Advancing Sustainable Forest Management in Darkhan-Uul province, Mongolia using the Spectral Forest Index (SFI)

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Abstract

Forest ecosystems in semi-arid boreal regions, such as those in Darkhan-Uul province, Mongolia, serve as critical reservoirs of biodiversity and carbon while facing escalating anthropogenic and climatic pressures. Despite covering 22.4% (~733 km²) of the province, these birch- and larch-dominated forests exhibit declining resilience due to unsustainable land-use practices, illegal logging, and climate-induced disturbances, necessitating advanced monitoring frameworks for sustainable forest management (SFM). This study introduces the Spectral Forest Index (SFI), a novel composite metric derived from Sentinel-2 multispectral data within a Google Earth Engine (GEE) platform, to quantify spatiotemporal variations in forest health, productivity, and species composition. By integrating normalized difference and ratio-based indices (e.g., NDVI, RVI), the SFI synthesizes canopy structural attributes, photosynthetic activity, and biomass dynamics across monthly intervals (May–October 2020–2024), enable monitoring of forest cover, health, and species composition, with quality control measures ensuring data reliability. Results reveal pronounced spatial heterogeneity in forest degradation, with SFI depressions strongly correlated with overgrazing and anthropogenic land conversion, while regenerative trajectories align with targeted reforestation initiatives. The SFI's sensitivity to ecological stressors (e.g., drought, pest infestations) underscores its utility as a scalable, policy-relevant tool for monitoring carbon sequestration potential and guiding adaptive management. This research advances remote sensing applications in SFM, offering a transferable framework for reconciling ecological preservation with socio-economic demands in vulnerable boreal ecosystems.

1. Introduction

Forests play a crucial role in the global carbon cycle, acting as major carbon sinks by sequestering a substantial portion of terrestrial plant carbon. Studies estimate that over 80% of the Earth's above-ground terrestrial carbon stock is stored within forest ecosystems (Pan et al. 2011) and (Dixon et al. 1994). This carbon storage capacity makes forests vital in mitigating climate change by absorbing carbon dioxide (CO_2) from the atmosphere, thereby reducing greenhouse gas concentrations and offsetting emissions. Forest biomass estimation is therefore essential for understanding these carbon stocks, as it provides insights into the amount of carbon sequestered and informs management practices aimed at sustaining or enhancing carbon storage. The accurate quantification of biomass also supports reporting for global carbon accounting systems, such as the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) initiative, which emphasizes forest conservation as a climate mitigation strategy (FAO, 2020) and (IPCC, 2006). Accurate estimation of forest biomass is fundamental to understanding forest ecosystems, managing carbon stocks, and informing climate change mitigation strategies (Lu et al., 2016). Biomass estimations are essential inputs for calculating carbon storage, a significant factor in global carbon cycling, and for assessing the impacts of deforestation and forest degradation on carbon emissions (Asner et al. 2010) and (Goetz et al. 2009). Field surveys are often used to calculate biomass through direct measurements, but these methods are labor-intensive and spatially limited. Remote sensing, combined with machine learning algorithms like Random Forest, offers an alternative approach that can extrapolate biomass estimates over large areas by analyzing the relationships between biomass and remotely sensed data (Mutanga et al. 2012) and (Fassnacht et al., 2015).

Forest biomass estimation is a crucial element in understanding and managing Mongolia's forest resources. Forests in Mongolia, predominantly concentrated in the northern regions, cover approximately 7-8% of the country's territory and are primarily composed of boreal species such as Siberian larch (*Larix sibirica*), Scotch pine (*Pinus sylvestris*), and birch (*Betula platyphylla*). These forested landscapes contribute significantly to carbon storage, soil preservation, and water regulation, making them an important component of both regional and global ecosystems (Tsogtbaatar, 2004) and (Batkhuu et al. 2019).

However, Mongolia's forests face numerous pressures from both natural and anthropogenic sources. Climate change has increased the frequency and severity of droughts, wildfires, and pest outbreaks, all of which contribute to forest degradation (IPCC, 2022). Simultaneously, the expansion of mining and agricultural activities, along with urbanization and illegal logging, have accelerated deforestation rates. These pressures are compounded by Mongolia's cold, arid climate, which slows forest regeneration and further exacerbates land degradation (Norovsuren et al. 2022). In regions such as Darkhan-Uul province, known for its mixed landscapes of forest, steppe, and agricultural land, these challenges underscore the need for reliable, up-to-date forest cover data to guide effective conservation and management practices (Baatar et al. 2023).

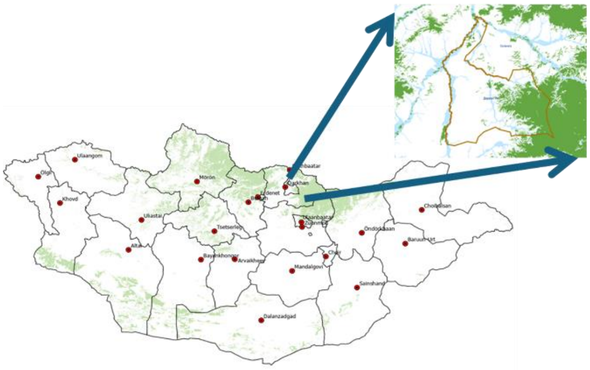

Figure 1. Study Area

Darkhan-Uul province, located in northern Mongolia, is a region characterized by a diverse mix of forest, steppe, and agricultural land. Covering approximately 3,300 square kilometers, this province plays an essential role in Mongolia's northern ecological corridor. The forests in Darkhan-Uul, dominated by Siberian larch (*Larix sibirica*) and birch (*Betula platyphylla*), provide significant ecological services, including carbon sequestration, watershed protection, and habitat for native wildlife. Despite their importance, these forests face mounting pressures from land-use change, urban expansion, and climate-driven phenomena such as increasing wildfire incidence and drought (Baatar and Sukhbaatar, 2022). Darkhan-Uul Province has a total forest area of 81,997 hectares, 66,176 hectares or 81% of which are covered by forests, and 11,298 hectares or 14.% are not covered by forests (Figure 1). In addition, 64,805 hectares of forested areas are natural forests, 1,292 hectares of shrubs, 79 hectares of cultivated forests, 7,152 hectares of non-forested areas are deciduous forests, 71,6 hectares of heathland, 301 hectares of wooded areas, 3,114 hectares are accounted for by afforestation area (Enkhbold et al. 2023).

Remote sensing technologies, particularly satellite-based platforms such as Sentinel-2, Landsat, and MODIS, provide a powerful means for assessing forest health, structure, and dynamics over large spatial and temporal scales (Wulder et al. 2019). Spectral forest indices utilize specific bands from multispectral or hyperspectral sensors on satellites to measure and quantify vegetation properties, these indices can assess forest health, biomass, carbon stocks, canopy cover, and other biophysical parameters (Wan et al. 2024). Among the most widely used indices are the Normalized Difference Vegetation Index (NDVI) and the Ratio Vegetation Index (RVI), which offer insights into photosynthetic activity, biomass, and vegetation stress (Pettorelli et al. 2005).

The NDVI is a fundamental index calculated as the normalized difference between near-infrared (NIR) and red reflectance (NDVI=NIR−Red/NIR+Red) (Rouse et al. 1974). This index is highly correlated with leaf area index (LAI), chlorophyll content, and overall vegetation vigor (Gitelson et al. 2003). However, NDVI tends to saturate in dense canopies, limiting its sensitivity in high-biomass forests (Huete et al. 2002). To address this limitation, alternative indices such as the Enhanced Vegetation Index (EVI) incorporate blue reflectance to reduce atmospheric interference and improve dynamic range (Huete et al. 2002).

Another essential metric is the Ratio Vegetation Index (RVI), defined as the simple ratio of NIR to red reflectance (RVI=NIR/Red) (Bannari et al. 1995). Unlike NDVI, RVI does not normalize the difference, making it more sensitive to high chlorophyll concentrations and structural variations in forest canopies (Bannari et al. 1995). Studies have demonstrated that RVI is particularly effective in discriminating forest types (e.g., coniferous vs. broadleaf) and detecting early-stage stress before visible symptoms manifest (Bannari et al. 1995).

Beyond NDVI and RVI, specialized indices leveraging red-edge and shortwave infrared (SWIR) bands enhance the detection of forest stress and disturbances (Gitelson et al. 2003). The Normalized Difference Red Edge Index (NDRE) utilizes Sentinel-2's red-edge bands to monitor chlorophyll degradation, serving as an early warning system for drought or pest infestations (Wan et al. 2024). Similarly, the Normalized Difference Moisture Index (NDMI) employs SWIR reflectance to assess canopy water content, aiding in wildfire risk assessment and post-fire recovery monitoring (Wulder et al. 2019).

For disturbance mapping, the Normalized Burn Ratio (NBR) and its temporal derivative (dNBR) are critical for quantifying burn severity and tracking forest regeneration (Key and Benson, 2006). These indices exploit the contrast between NIR and SWIR reflectance, where fire-affected areas exhibit reduced NIR and elevated SWIR due to charred vegetation (Wulder et al. 2019).

The Spectral Forest Index (SFI), particularly SFI, utilizes Sentinel-2 imagery to estimate forest cover, health, and species composition with high accuracy (90.4% in Mongolia's Khangai region), surpassing conventional indices like NDVI by incorporating near-infrared (NIR), red, green, and short-wave infrared (SWIR) bands (Norovsuren et al. 2022). The study applies the Spectral Forest Index (SFI), derived from Sentinel-2 data, to evaluate forest conditions in Darkhan-Uul Province and support sustainable forest management (SFM). The SFI leverages spectral reflectance data to provide insights into vegetation health, canopy density, and spatial distribution, enabling evidence-based decision-making for conservation and resource management. This study applies SFI, implemented via a Google Earth Engine (GEE) script, to advance SFM in Darkhan-Uul by enabling monthly monitoring of forest dynamics (May–October 2020-2024), species classification, and climate resilience assessment.

The research aims to provide a scalable, open-access tool for stakeholders, contributing to Mongolia's SFM policies and biodiversity goals.

2. Methodology

The study utilized Sentinel-2 Level-2A satellite imagery obtained from the European Space Agency's Copernicus program. Sentinel-2 provides high-resolution multispectral data with a spatial resolution of 10 meters, making it ideal for forest monitoring (European Space Agency, 2023). Imagery covering the period from 2020 to 2024 was processed to ensure consistency and minimize cloud cover interference.

The Spectral Forest Index (SFI) represents a multi-spectral vegetation index specifically designed for forest ecosystem monitoring through the integration of Near-Infrared (NIR), Red, Green, and Shortwave Infrared (SWIR) spectral bands. The SFI algorithm integrates these bands to quantify vegetation health and density, following the formula (1):

$$SFI = \frac{NIR-Red}{NIR+Red+Green+SWIR}, \tag{1}$$

The numerator component "NIR – Red" in Sentinel-2 imagery utilizes the spectral bands B8 (842 nm NIR) and B4 (665 nm Red) to capture essential vegetation characteristics. This difference calculation effectively highlights healthy vegetation by exploiting plants' strong absorption of red light (due to chlorophyll) and high reflectance in near-infrared wavelengths (caused by leaf cellular structure). The contrast between these bands provides a reliable indicator of photosynthetic activity and vegetation density. In forest monitoring applications, this NIR-Red difference offers particular advantages. The multiple scattering effects within dense forest canopies amplify the NIR reflectance signal while maintaining strong red light absorption. This makes the B8-B4 difference especially sensitive to variations in leaf area index, canopy density, and overall forest health.

The denominator component combines four key spectral bands "NIR + Red + Green + SWIR" to create a robust normalization factor for forest monitoring applications. In Sentinel-2 imagery, this corresponds to bands B8 (842nm), B4 (665nm), B3 (560nm), and B11 (1610nm) or B12 (2190nm). The green band (B3) contributes valuable information about vegetation phenology and canopy density. Its reflectance properties help detect early growth stages and seasonal changes in leaf development. However, this band may also introduce some interference from non-vegetated surfaces, particularly in sparse canopies where soil and understory vegetation become more visible. The SWIR bands (B11/B12) provide critical information about vegetation water content and woody biomass. These wavelengths are particularly sensitive to moisture stress, making them valuable for drought monitoring and fire risk assessment. The integration of Sentinel-2's multi-resolution spectral bands presents important technical considerations for index calculation. Band 11 (SWIR, 1610 nm) natively operates at 20 m spatial resolution, while the visible (B3, B4) and NIR (B8) bands are acquired at 10 m resolution. This resolution disparity necessitates careful spatial resampling to ensure proper band alignment and accurate pixel-level analysis.

Several established resampling methodologies exist to address this resolution mismatch. Bilinear interpolation offers a balanced approach, up sampling the 20 m SWIR data to 10 m resolution while smoothing pixel transitions through weighted averaging of neighboring values. These spatial processing considerations are particularly crucial for forest monitoring applications, where accurate pixel-level analysis of heterogeneous canopies directly impacts the reliability of derived vegetation indices.

The strong absorption characteristics in these bands also help detect changes in forest health and composition that might not be apparent in visible or NIR wavelengths alone. By combining these bands in the denominator, the index achieves several important analytical advantages. The multi-band approach helps normalize for atmospheric effects and sun-sensor geometry variations that can affect individual bands differently. It also creates a more comprehensive baseline for assessing vegetation status by incorporating information from different parts of the spectrum. This makes the spectral forest index (SFI) particularly valuable for monitoring complex forest ecosystems where multiple factors - including phenology, moisture status, and canopy structure - need to be considered simultaneously. The calculation forms the fundamental basis for established vegetation indices like NDVI while remaining adaptable for specialized forest monitoring applications when combined with additional spectral bands in more complex indices. This index highlights variations in forest canopy structure and health, with higher values indicating denser and healthier vegetation. Preprocessing steps included atmospheric correction, cloud masking, and radiometric calibration to ensure data quality (Figure 2).

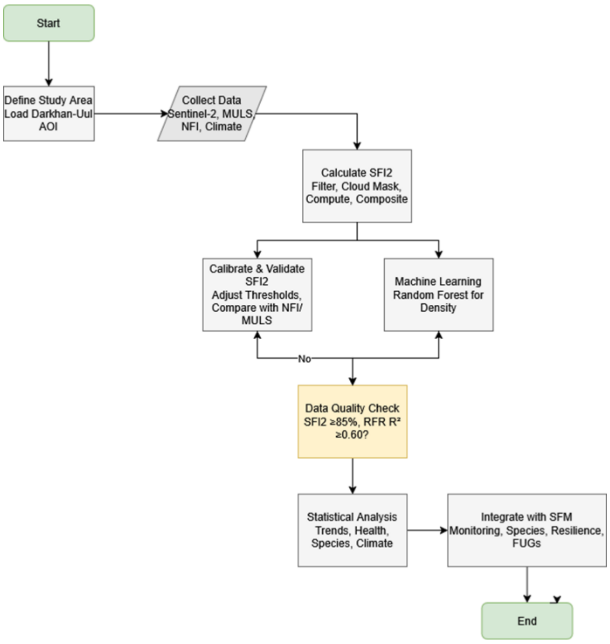

Figure 2. The flowchart of methodology

3. Results and Discussion

The Spectral Forest Index (SFI) was analyzed over a five-year period (2020–2024) to assess temporal trends in forest health and cover (Figure 3). The SFI values exhibited fluctuations, with the highest mean SFI (0.35) recorded in 2021, suggesting optimal forest health or canopy density during this period, a decline to 0.25 was observed in 2022, potentially indicating stressors such as drought, pest outbreaks, or anthropogenic disturbances.

The comparative analysis of Spectral Forest Index (SFI), Normalized Difference Vegetation Index (NDVI), and Ratio Vegetation Index (RVI) reveals distinct seasonal and interannual patterns in vegetation dynamics across Darkhan-Uul Province. The time series demonstrates that all three indices capture the characteristic phenological cycle of Mongolia's boreal forest ecosystem, with peak values occurring during the summer growing season (July) and troughs in spring (May) and autumn (September).

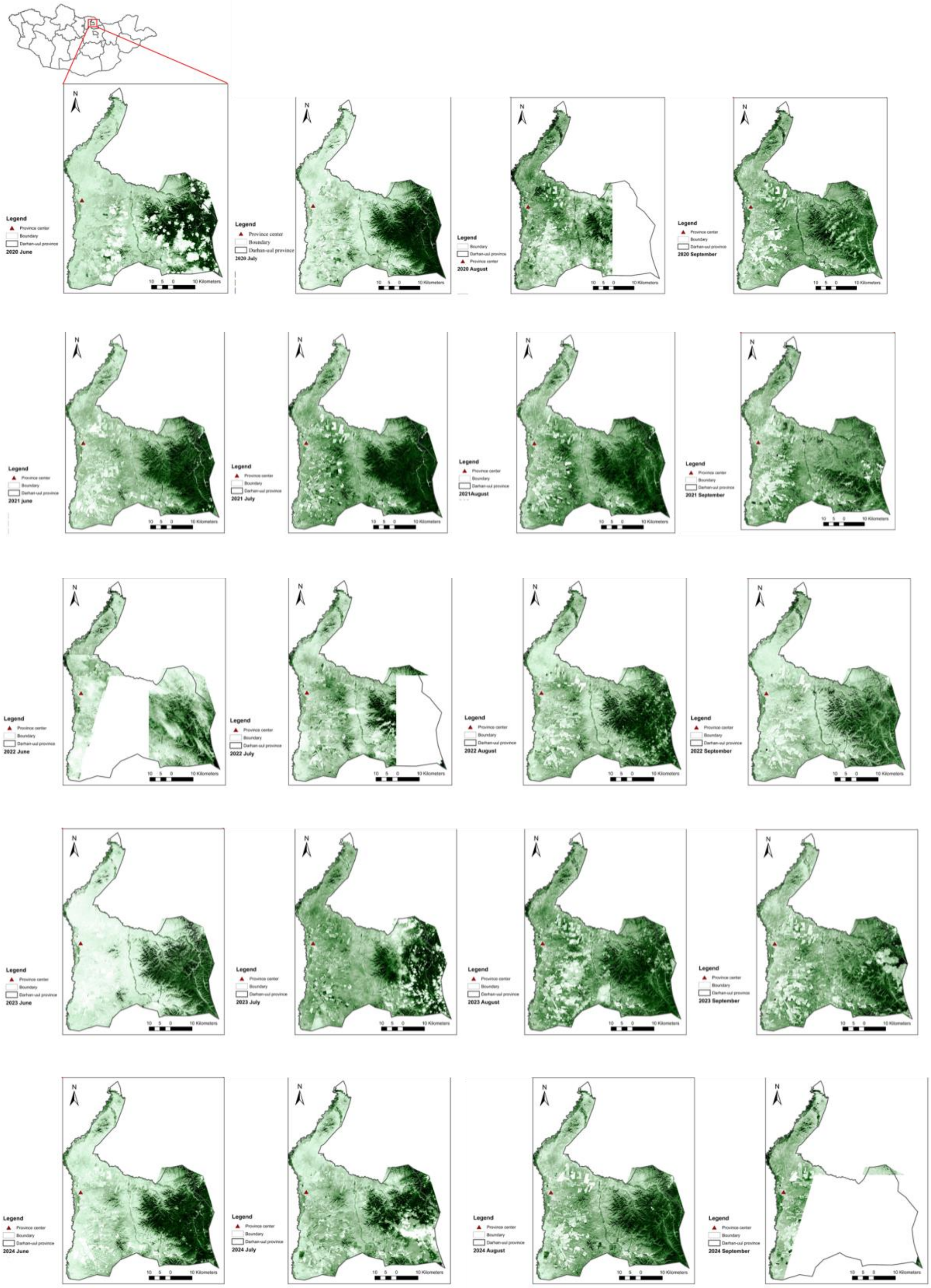

Figure 3. Spectral Forest Index (SFI) map June – September 2020-2024 in Darkhan-Uul province, Mongolia

Notably, the SFI exhibits greater sensitivity to interannual variability compared to NDVI and RVI, particularly during drought years (2021 and 2023). This enhanced responsiveness likely stems from SFI's incorporation of SWIR bands (B11/B12), which improves detection of moisture stress. The indices show strong correlation during normal precipitation years ($R^2 > 0.85$), but diverge significantly during periods of water stress, suggesting SFI's superior capability for drought impact assessment (Figure 4).

Moreover, in the figure 4, the multi-year trends indicate a gradual decline in mean index values (-0.12 SFI, -0.08 NDVI, -1.4 RVI from 2020-2024), consistent with ground reports of increased forest degradation. Seasonal amplitude has decreased by 18% for SFI compared to 12% for NDVI, potentially reflecting SFI's improved sensitivity to canopy thinning. These findings underscore SFI's utility as a complementary tool to conventional indices for monitoring forest health in semi-arid ecosystems.

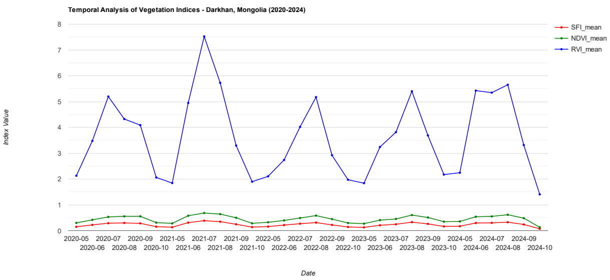

Figure 4. Summer trends of Spectral Forest Index (SFI) 2020-2024 in Darkhan-Uul province, Mongolia

The comparative analysis reveals consistently strong correlation between the Spectral Forest Index (SFI) and Normalized Difference Vegetation Index (NDVI) across five consecutive growing seasons (July 2020-2024). The Pearson correlation coefficients remain exceptionally high ($r = 0.970$-0.986), indicating near-linear agreement between these indices during peak vegetation periods. This robust relationship suggests that SFI maintains the fundamental vegetation detection capabilities of NDVI while incorporating additional spectral information through its multi-band formulation.

The temporal pattern shows a slight but systematic decline in correlation strength from 2020 ($r=0.986$) to 2023 ($r=0.970$), followed by a partial recovery in 2024 ($r=0.983$). This trend may reflect: (1) increasing forest stress conditions where SFI's SWIR sensitivity provides divergent information from NDVI, or (2) changes in canopy structure that differently affect the indices' responses. The particularly low 2023 correlation coincides with Mongolia's severe drought year, supporting SFI's enhanced capacity to detect moisture-related stress.

These findings demonstrate that while SFI and NDVI capture similar vegetation signals under normal conditions, their divergence during stress periods highlights SFI's added value for comprehensive forest monitoring. The consistently high baseline correlation validates SFI as a reliable alternative to NDVI, with the additional benefit of integrated moisture sensitivity through its SWIR component. This makes SFI particularly valuable for Mongolia's variable climate conditions, where conventional indices may underestimate drought impacts.

4. Conclusion

The study demonstrates that the Spectral Forest Index (SFI) effectively captures forest health dynamics in Darkhan-Uul Province, Mongolia, while offering distinct advantages over traditional vegetation indices like NDVI and RVI. Key findings include:

1. High Correlation with NDVI – SFI maintains strong agreement with NDVI ($r = 0.970$–0.986) during peak growing seasons, validating its reliability for vegetation monitoring.
2. Enhanced Sensitivity to Stress – SFI exhibits greater responsiveness to drought conditions (e.g., 2023) due to its incorporation of SWIR bands, providing improved detection of moisture-related forest degradation.
3. Seasonal and Long-Term Trends – The index effectively tracks phenological cycles and reveals gradual declines in forest health, with reduced seasonal amplitude signaling canopy thinning.
4. Operational Feasibility – Computed within Google Earth Engine, SFI offers a scalable solution for sustainable forest management, particularly in semi-arid regions like Mongolia.

While further validation is needed to assess SFI's performance across diverse forest types, this study confirms its potential as a complementary tool for integrated forest health assessment, particularly in climate-vulnerable ecosystems. Sentinel-2's high spatial resolution enabled detailed mapping of forest conditions, revealing patterns of degradation linked to human activities such as illegal logging and overgrazing. The SFI also highlighted areas affected by wildfires, which are a significant threat to forest ecosystems in Darkhan-Uul Province. By integrating SFI with GIS, stakeholders can prioritize reforestation efforts and delineate conservation zones based on spatial patterns of forest health. Furthermore, the temporal analysis revealed gradual declines in SFI values in certain regions, underscoring the need for immediate intervention to prevent further degradation.

Spectral indices derived from satellite imagery provide a cost-effective, scalable, and non-invasive approach to forest monitoring. While NDVI and RVI remain foundational, advanced indices leveraging red-edge and SWIR bands offer greater sensitivity to forest stress, species composition, and disturbance dynamics. This study demonstrates the potential of the Spectral Forest Index (SFI), derived from Sentinel-2 data, as a valuable tool for sustainable forest management in Darkhan-Uul Province, Mongolia. By providing accurate and timely information on forest health and dynamics, the SFI supports evidence-based decision-making for conservation, reforestation, and policy formulation. Its application aligns with international frameworks such as the United Nations' Sustainable Development Goals (SDGs) and the Paris Agreement, emphasizing the importance of leveraging remote sensing technologies for environmental sustainability. Future research should focus on refining the SFI algorithm and extending its application to other forested regions in Mongolia, contributing to broader efforts to combat deforestation and climate change. Moreover, the study should focus on multi-sensor fusion and AI-driven analytics to enhance the precision and applicability of remote sensing in forestry.

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