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Can vegetation breakpoints in Eastern Mongolia rangeland be detected using Sentinel-1 coherence time series data?

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[a]Department of Geography, Ludwig-Maximilian-university of Munich, Munich, Germany; [b]Department of Agricultural and Applied Economics, School of Economics and Business, Mongolian University of Life Sciences, Ulaanbaatar, Mongolia; [c]Department of Cybernetics, School of Economics and Business, Mongolian University of Life Sciences, Ulaanbaatar, Mongolia; [d]Department of Statistics and Econometrics, School of Economics and Business, Mongolian University of Life Sciences, Ulaanbaatar, Mongolia; [e]Institute of Natural Resource and Agricultural Economics, Ulaanbaatar, Mongolia; [f]Institute for Social-Ecological Research, Frankfurt am Main, Germany; [g]Senckenberg Biodiversity and Climate Research Centre, Senckenberg Gesellschaft für Naturforschung, Frankfurt (Main), Germany; [h]Department of Management, School of Economics and Business, Mongolian University of Life Sciences, Ulaanbaatar, Mongolia; [i]Department of Accounting, School of Economics and Business, Mongolian University of Life Sciences, Ulaanbaatar, Mongolia; [j]Department of Finance, School of Economics and Business, Mongolian University of Life Sciences, Ulaanbaatar, Mongolia; [k]Institute of Meteorology and Climate Research Atmospheric Environmental Research (IMK-IFU), Karlsruhe Institute of Technology, Garmisch-Partenkirchen, Germany

ABSTRACT

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

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CONTACT Shuxin Ji shuxin.ji@iggf.geo.uni-muenchen.de
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attribute the occurrence of pasture breakpoints solely to herder movements especially in the eastern and southern parts of the eastern Mongolian steppe ecosystem.

1. Introduction

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

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

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

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

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

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

(1) Train a Random Forest model to identify breakpoints in InSAR coherence data that correspond to shifts in grazing intensity;

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

2. Materials and methods

2.1. Study area

Approximately 83% of Mongolia's territory (1.3 million km^2) is covered with rangeland (including grasslands, shrublands, forest steppes, and deserts where livestock graze) (Angerer et al. 2008), peaked in supporting 71 million heads of livestock in 2019 (Oyunchimeg et al., 2021). There is a long tradition of nomadic herding, which has been the main form of agricultural production for centuries. Livestock graze freely, centered around Gers (traditional Mongolian tents), and the livestock include cattle (*Bos taurus*), horses (*Equus*), camels (*Camelidae*), goats (*Capra*), and sheep (*Ovis aries*). In summer, herders commonly choose to set up their camps close to riverbanks, while in winter, they stay on wind-sheltered slopes. We conducted field data collection in 10 study sites in Eastern Mongolia, which cover gradients in rainfall from 148 mm to 447 mm annually (Figure 1). Consequently, the study sites represent different rangeland types that are characteristic of the Mongolian Steppe Ecosystem. In addition, the grazing intensities vary along the gradient from the west (higher grazing intensity by livestock) to the east (lower). The gradient in numbers of wildlife is reverse, with higher densities in the east.

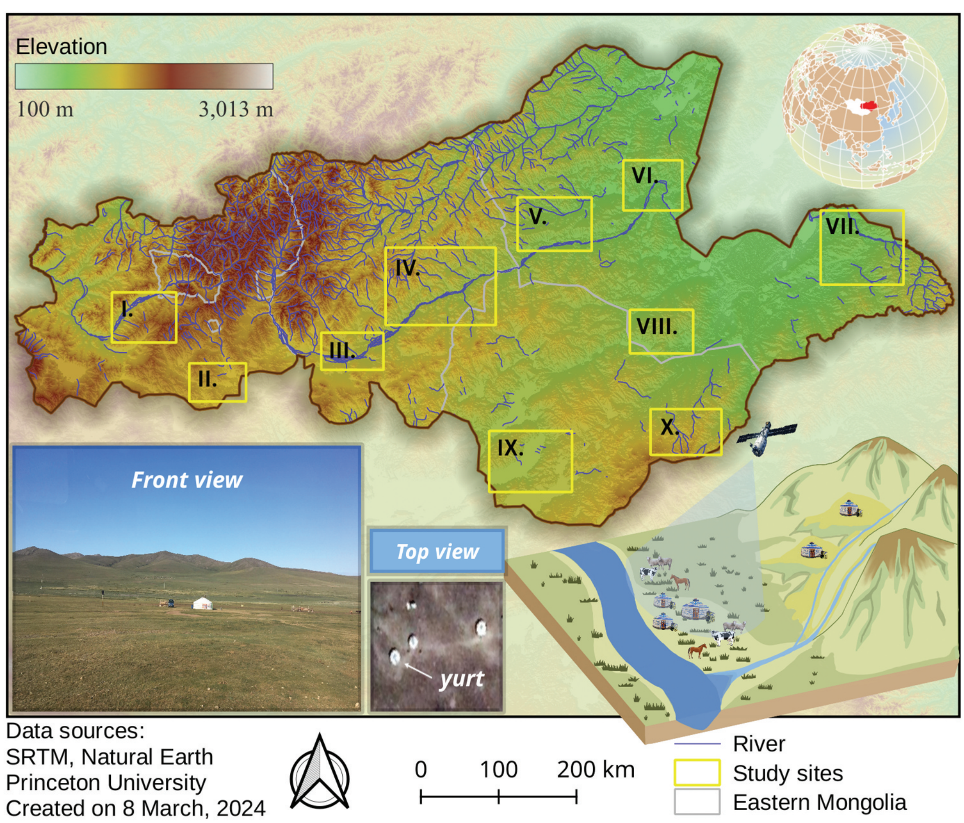

Figure 1. Location of the study area. Camps in the lower left corner are the residence place for local herders, and livestock graze around the camps. Number I to X: the core sites where we design the experiment and interview with herder families.

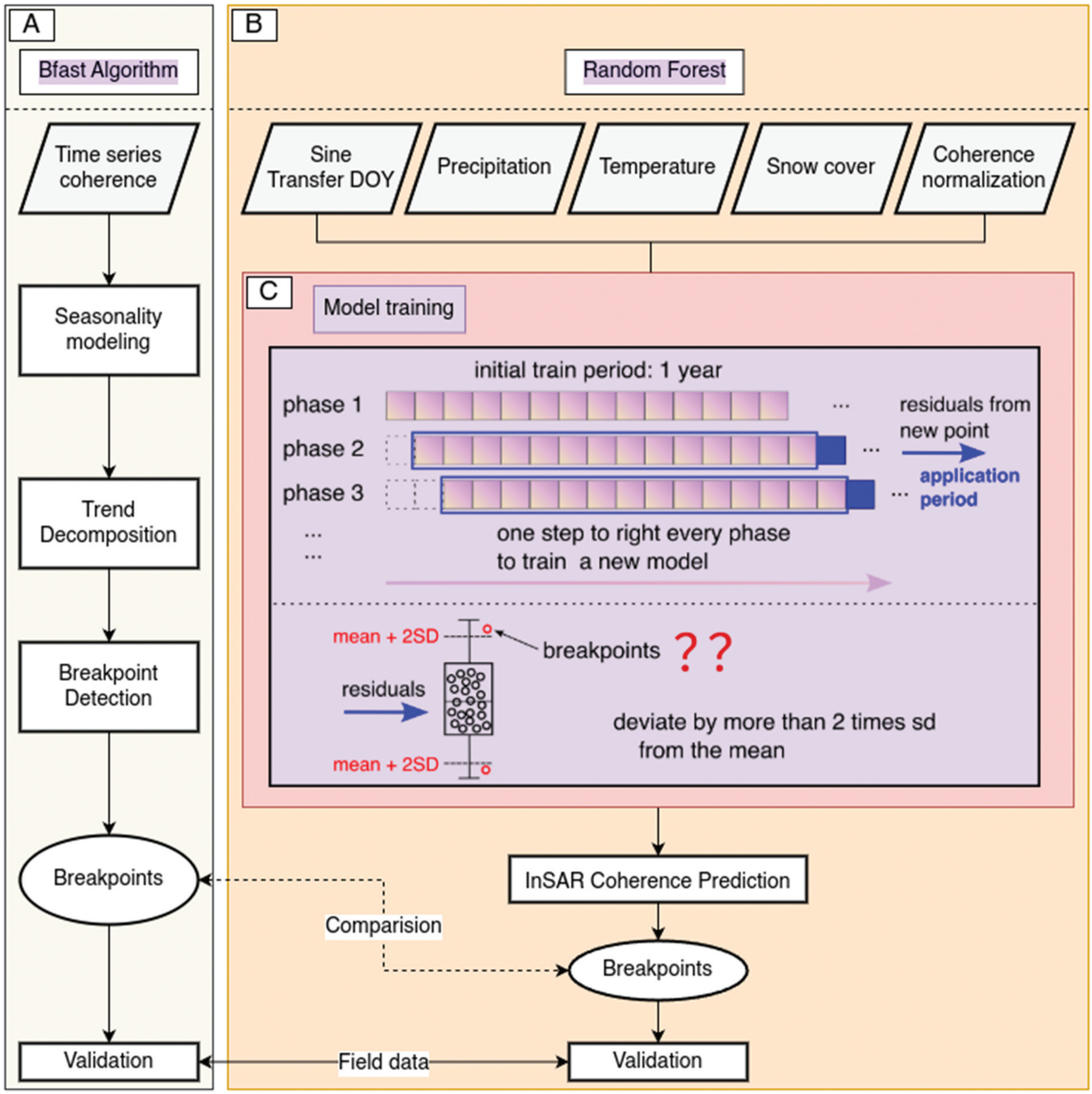

Figure 2. Overview of the study's workflow, (a) General steps of the BFAST algorithm, (b) Parameters and workflow of the random forest model used in this study and (c) Data processing and model building (for details, refer to sect. 2.3.2).

Table 1. Movement characteristics of respondents.

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

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

2.2. Data collection and pre-processing

This section begins by summarizing the field data collection process, which serves as a reference for our analysis. We then provide a detailed description of the satellite data and associated preprocessing steps included. An overview of the applied methods can be found in Figure 2. Following this, the build processes of the two algorithms employed in this study, BFAST and the random forest-based machine learning method, are described in detail.

2.2.1. In situ data collection

Field surveys were conducted in 2019, 2020, and 2022 at the summer camp sites using structured interviews as the primary data collection method (Table 1). Over the course of three years, a total of 862 households were interviewed, including some that were revisited in more than one survey year. Each household corresponds to a seasonal camp and is treated as one sample in the subsequent analysis. Household sizes ranged between 2 and 9 members, with interviews conducted with the male or female head of the household. On each camp site, we crafted a comprehensive dataset covering various aspects of grazing management. This dataset serves as an invaluable reference, helping us to gain insight into important parameters such as arrival and departure dates at/from the camps, livestock numbers, and perceptions of rangeland degradation by local herders. It is important to note that these data were carefully collected by field staff and derived from interviews with the herders themselves, as documented in the original questionnaire. Locations of the summer camp sites were collected using a GPS device. For detailed information regarding the survey questionnaires, please refer to Table S1 in the Appendix.

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

To delineate the effective area of grazing around the gers, we utilized GPS collar data from livestock. GPS tags were deployed on 89 individual livestock (30 goats, 31 horses, 26 cows, and 2 camels) across 10 core sites in Figure 1, with data recorded every 30 minutes (Michler et al. 2022). The maximum range of livestock movement was up to 8 km from the camps. With increasing distance, grazing pressure decreases and intersection with grazing grounds of neighboring families increases. The direct vicinity of the camps is usually heavily disturbed especially at the winter camp locations. Consequently, we developed a ring around each camp, excluding the central 50-meter area to avoid the direct influence of human activities, and then extending outward from 50 meters to a 950-meter range resulting in a total area from 50 meters to 1 kilometer for further analysis. This ensures that the grazing pressure on the rangeland is assessed without the confounding effects of human disturbance near the camps.

2.2.2. InSAR coherence

The two Sentinel-1 satellites (Sentinel-1A and Sentinel-1B, abbreviated with S1 in the following) are equipped with a C-band synthetic aperture radar (SAR) operating at a center frequency of 5.405 GHz (wavelength of approximately 5.54 cm). While S1 provides a 6-day revisit time in Europe, its temporal resolution for most of the rest of the world is 12 days (Torres et al. 2012). Since S1-B suffered technical problems on 23 December 2021 leading to its cessation of operations, we used a 12-days interval to derive S1 InSAR coherence.

The Hybrid Pluggable Processing Pipeline (HyP3) provided by the Alaska Satellite Facility was used for small baseline InSAR processing (Hogenson et al. 2024). Key steps included the selection of temporally close interferometric pairs, precise co-registration of master and slave images, interferogram generation, and coherence calculation. InSAR coherence, a dimensionless measure ranging from 0 to 1, quantifies the similarity between two complex SAR signals acquired at different times. Higher coherence values indicate temporal stability of surface scattering properties, while lower values reflect decorrelation caused by vegetation dynamics, soil moisture variation, or anthropogenic disturbances.

The use of HyP3 benefits from the tool’s high level of integration and ultra-high arithmetic power relied on Amazon services (Hogenson et al. 2024). From 2018/01/01 to 2021/12/31, a total of 745 coherence images with a 40 m spatial resolution were processed for 10 study sites.

2.2.3. Weather data

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

2.3. Experiment design and model building

2.3.1. Detection of breakpoints using random forest

This study proposes a novel methodology for breakpoint detection using random forest, based on the assumption that a random forest model learns the relationship between weather conditions (predictor variables) and the signal at the satellite (response variable, in our case coherence of S1 data). Consequently, if the model fails to predict the satellite signal correctly, this failure can be caused by changes in rangeland usage by livestock and/or wildlife. Therefore, breakpoints detected by the machine learning method are those points in time, where absolute values of residuals of the predicted coherence vs. the measured coherence are high. From a technical perspective, we used a sliding window of training and prediction periods for which separate random forest models are trained and validated. This encompassed the following steps, which are conducted separately for each herder location (shown in Figure 2(b)):

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

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

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

temporal changes in the input data and provided new residuals for each time step as the window progresses.

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

2.3.2. BFAST algorithm

BFAST is a data-based unsupervised statistical algorithm. Based on models of stable historical behavior, abnormal changes in newly acquired data can be detected (Fang et al. 2018; Watts and Laffan 2014). Initially, regression coefficients are estimated from historical observations and used to predict the values of observations in the monitoring period. Subsequently, if the predicted values statistically differ from the observed values, it indicates the presence of abnormal changes (Browning et al. 2017; Ma et al. 2020). Parameters were set as follows: the historical period comprised one full year, followed by another year as the monitoring or detection period. The sbin parameter, which controls the number of seasonal dummies, was set to 3, and the h parameter, representing the minimum segment size, was set to 0.5, allowing the detection of significant breaks or changes within the monitoring period (Figure 2(a)). The function used in this study comes from *BFAST* package for R statistical computing (version: 1.6.1, Verbesselt, Zeileis, and Herold 2012).

2.3.3. Assessing the model accuracy

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

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

3. Results

3.1. Breakpoints prediction and validation

Observed coherence (Figure 3(a)) aligned well with predicted coherence (Figure 3(b)) in time series. Accuracies in coherence prediction among the models ranged from moderate to high (RMSE between 0.28 and 0.08). Since the initial training phase is limited to the first year, values are always the same, then the RMSE remains 0 during this phase. (RMSE is always calculated for each model from every new phase) (Figure 3(c)). Most of the residuals are concentrated around 0, indicating that the overall prediction deviation is small (Figure 3(d)). At the two points marked by the red dotted line, the residuals deviate significantly from 0 and are detected as breakpoints.

3.2. Variable importance

Among the variables in the model training process, the sine transformation of the day of the year (Figure 4(b)) and the left-aligned rolling sum across 6 days of precipitation (Figure 4(d)) had the greatest

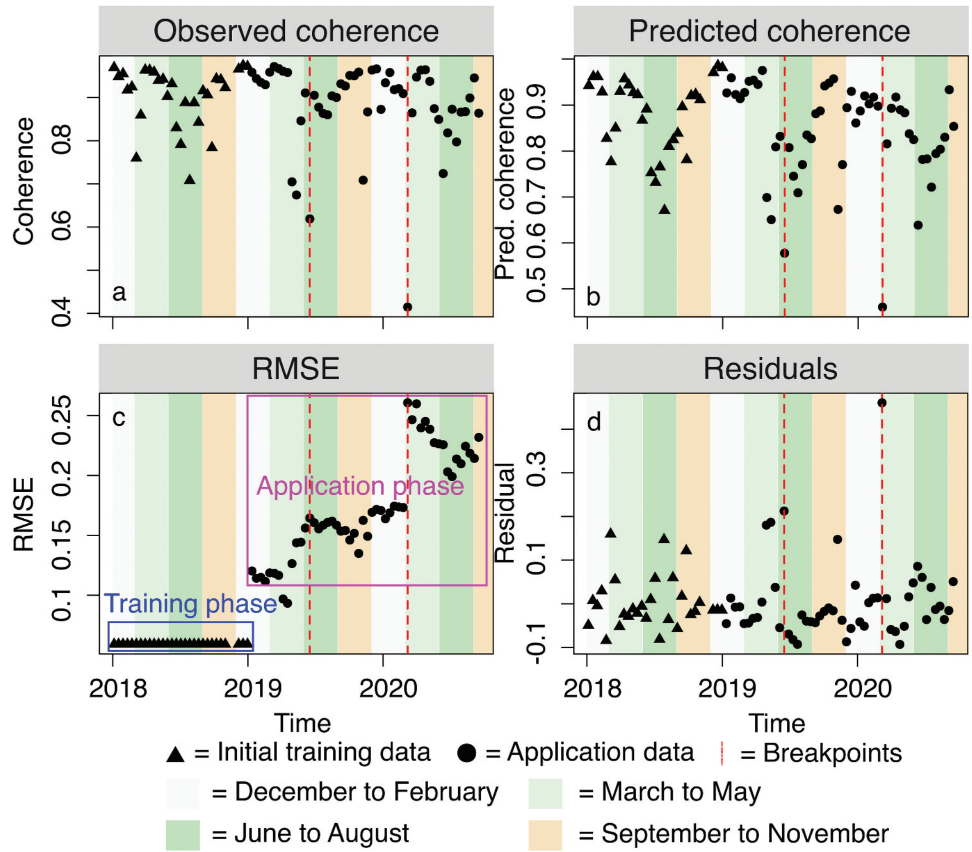

Figure 3. Breakpoints detection using random forest model for a sample point. (a) Observed coherence from 2018 to 2020; (b) Predicted coherence using the random forest model developed above; (c) RMSE of each model in successive moving windows, since the initial training phase encompasses the first year, RMSE values are constant over the first year and set to 0 during this phase. (d) Residuals in the model training process. Triangles represent initial training data, circles represent application period data. Breakpoints are marked with red dashed lines, background colors indicate seasonal periods.
Note: This figure demonstrates the model training and prediction process for one of the sample points in the dataset comes from the middle of Hentii province.

variable importance in the model. The left-aligned rolling sum across 3 days (Figure 4(c)), the left-aligned rolling sum across 12 days of precipitation (Figure 4(f)) and temperature (Figure 4(g)) had medium contribution to the model. While snow cover was partly important in single models (Figure 4(a)) and the left-aligned rolling sum across 9 days of precipitation (Figure 4(e)) had the lowest contribution to the model.

3.3. Application on temporal breakpoints detection

The random forest method successfully predicted 149 breakpoints across 200 summer camp sites (Figure 5), with the majority of these breakpoints occurring between April and June (Figure 6(a)). Notably, the random forest algorithm detected 44% of breakpoints occurring after herders moved to their summer pastures (Figure 6(e)). To benchmark the performance of the random forest method, we applied the well-established BFAST algorithm to the coherence time-series data. Breakpoints were detected for every month except January (Figure 6(c)). Of the 200 camp sites, 115 breakpoints were detected throughout the year using BFAST, but only 28% of them occurred after herders arrived at the summer camp sites (Figure 6(f)).

Acorss 761 winter camp sites, the random forest method detected 614 breakpoints (Figure 5), primarily occurring in February, March, and from October to November (Figure 6(b)). In comparison, BFAST was much less effective at detecting breakpoints at winter camp sites, identifying only 319 breakpoints (Figure 5). Moreover, the temporal distribution of breakpoints detected by BFAST was less concentrated during the winter months, with breakpoints detected in nearly every month except January (Figure 6(d)).

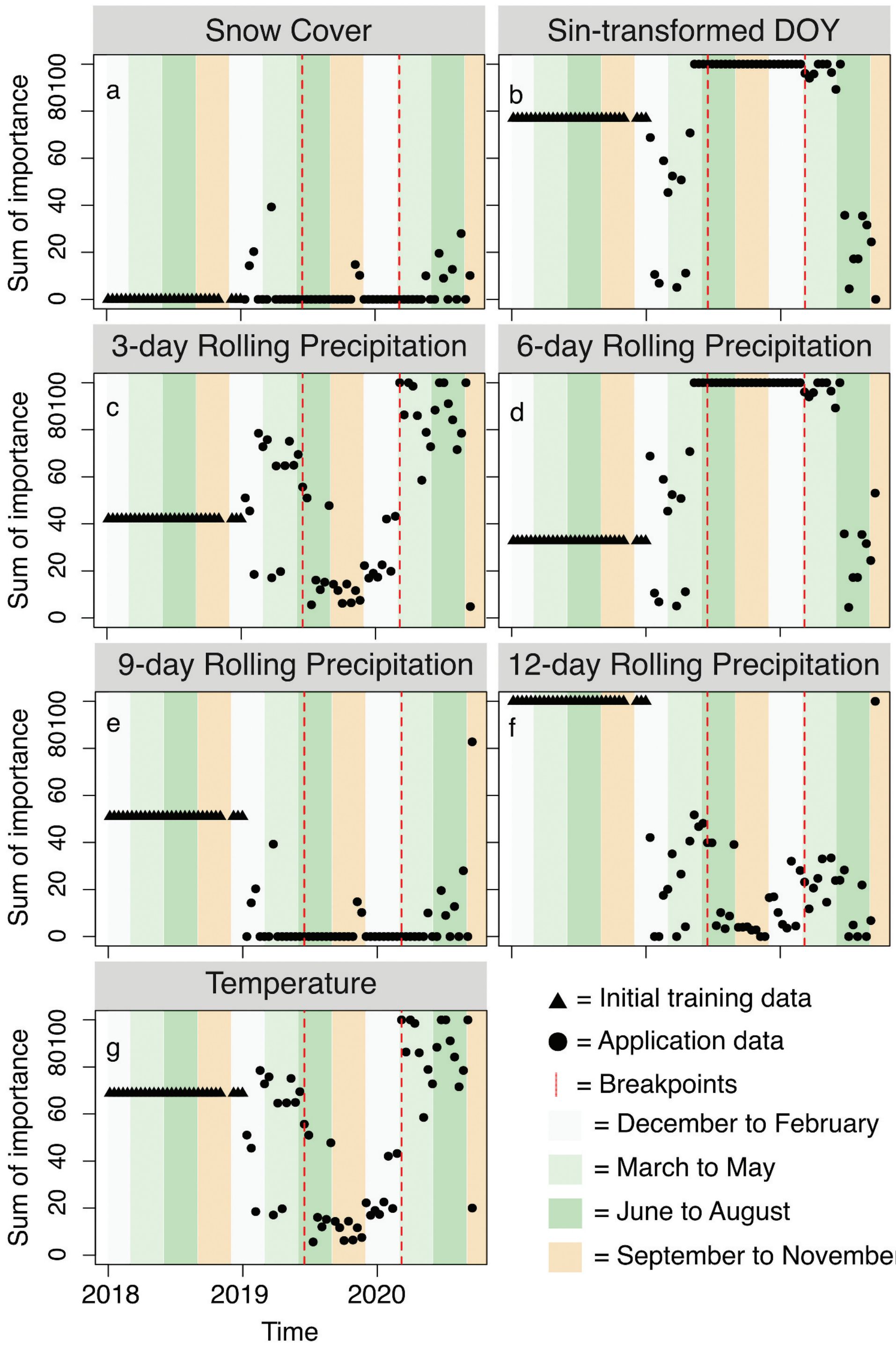

Figure 4. Sum of variable importance in random forest model, (a) Snow cover, (b) Sine transformation of day of the year, (c) Precipitation 3 days rolling sum, (d) Precipitation 6 days rolling sum, (e) Precipitation 9 days rolling sum, (f) Precipitation 12 days rolling sum and (g) Temperature.

3.4. *Spatial prediction of breakpoints*

Based on the method developed in Section 2.3.2, we performed spatial predictions for the year 2019 for the four steppe sites in Eastern Mongolia labeled as I, V, VII, and IX in Figure 7. The figure illustrates that summer breakpoints are primarily detected along riverbanks in regions I (UB) and V (Khentii), exhibiting a relatively clustered distribution. Correspondingly, winter breakpoints are

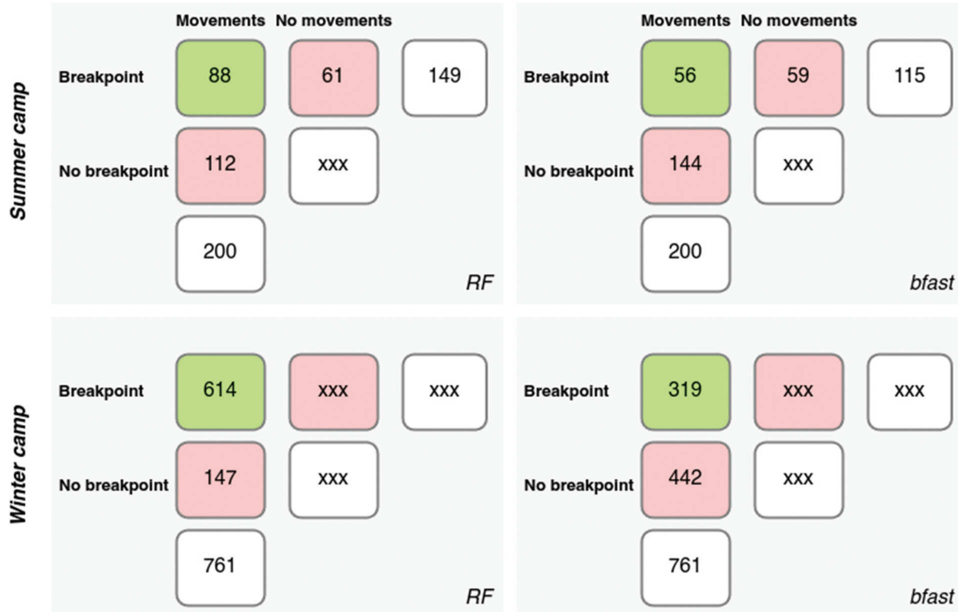

Figure 5. Confusion matrix of breakpoints detection using random forest and BFAST algorithm. No comparison is possible for winter camps because the movement dates cannot be aligned with the winter locations detected from high resolution satellite data.

distributed in adjacent areas. In Region VII, located in Dornod Province, summer breakpoints are rarely detected, with winter breakpoints dominating most of the region. In contrast, Region IX, situated in the southern part of Sukhbaatar Province, exhibits a prevalence of summer breakpoints, while winter breakpoints are less frequently observed.

4. Discussion

4.1. Methodological performance: random forest vs. BFAST in breakpoint detection

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

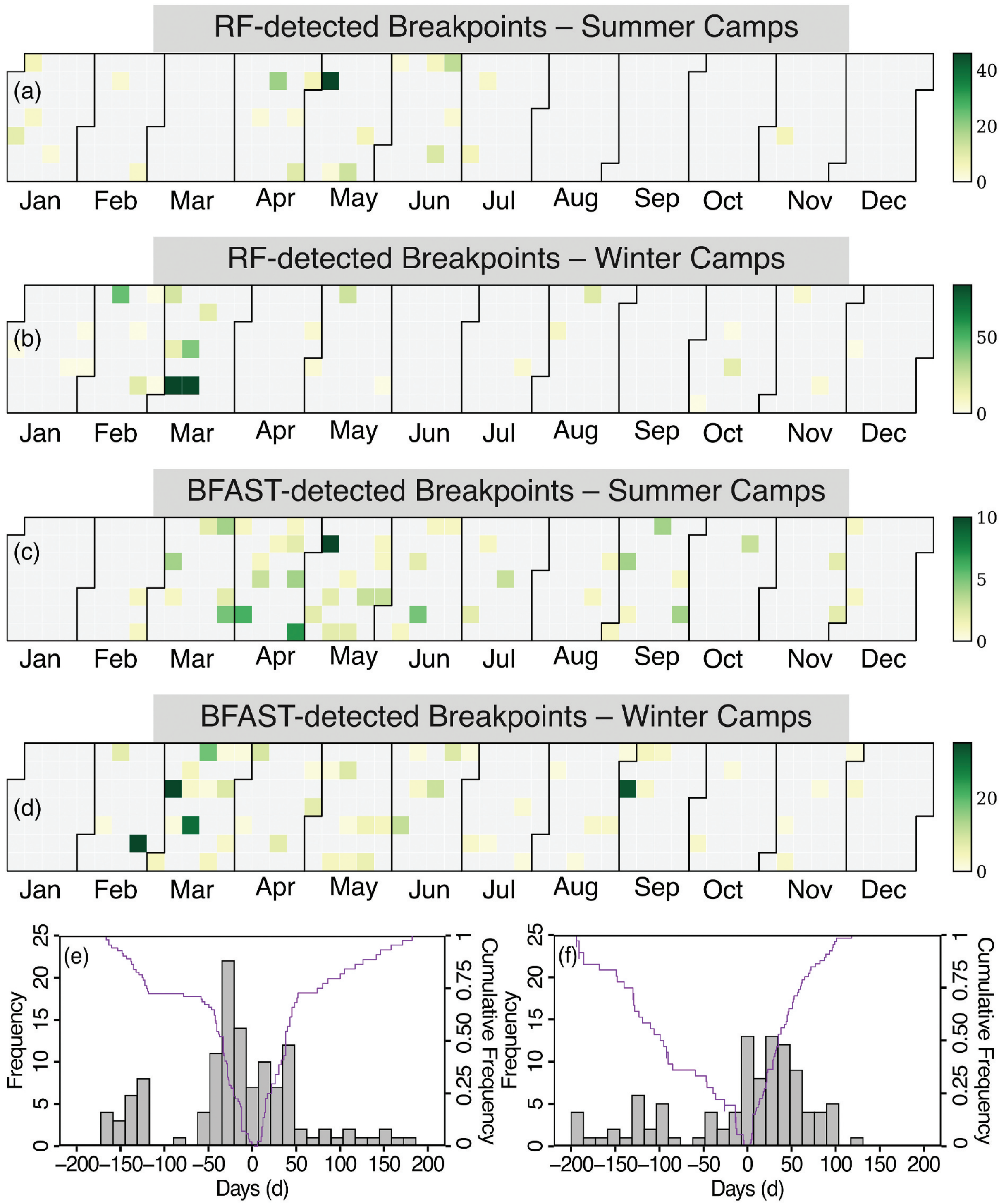

Figure 6. (a) and (b):heatmaps of breakpoints detected by random forest method for summer and winter camp sites respectively. (c) and (d): heatmaps of breakpoints detected by BFAST method for summer and winter camp sites respectively. Each heatmap shows the temporal distribution of breakpoints aggregated across all sites; colored blocks indicate frequency on specific day. (e): difference in days between detected breakpoint and actual moving dates using the random forest method. (f): same as (e) but for BFAST (bars indicate frequency distribution; the purple line indicates cumulative frequency).

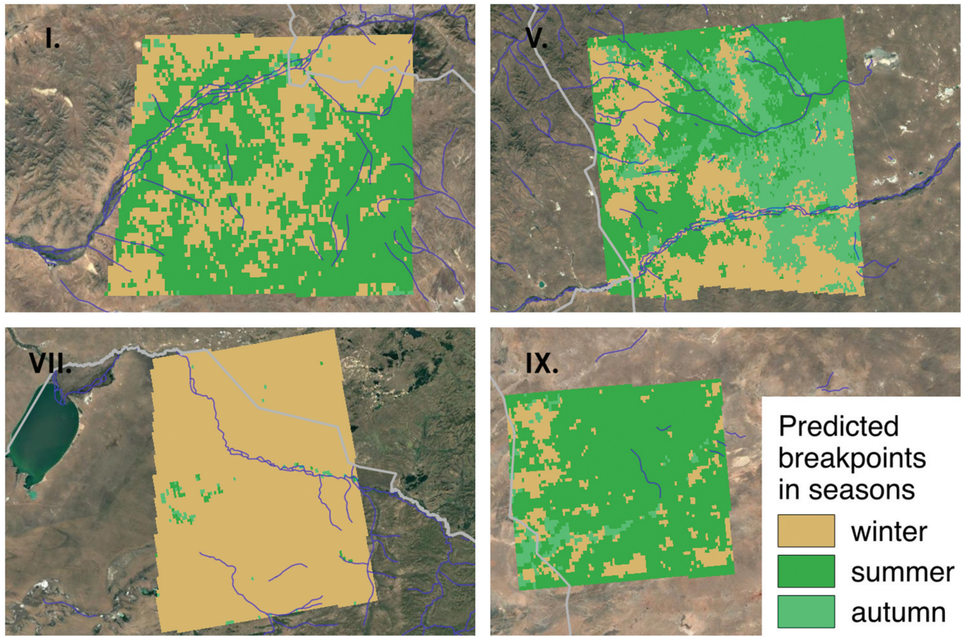

Figure 7. Seasons when breakpoints have been detected four different areas in Eastern Mongolia. (I, V, VII, and IX comes from Figure 1, winter is from December to March, summer is from June to August).

4.2. Seasonal and spatial breakpoint patterns

Breakpoint patterns differed markedly between seasons. In winter camp sites, most breakpoints occurred between February and March (Figure 6(b)), when snow is the main natural driver of coherence. This is likely due to the impact of snow cover on InSAR signal quality, which can hinder the detection of displacement signals (Eppler and Rabus 2022). Unlike summer camp sites, where grazing pressure necessitates careful management, herders often designate specific areas as winter pastures during the growing season (Ono and Ishikawa 2020). These areas are monitored and protected to prevent unauthorized grazing during the summer, allowing forages to accumulate for livestock use in winter. Hay feeding also plays a critical role, our interview data indicate that in 2019, herders reported spending an average of 105,000 Mongolian Tugrik on hay for livestock feeding. Thus, the main energy source for livestock is hay fed by herders, rather than relying heavily on free grazing (Tsevegemed et al. 2019).

From a spatial perspective, random forest successfully predicted seasonal breakpoints across all four study sites (Figure 7). At sites near river systems, such as site I (near Ulaanbaatar) and site V (northern Khentii), summer breakpoints predominantly aligned along river systems, exhibiting pronounced clustering effects. The proximity of summer camps to rivers is plausible, as herders typically avoid valley bottoms during winter due to lower nighttime temperatures and the lack of natural wind shelters compared to locations at slope feet. Since the 1990s, water resources, particularly river flow and depth, have steadily declined in Eastern Mongolia, increasingly constraining herders' ability to graze livestock along riverbanks, which are critical for ensuring adequate water intake (Tugjamba, Walkerden, and Miller 2021b).

In contrast, breakpoint patterns at sites VII and IX were less related to topography because summer pastures have been predicted both in mountainous and flat areas around the rivers. This may be a consequence of extensive grazing in the eastern study sites, where low population densities and low livestock numbers reduce the grazing signal within coherence time series (Hilker et al. 2014). Moreover, the eastern region hosts higher numbers of wildlife, such as Mongolian gazelles, whose roaming contributes to general grazing signals without seasonal cycles. This overlap with livestock grazing activities complicates the identification of breakpoints caused solely by livestock (Yoshihara et al. 2008, Nandintsetseg et al. 2019). In the southern study sites, located at the grassland-desert boundary, shorter vegetation further complicates the detection of grazing signals, because the signal of vegetation in the InSAR-data is generally low (Batsukh et al. 2021; Pan et al. 2022). Even biomass estimation in this region demonstrates lower accuracy compared to other areas (Ji et al. 2024). Additionally, the uncertain spatial distribution of grazing activities contributes to monitoring challenges, as some areas are heavily grazed by livestock from multiple households, while others are rarely utilized.

4.3. Drivers of grazing patterns

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

4.4. Limitations and future work

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

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

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

5. Conclusion

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

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

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

CrediT authorship contribution statement

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

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Author contributions

CRediT: **Shuxin Ji:** Conceptualization, Data curation, Methodology, Visualization, Writing – original draft, Writing – review & editing; **Ganzorig Gonchigsumlaa:** Conceptualization, Investigation; **Sugar Damdindorj:** Investigation; **Tserendavaa Tseren:** Investigation; **Densmaa Sharavjamts:** Investigation; **Amartuvshin Otgondemberel:** Investigation; **Enkh-Amgalan Gurjav:** Investigation; **Munguntsetseg Puntsagsuren:** Investigation; **Batnaran Tsabatshir:** Investigation; **Tumendemberel Gungaa:** Investigation; **Narantsetseg Batbold:** Investigation; **Lukas Drees:** Investigation; **Bayarchimeg Ganbayar:** Investigation; **Dulamragchaa Orosoo:** Investigation; **Bayartsetseg Lkhamsuren:** Investigation; **Badamtsetseg Ganbat:** Investigation; **Myagmarsuren Damdinsuren:** Investigation; **Gantogoo Gombosuren:** Investigation; **Batnyambuu Dashpurev:** Investigation; **Thanh Noi Phan:** Investigation; **Nandintsetseg Dejid:** Investigation; **Thomas Müller:** Conceptualization, Writing – review & editing; **Lukas Lehnert:** Conceptualization, Methodology, Writing – review & editing.

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ORCID

Shuxin Ji http://orcid.org/0000-0003-4081-5506

Data availability statement

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

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