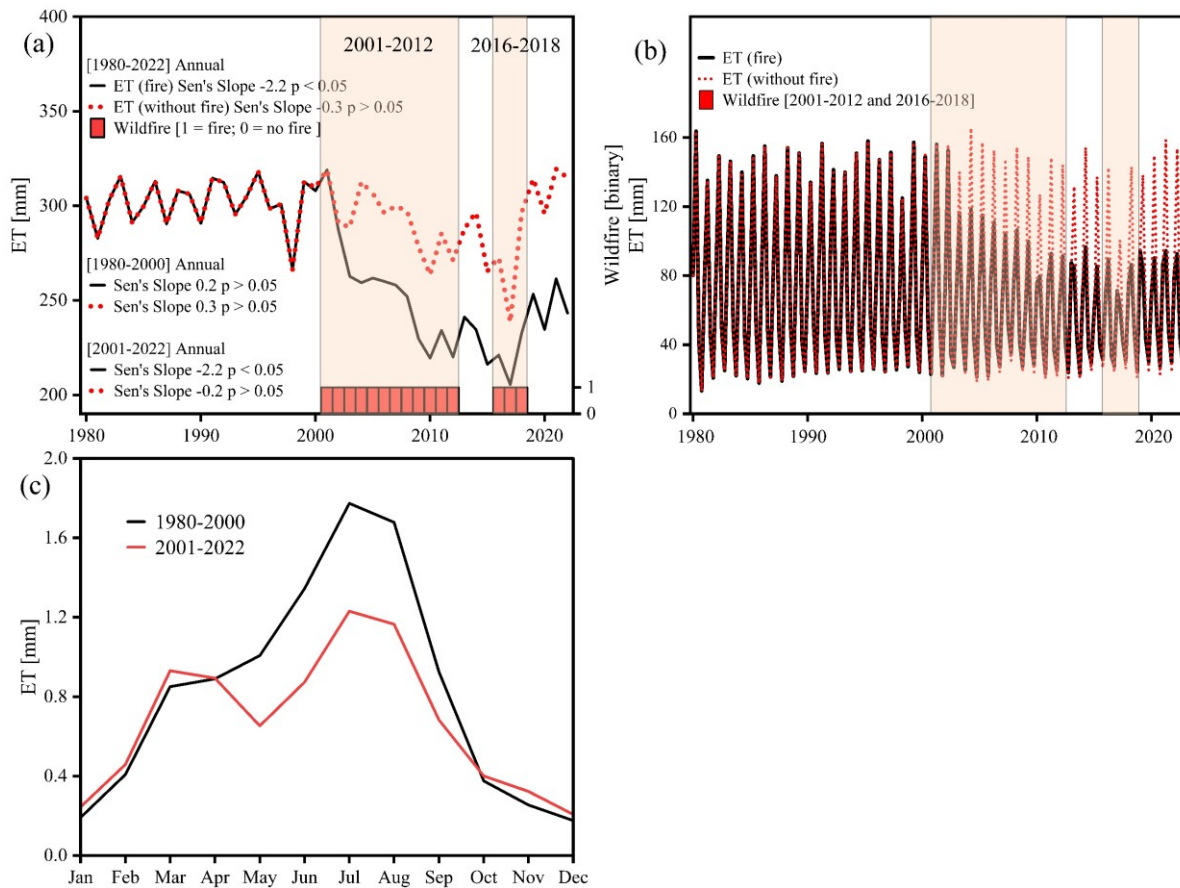


Figure 6.18: Simulated ET during 1980–2022 with and without fire. (a) Mean annual ET. (b) Mean seasonal ET. (c) Overall ET regime during 1980–2000 and 2001–2022.

We investigated the seasonal variations in ET over 1980–2022 (Figure 6.19). Interestingly, wildfires had the greatest impact during the summer months (Figure 6.19b). Minderlein and Menzel (2015) measured summer ET in shrublands at Sugnugur Valley and reported values of ~ 101 mm in 2012. Similarly, we observed 93 mm of ET for the same period (red dot in Figure 6.19c). Even during wildfire periods, ET increased in some years, likely due to enhanced precipitation and snowfall events (Figure 6.19c). In contrast, winter ET increased during 1980–2022 at 0.2 mm/year with fire compared to 0.06 mm/year without fire.

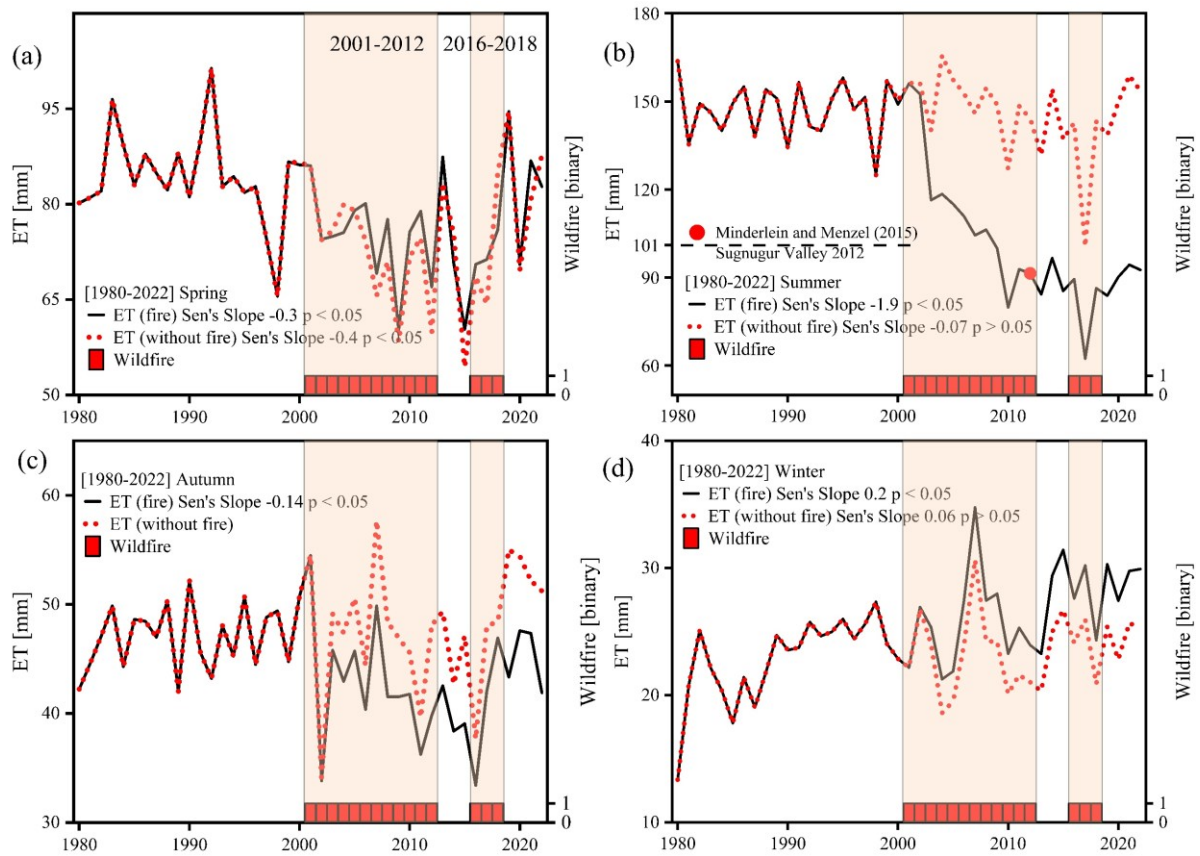


Figure 6.19: Mean seasonal ET with and without wildfire. (a) Spring, (b) Summer [red dot indicates the mean ET for the shrubland in Sugnugur Valley estimated by Minderlein and Menzel (2015) for summer 2012], (c) Autumn, and (d) Winter.

We investigated the TRAIN-simulated ET for the gridded forest at Sugnugur Valley considering the effects of wildfire (Figure 6.20). Annual and seasonal ET and precipitation were higher in the first than in the second period (Figure 6.20a–e). In the second period, annual ET and precipitation declined gradually or rapidly until 2017, likely due to continuous wildfire and limited precipitation. However, both ET and precipitation increased in 2019 and 2020, likely due to reduced wildfires and increased precipitation. ET was drastically lower during summers with than those without fire. Again, the simulated ET for the summer of 2012 (with fire, Figure 6.20c) was largely comparable with that of Minderlein and Menzel (2015). During the winter, ET increased both with and without fire in the second period (Figure 6.20e), potentially due to reduced canopy cover. Gui et al. (2024) found that wildfire-induced canopy loss in southeastern Siberia was associated with earlier and more pronounced snow melt, which contributes to increased surface temperatures and higher ET. Additionally, Cho et al. (2025) found that the loss of trees after wildfire promoted turbulent wind mixing, increasing the exchange of heat and moisture between the ground and overlaying air, and promoting ET.

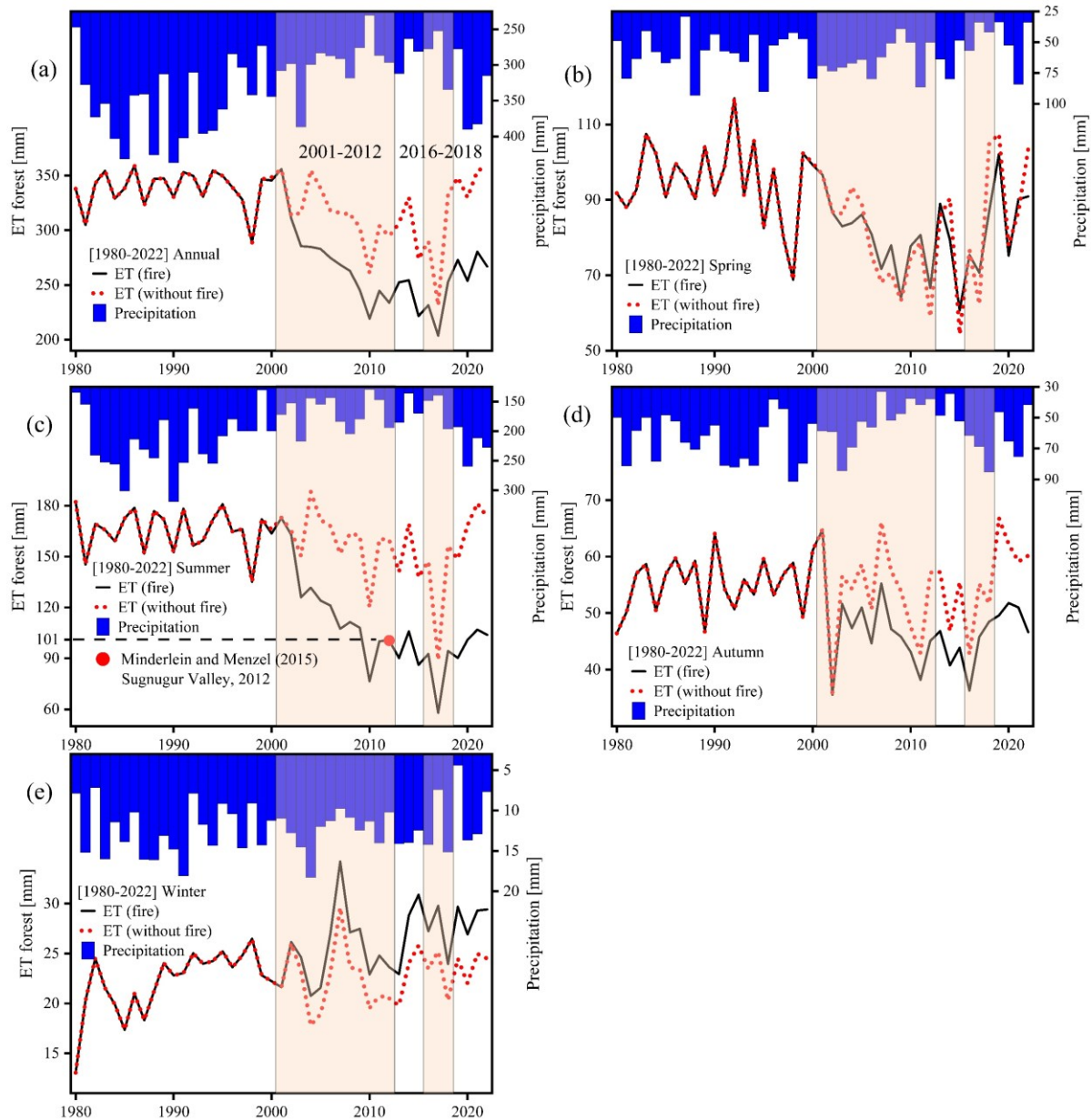


Figure 6.20: TRAIN-simulated ET for gridded forest area in Sugnugur Valley with precipitation for 1980–2022. (a) Mean annual simulated ET; mean seasonal simulated ET in (b) Spring, (c) Summer, (d) Autumn, and (e) Winter. The red dot indicates the mean ET for the shrubland in Sugnugur Valley estimated by Minderlein and Menzel (2015) during the summer of 2012.

6.8 Discussion

6.8.1 Hydrological dynamics and regime shifts in Sugnugur Valley

Chapter 6 aimed to clarify the long-term hydrological responses and regime shifts in northern Mongolia's forest–steppe ecotone and discontinuous permafrost zone under the dual influences of climate change and repeated wildfires. By employing the TRAIN model alongside multiple field measurements, global reanalysis, and remote sensing datasets (ERA5-Land, GLEAM, SMAP, and MODIS), we elucidated the spatiotemporal dynamics of important hydrological components, including ET, RZSM, snow events, and river runoff over 1980–2022, both with and without the influence of wildfire.

6.8.2 Soil moisture and evapotranspiration

Our modeling results emphasize the critical function of RZSM in partitioning water between ET and runoff throughout Sugnugur Valley, consistent with previous field-based studies in Mongolia's forest–steppe ecotone. Minderlein and Menzel (2015) found that, on exposed steppe slopes, volumetric SM could drop to around $0.05 \text{ m}^3/\text{m}^3$ during dry periods, which effectively limits ET to $\sim 0.4 \text{ mm/d}$. Under such water-stressed conditions, nearly all incoming rainfall is absorbed by the soil, leading to minimal immediate runoff. Conversely, when SM reaches $0.4 \text{ m}^3/\text{m}^3$, the ecosystem transitions to an energy-limited regime with ET rates surpassing 6 mm/d . The TRAIN simulation performed well in capturing these extremes, and indicated that changes in precipitation and SM appropriately reflected the total ET in moisture-deficit periods, resulting in negligible net runoff.

Interestingly, our simulations showed that RZSM was higher in periods with than without wildfire. This could be due to the removal of vegetation cover and leaf litter in turn reducing transpiration loss, with less canopy interception and low or no water uptake by the remaining vegetation. Similarly, Minderlein and Menzel (2015) found that wildfire disturbances can lead to higher RZSM. With less vegetation to take up water, a greater fraction of precipitation may infiltrate the soil and supplement the RZSM. Based on our findings, ET was lower with than without wildfires. Minderlein and Menzel (2015) observed that, under water-stressed conditions, low volumetric soil water content and reduced vegetation cover limit ET. This could explain some of the hydrological changes observed in Sugnugur Valley in response to wildfires.

6.8.3 Snow cover and seasonal runoff

Snow processes play crucial roles in determining the seasonal water balance in Sugnugur Valley. Remote sensing analyses by Munkhjargal (2020) showed that $\sim 94\%$ of the catchment is covered by a persistent snowpack each winter for 124–226 d, depending on elevation. Similarly, we found that the duration of snow cover gradually decreased from ~ 180 to ~ 140 d at the hydroclimatic Xoxoo station from 1980 to 2022, with high interannual variability in snow onset and melt timing, and no significant long-term trend since 2001, suggesting that annual climatic fluctuations mask the gradual warming effects on snow persistence. Notably, the simulated reduction in onset days since 1980 indicates that snow events occur later, starting around mid-October and shifting towards the beginning of November, whereas snow melting days are shifting from April towards February.

In this region, the winter snowpack not only drives the spring runoff cycle but also influences water loss via sublimation and meltwater evaporation. Munkhjargal et al. (2020b) reported that approximately 20% of the annual ET in the region is attributable to the winter processes, meaning that a significant fraction of snowfall is lost before it can contribute to streamflow. Additionally, Kopp et al. (2016) found that the melt dynamics of snowpack play an important role in regulating SM and runoff. Similarly, our simulation showed that runoff increased with intense snow events in spring. During summer, runoff increased during periods of wildfire. Kopp et al. (2017) found that loss of the organic layer increases soil temperatures and accelerates permafrost degradation, creating a network of preferential flow paths that rapidly channel water to streams. We also found decreased volumetric soil water content in fire-affected areas following storm events, indicative of reduced water retention capacity. The establishment of preferential flow paths could allow water to bypass the normal infiltration and storage processes, enhancing runoff during precipitation events.

The findings of Minderlein and Menzel (2015), Kopp et al. (2016), Munkhjargal et al. (2020a), and Han and Menzel (2022) provide strong scientific support for our TRAIN simulation. Similarly, the consistency between our simulations and field observations supports the robustness of our model for capturing the essential hydrological responses in Sugnugur Valley and its applicability for future research in the Black Forest and other similar environments.

6.8.4 Limitations of reanalysis data in a complex fire-prone basin

While the TRAIN model provided valuable insights, there are some important limitations. Data scarcity in this remote region poses a fundamental challenge. The Sugnugur catchment has only one primary hydrometeorological station, limiting our ability to validate model outputs across different elevations and land cover types. Moreover, snow cover and precipitation are highly variable in space due to varied topography and orographic effects.

While they are valuable for providing continuous long-term coverage, some uncertainties may arise in our modeling approach from the use of coarse global datasets (ERA5-Land reanalysis, GLEAM ET, and SMAP SM) in small topographically complex fire-disturbed areas. The global products have spatial scales (~ 9 km for ERA5-Land, $\sim 0.25^\circ$ for GLEAM, and ~ 9 km for SMAP) that are much larger than the scale of many hydrological features in the valley. This coarse resolution smooths out local heterogeneity in terrain, land cover, and microclimate. For example, ERA5-Land cannot fully capture steep precipitation gradients and reanalysis datasets may introduce biases on the order of tens of millimeters in monthly precipitation compared to hydroclimatic station data in mountainous regions (Dalla Torre et al., 2024). Nevertheless, Clelland et al. (2024) found that ERA5-Land can reproduce broad seasonal cycles of temperature and precipitation with reasonable accuracy in high-latitude regions such as southern Siberia, despite underestimating/overestimating some local extremes (e.g., heavy precipitation), reflecting its overall applicability for assessing long-term hydrological variability.

Persistent cloud cover or heavy smoke (during wildfires) can obscure the land surface in optical MODIS imagery, leading to uncertainties in snow cover and vegetation indices. Moreover, repeated fire, immediate land-cover change, and complex terrain may add non-linear local effects that are difficult to resolve using global products, potentially introducing errors in modeling and data interpretation. Therefore, based on the study context, the data used for model parametrization should be carefully considered and preferentially validated against comparable climate products.

6.9 Summary

In Chapter 6, we investigated the long-term hydrological dynamics in the Sugnugur basin, northern Mongolia, under the influence of climate change and wildfire. We found that the drier spring seasons along with low precipitation and high windspeed create suitable conditions for wildfire ignition. The main conclusions are as follows:

1. The study integrated diverse datasets including remote sensing products, global reanalysis data (ERA5-Land, GLEAM, SMAP, and MODIS), and detailed in-situ measurements from the hydroclimatic Xoxoo station to capture hydrological variables in a data-scarce region impacted by frequent wildfires.
2. The TRAIN model simulations captured important hydrological processes such as ET, RZSM, SWE, and runoff associated with the regional water balance, both with and without the effects of wildfires. Comparisons with satellite data and station observations validated the

robustness of the TRAIN model, despite some inherent uncertainties owing to the small scale of the study site and topography- and wildfire-induced heterogeneity.

3. The analysis indicated shifts in seasonal hydrological regimes, a decline in snow cover days, altered snow onset and melt timings, and potential changes in runoff patterns. Within the last few decades, increasing temperatures and reduced summer precipitation, compounded by wildfire, have reshaped the water balance in the Sugnugur basin.

Along with insights from previous chapters relating to the impacts of wildfire, the integrated approach presented in Chapter 6 provides valuable insight into how wildfire disturbances affect hydrological processes in northern Mongolia.

Chapter 7

7 Main conclusions, implications, and future perspectives on the forest and hydrological impacts of wildfires in northern Mongolia

7.1 Study scope in brief

In this thesis, we investigated the hydroclimatic dynamics of the semi-arid Sugnugur Valley, providing crucial information for this data-scarce region in terms of how wildfires and important anthropogenic disturbances affect forest structure and hydrological processes (including water-balance, SM, runoff, and snow cover) in the boreal–steppe transitional zone of northern Mongolia. To meet our study aims, we employed a comprehensive research methodology including the collection of field data, analysis of long-term remote sensing products, and selection and optimization of several statistical techniques to assess key hydrological parameters in different forest types.

7.2 Key findings

The combined insights from the field observations, global reanalysis datasets, and hydrological modeling provide a holistic view of the water dynamics under different disturbances in this boreal forest.

1. The study contributes valuable records for this data-scarce region. Regular field observations using suitable techniques are urgently needed to monitor the effects of the rapidly changing environment (Chapter 1). Global reanalysis datasets combined with field measurements provide a robust approach for capturing local and regional environmental characteristics (Chapter 2). The use of modern remote sensing technologies, including HP, LQS, and UAV-based imagery, allowed us to obtain accurate LAI and forest structure data for determining the dynamics and productivity of forest stands under different disturbance regimes (Chapters 3 and 4), providing a robust framework for analyzing wildfire impacts and key input for hydrological modeling.

2. Field observations are crucial in this region due to the high levels of geographic and human-induced heterogeneity. The global reanalysis datasets provide important long-term information on the region, though their coarse resolution cannot adequately capture local climatic changes. In this case, frequent field observations were invaluable for validating and interpreting the reanalysis datasets.

3. Our analyses confirmed the threat posed by anthropogenic disturbances such as climate change, wildfire, and direct human disturbance, which compound to alter environmental conditions at an increasing pace (Chapter 5). Field measurements and spatial analysis demonstrated a drastic change in wildfire behavior over the last two decades. Notably, 80% of wildfires were associated with human activity, which may be enhanced by the warming effects of climate change, especially in this semi-arid area. Indeed, climate change is a major driver of wildfire ignition. The drier spring seasons along with warmer temperatures, high wind speeds, early snow melting, and low precipitation create favorable conditions for wildfires. Repeated fire intervals were found to strongly inhibit forest recovery, often preventing young seedlings and saplings from establishing. Several years of repeated wildfires

destroy the vegetation before maturity and seed production. In burned sites, we observed a shift in vegetation composition favoring fast-growing species. This change could contribute to a decline in biodiversity and potentially alter forest function. In this region, forest-floor vegetation, such as moss, and permafrost are integral drivers of forest LAI—leaf area per unit ground area—which is closely associated with microclimatic conditions, such as temperature and humidity. LAI was nearly zero in burned forests, reflecting the decline in forest floor vegetation—a critical ecosystem component for retaining SM. Other anthropogenic disturbances such as logging, fuelwood collection, and grazing may also affect forest structure by directly reducing vegetation cover. These disturbances in combination with repeated wildfire damage could trigger irreversible environmental changes and may introduce large uncertainties in hydrological models. Our field observations indicated that the discontinuous permafrost, once widespread under intact forest, could further be lost after years of repeated wildfires due to increased solar irradiation and soil temperatures combined with the decrease in precipitation over the last two decades.

4. The TRAIN model indicated hydrological regime shifts associated with climate change and wildfire (Chapter 6). Our long-term water balance simulation of the Sugnugur basin for 1980–2022 captured the environmental changes with and without wildfires. Despite some uncertainties, our modelling approach performed well in representing the local hydroclimatic conditions. The model predicted clear shifts in hydrological processes attributable to climate change and repeated fires, especially over 2001–2012. The model accurately reproduced extreme events characteristic of the regional water balance. Periods with wildfire disturbance had visibly different ET, RZSM, and runoff trends than periods without wildfire: The simulated ET declined while RZSM remained high following wildfire, even in dry years. This could reflect the removal of vegetation cover in turn reducing canopy interception and transpiration, thereby promoting the percolation of water into the soil. Wildfires led to a net increase in near-surface SM and decrease in total ET at the local level, consistent with the trends observed by Minderlein and Menzel (2015) in shrubland sites of Sugnugur Valley. Precipitation and snow are some of the main contributors to the regional water balance. Combined with the remote sensing and hydroclimatic station data, the model revealed a shortening of the snow season over the past four decades. From 1980 to 2022, the duration of seasonal snow cover in the basin decreased from ~180 to ~140 d, while annual temperature gradually increased; winter temperatures showed a similar warming trend. Snow onset at the end of autumn is shifting towards early November and melting towards earlier in spring, with peak snow melt days shifting from April towards the end of February. We observed a clear overall reduction in snow cover days, which may directly affect runoff. A shorter snow season could indicate earlier spring runoff and potentially drier late-spring soils. The model captured the importance of the winter snowpack in determining spring streamflow. Both with and without fires over the last two decades, the model showed that the increasing temperatures, decreasing annual and summer precipitation, and periodic fire disturbances produced noticeable regime shifts. These findings, along with the estimated reduction in LAI and forest cover (Chapter 5), indicate how changes in forest structure can affect RZSM, ET, and runoff, and thereby alter the regional water balance.

7.3 Implications

7.3.1 ET and water balance

This study provides important insights into how climate change and wildfires can reshape hydrological processes in semi-arid high-latitude regions. The various effects of climate change on temperature and precipitation create favorable conditions for wildfires. Periods of wildfire were associated with a rapid reduction in ET through the removal of vegetation cover,

directly reducing transpiration while increasing soil water evaporation. This could have various adverse consequences in semi-arid boreal ecosystems, especially in terms of erosion and ecosystem function. Lower ET after wildfire may reduce the short-term loss of water to the atmosphere and maintain some SM. However, the loss of vegetation reduces rainfall interception—the portion of precipitation briefly captured by plants—directly exacerbating runoff and erosion risk.

7.3.2 RZSM dynamics

The study highlighted a nuanced trade-off in SM dynamics. Because root water uptake is reduced after wildfires along with vegetation cover, SM may accumulate following adequate precipitation. However, without the protective canopy, exposure to direct sunlight and wind promotes drying of the topsoil. Higher temperatures and increased solar radiation on the forest floor could accelerate evaporation from and desiccation of the top soil profile. In scenarios with and without wildfires, RZSM was higher in burned than in unburned forests during dry periods (low precipitation years). However, repeated wildfires increased the variability of the SM profile and caused more severe drying during extended dry periods than in unburned forests.

7.3.3 Snow dynamics and runoff

Snow dynamics are closely associated with the hydrological processes of northern-latitude mountainous headwater areas. The study found a significant shift in seasonal snow behavior along with a general warming climate trend over 1980–2022. The duration of snow cover has declined in northern Mongolia, likely due to the warming-induced earlier spring melt, which has direct implications on the timing and intensity of runoff. Snow onset in the autumn has shifted from October to November, consistent with changing climate trends. Persistent snow melting may alter runoff patterns and exacerbate erosion risk.

7.3.4 LAI and climate change

LAI is a crucial parameter for reflecting crucial hydrological processes such as rainfall interception, canopy transpiration, and runoff generation. Repeated wildfires led to severe reductions in LAI; in some locations, the forest failed to restore the original canopy structure and favored the growth of selected species. The associated microclimatic changes limit the growth potential of young saplings and forest-floor vegetation. This overall loss in LAI diminishes the forest's capacity to intercept rainfall, increasing the proportion of precipitation received by the ground directly. Disturbance of the forest canopy promotes soil exposure to solar irradiation, which reduces long-term RZSM, inhibits regrowth, promotes reburns, and ultimately exacerbates surface runoff and erosion risk.

7.4 Outlook

This study provides a useful framework for future research on the hydrological processes of data-scarce regions of the high northern latitudes. Consistent with our study design, Kopp et al. (2017) emphasized that thorough hydrological assessments of sparsely recorded headwater basins are only possible through comprehensive field measurements coupled with modeling. Likewise, Munkhjargal et al. (2020) recommends the use of ground observations and finer scale remote sensing to capture critical variables in water-balance models of mountainous regions.

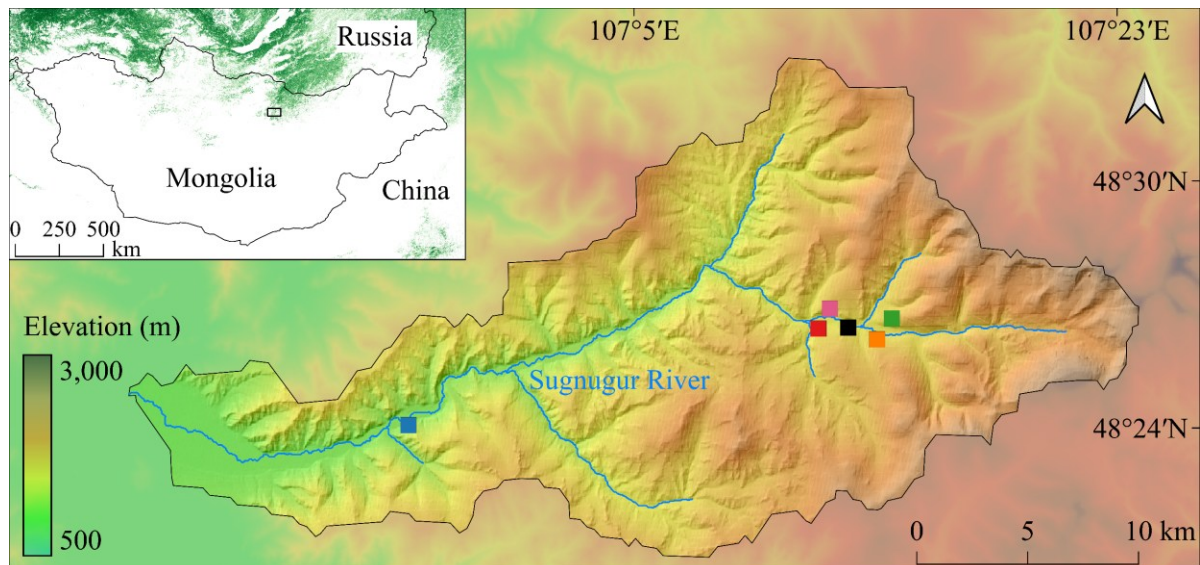
In the data-scarce Sugnugur Valley, field investigation was invaluable for model parameterization. To fully capture local head water characteristics, it may be important to combine several appropriate research techniques. Our comprehensive investigation identified 15 years of intense wildfire in the last two decades. This could point to large spatiotemporal variations in the water balance between years. High-resolution global datasets in combination with field investigations will be crucial for the continuous monitoring and accurate modeling of water-balance dynamics.

The combined influence of climate and land-use change on water resources in northern Mongolia remains an important question. Our findings highlighted concerning trends in key climatic variables—more stochastic precipitation in 2000–2022 than in 1980–2000 and gradually increasing temperatures overall as well as in winter compared to other seasons. Long-term monitoring and modeling are needed to determine whether current trends will be exacerbated. With increasing data availability, scenario analyses will be useful for elucidating the effects of increasing wildfire frequency under different climate conditions in mountainous headwater areas.

In conclusion, this study of Sugnugur Valley provides new data along with a broad overview of the complex interactions between wildfire, climate, and hydrology in a boreal semi-arid mountain ecosystem. The unclear status of the permafrost and water resources of the Khentii Mountains requires urgent investigation with regards to the effects of climate change and increasing wildfires.

Appendices

Appendix A



DEM Source: NASA Shuttle Radar Topography Mission (2013). Sugnugur Basin Source: HydroSHEDS
 Forest Cover Source: Hansen/UMD/Google/USGS/NASA. International Boundaries Source: public.opendata.com

□ Sugnugur River Basin ■ Sugnugur River ■ DF ■ BF ■ PBF ■ NF ■ UBV ■ SB

Figure A.1 Forest in six study locations. Squares indicate locations for disturbed forest (DF), burned forest (BF), partly burned forest (PBF), and natural forest (NF), along with the locations of the transitional zones between the burned and unburned forest areas. The unburned valley (UBV) was located between the PBF and NF. The south-sided slope bottom (SB) was located between the NF and BF.

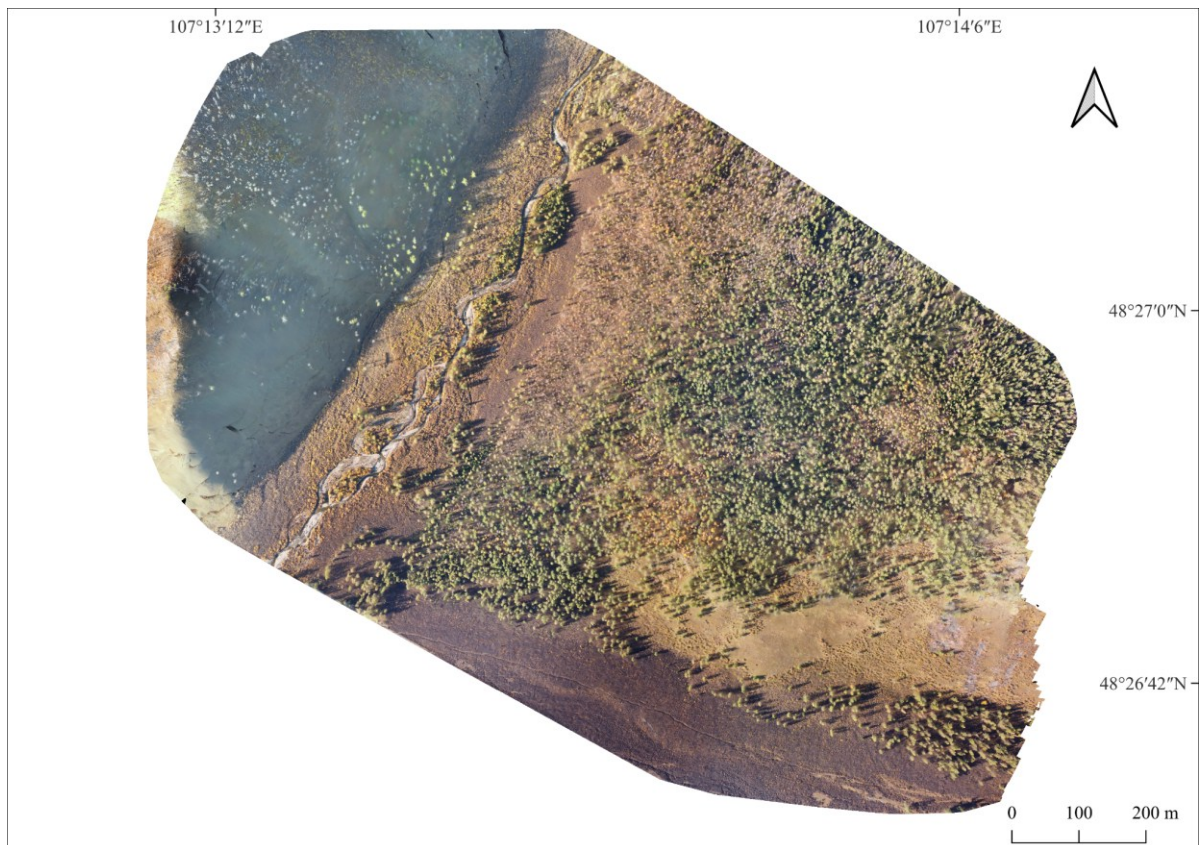


Figure A.2 Orthomosaic map of Sugnugur Valley developed using UAV imaging, portraying the topography of the study area, NF.

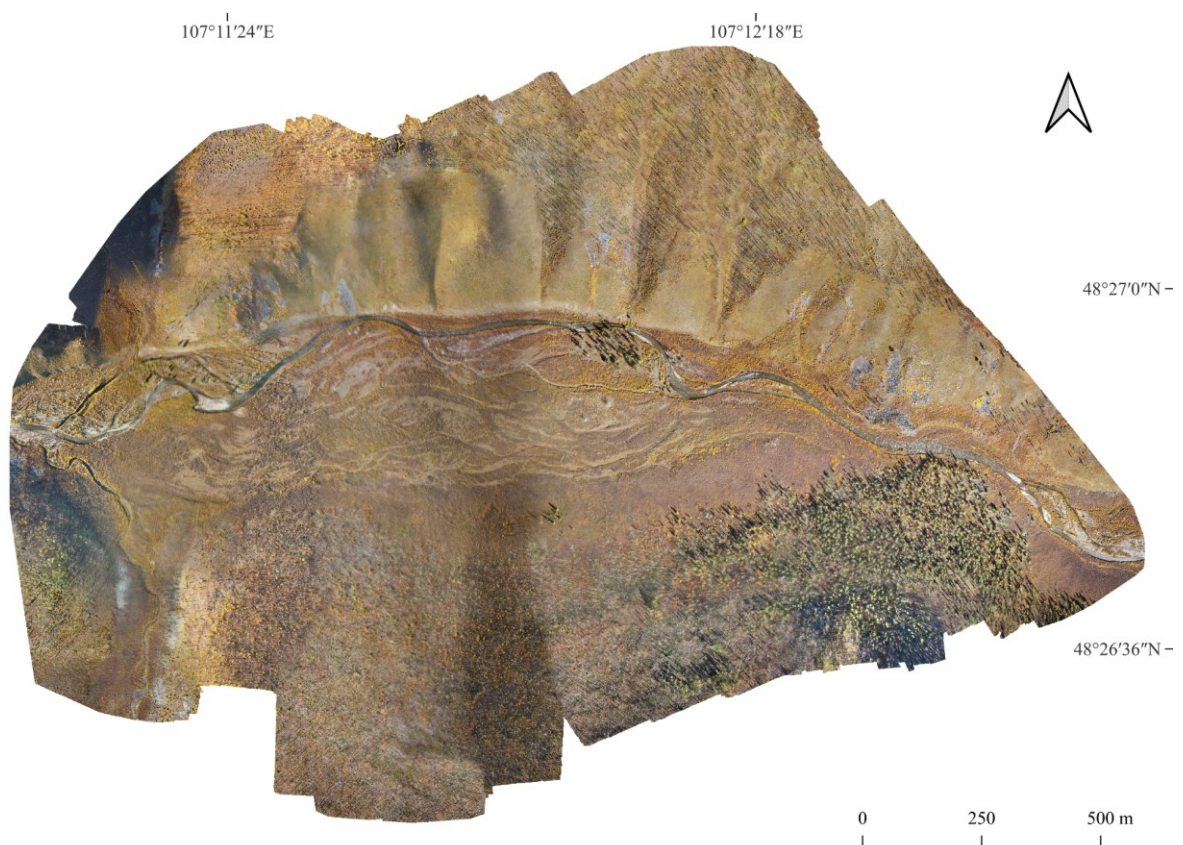


Figure A.3 Orthomosaic map of Sugnugur Valley developed using UAV imaging, portraying the topography of the study area. (A) Main valley, which includes both BF and PBF.

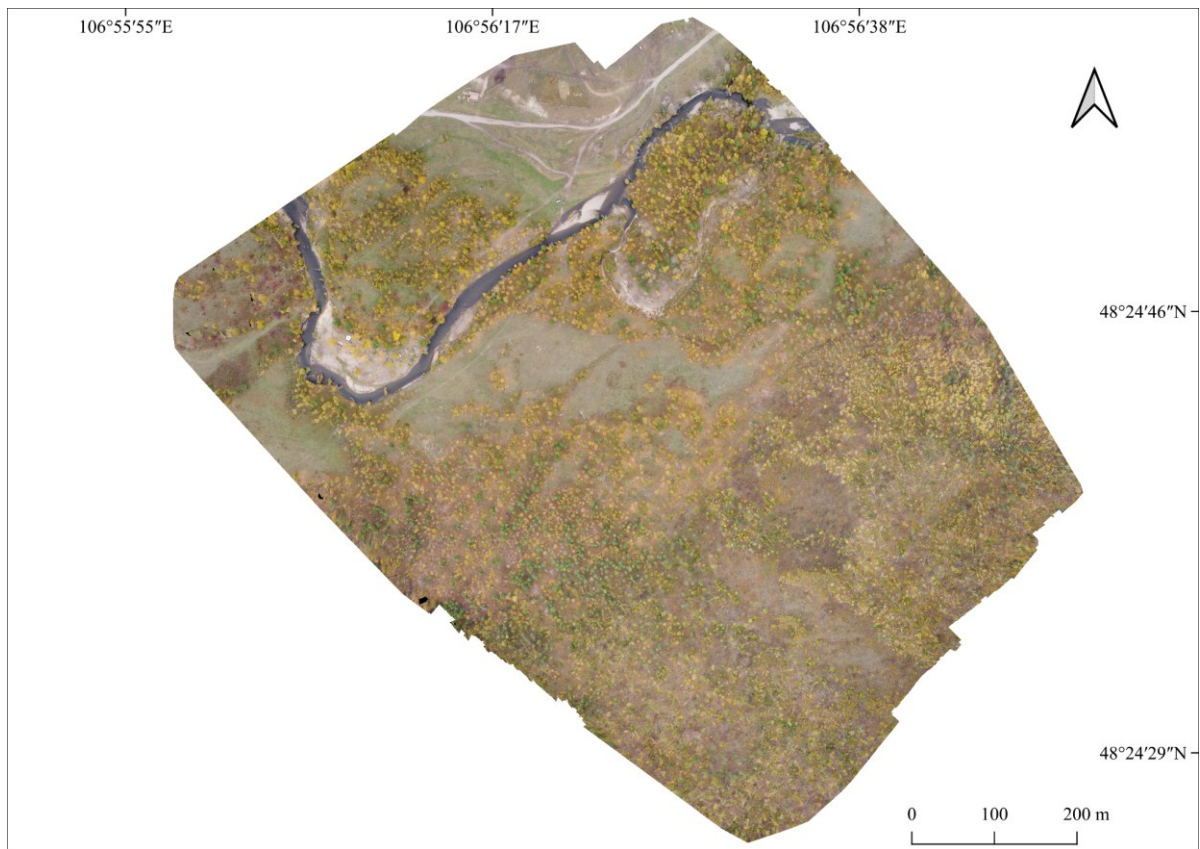


Figure A.4 Orthomosaic map of Sugnugur Valley developed using UAV imaging, portraying the topography of the study area, DF.

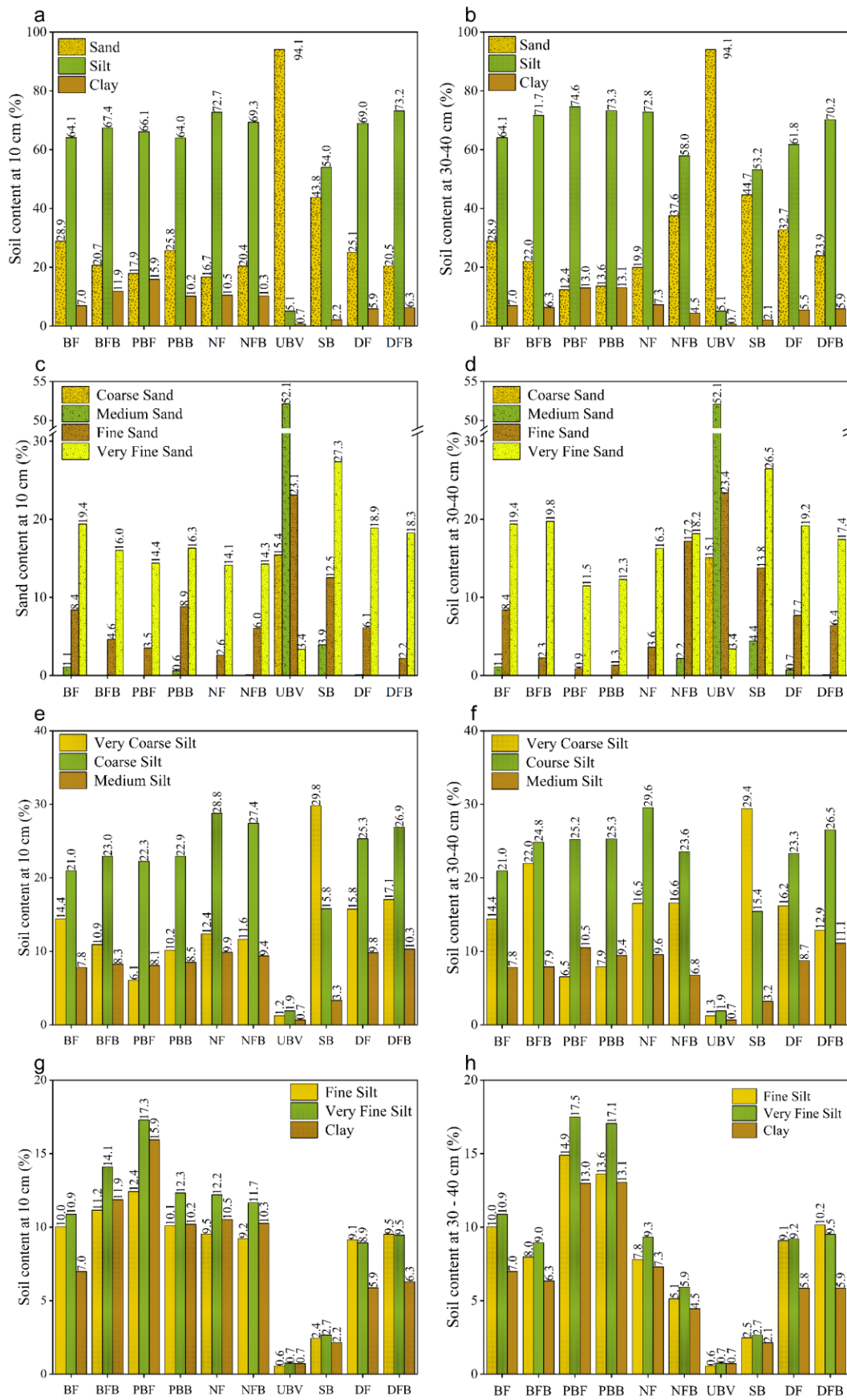


Figure A.5: Soil grain size distributions across sites.

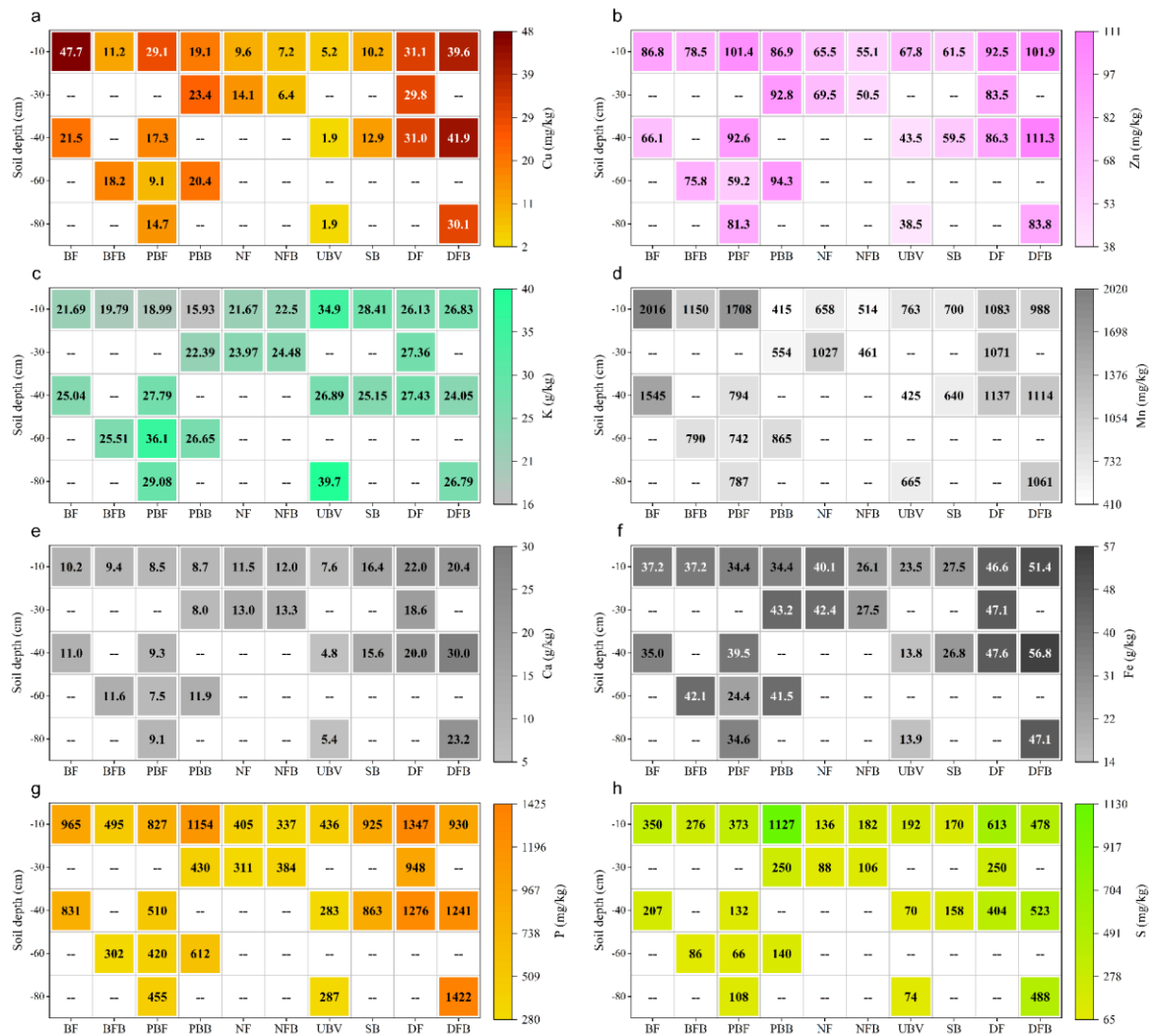


Figure A.6: Chemical compositions of soils at varying depths across study sites.

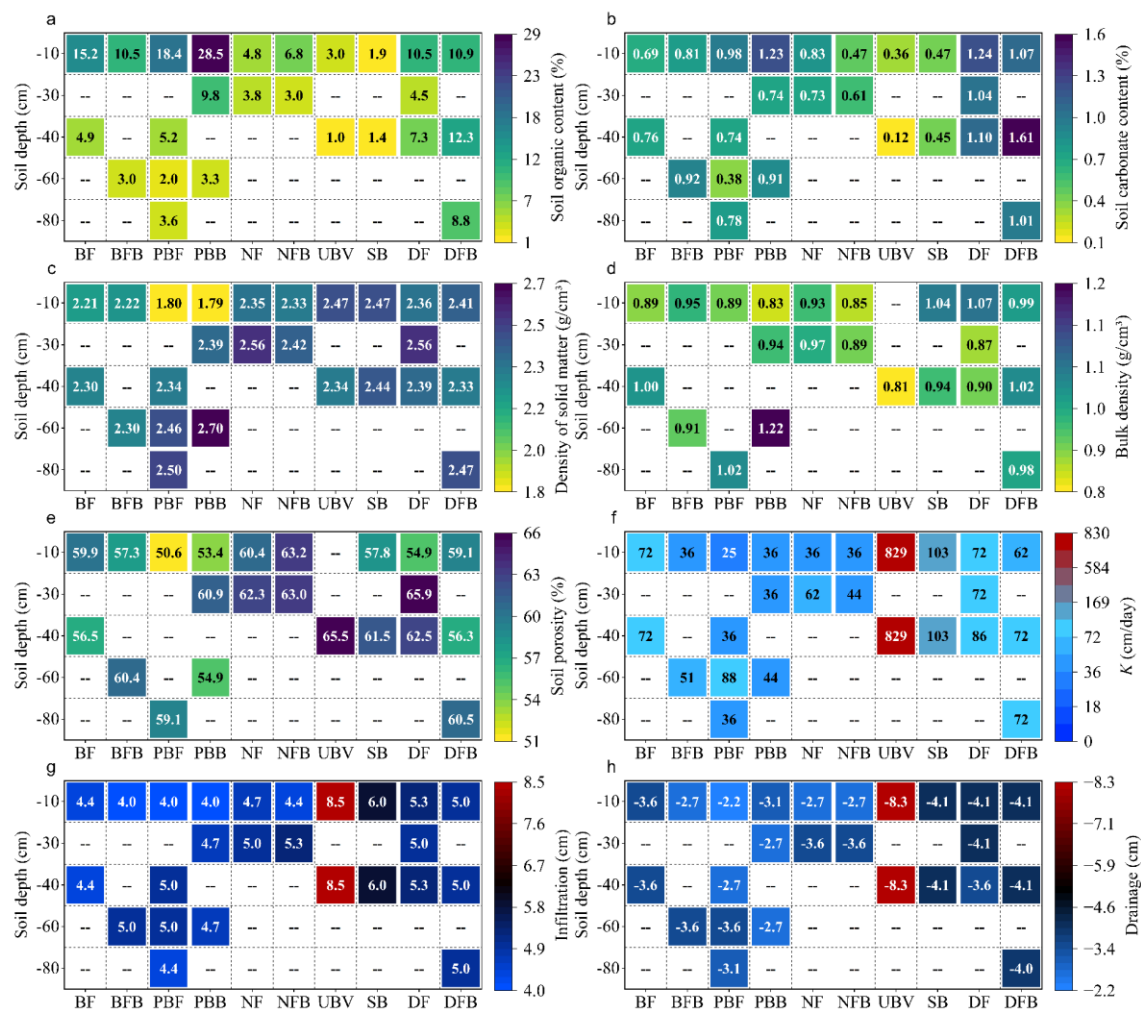


Figure A.7: Soil properties at various depths across study sites.

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Acknowledgments

I would like to thank various citizens of Germany and the German government for supporting me and facilitating my research through the DAAD-NaWaM, The Kurt-Heihle-Foundation, and Universität Heidelberg.

I am also grateful to my supervisor, Prof. Dr. Lucas Menzel (Universität Heidelberg), for giving me the opportunity to conduct my PhD research in his Hydrology and Climatology research group. I appreciate his guidance and scientific insights shared throughout this study.

I am extremely grateful for the important input provided by Dr. Martin Pfeiffer, a senior scientist at Universität Bayreuth.

I would be remiss to not express my gratitude to Drs. Erik Tjardeman, Li Han, and Munkhdavaa Munkhjargal.

I would like to thank all my colleagues: Leonard Kölsch-Kurtz for his support with modeling, Dr. Lea Bussiere for her scientific insights, Jianfeng Luo for his helpful suggestions, and Tim Jasny and Anna Pfitzner for their fieldwork support.

Lastly, thank you to my family.