A Data-Driven Framework for Rotational Grazing Management Based on Mixed-Effects Modeling of Reindeer Pastures

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***Abstract*—This paper presents a data-driven framework for rotational reindeer grazing management based on mixed-effects modeling of lichen pasture condition. The study analyzes long-term pasture data, including lichen cover, vegetation height, volume, biomass, reindeer density, habitat type, grazing access regime, year, districts, and transects. Linear regression with clustered standard errors and mixed-effects models were used to account for spatial heterogeneity and hierarchical data structure. The results showed that fenced plots had consistently higher lichen cover, while increased reindeer density was generally associated with a negative effect on pasture condition. Significant spatial differences between districts confirmed the need to include random effects in the analysis. Based on the results, a rotational grazing strategy with fenced recovery sectors and regular monitoring is proposed to support sustainable pasture use and lichen recovery**

Keywords— reindeer grazing, lichen pastures, mixed-effects modeling, rotational grazing, pasture management, spatial heterogeneity

I. INTRODUCTION

Arctic and subarctic pasture ecosystems are under increasing pressure from climate change, land-use transformation, and anthropogenic impacts. This issue is especially important for regions of traditional reindeer herding, since the condition of pastures directly determines forage availability, the sustainability of economic activity, and the conservation of vulnerable northern ecosystems. Recent studies show that rapid climate change in the Arctic affects vegetation productivity, biodiversity, and ecosystem functioning, while reindeer grazing systems are additionally exposed to winter thaw events, ice-crust formation, infrastructure development, and changes in vegetation composition [1].

One of the key components of winter reindeer pastures is ground lichens. They serve as an important forage resource during the cold season; however, they are characterized by slow recovery and high sensitivity to trampling, overgrazing, fires, forestry activities, and climate change [2]. Study [3] emphasizes that the reduction in the area and biomass of lichen pastures is becoming one of the main limiting factors for sustainable reindeer herding in northern regions.

At the same time, the impact of grazing on pasture vegetation is not unambiguous and depends on spatial conditions, habitat type, the initial state of the site, animal density, and duration of exposure [4]. Historical reconstructions of lichen cover along the Finnish–Norwegian border show that from 1959 to 2020, the cover of forage lichens declined considerably under different grazing regimes, while biomass losses may be associated not only with consumption but also with trampling and other forms of mechanical disturbance [5].

For practical pasture management, it is important not only to assess the fact of degradation itself, but also to develop a quantitative model that accounts for spatial heterogeneity. Simple linear models often fail to reflect the hierarchical structure of ecological data, since observations may be grouped by districts, transects, years, and habitat types [6]. Therefore, mixed-effects models are appropriate for analyzing such data, as they allow fixed factors, such as reindeer density, habitat type, and enclosure regime, to be estimated simultaneously with random spatial and temporal variation [7].

The relevance of this approach is further reinforced by the fact that modern studies increasingly consider reindeer herding as a socio-ecological system in which pasture productivity, economic performance, climate risks, and the long-term sustainability of the forage base must be considered simultaneously. For example, studies published in 2024 show that fluctuations in herd size significantly affect both the economic indicators of reindeer herding and pasture condition, while a more stable and moderate animal density may contribute to the conservation of lichen resources [8].

Climate change creates a particular challenge. On the one hand, warming may increase vegetation productivity in certain seasons; on the other hand, it raises the risk of ice-crust formation on pastures, reduces forage accessibility, and weakens the resilience of reindeer herding systems. Bioeconomic modeling for Norway and Sweden shows that additional days with ice crust may have a stronger negative effect than the positive impact of an earlier spring [9].

In recent years, machine learning methods have been increasingly applied in pasture monitoring, since traditional

field surveys require substantial labor and do not allow data to be collected regularly over large areas [10], [11]. Modern approaches combine satellite imagery, unmanned aerial vehicle data, meteorological indicators, and ground-based measurements, followed by the use of machine learning algorithms to estimate biomass, forage quality, and vegetation condition [12]. A 2025 review emphasizes that the integration of remote sensing and machine learning is becoming one of the main directions in digital pasture monitoring, especially for pasture classification, biomass estimation, and forage quality assessment [13], [14].

For pasture systems, machine learning is especially useful because it can process heterogeneous data. For example, spectral bands of satellite images, vegetation indices, weather parameters, and management-related data may be used to estimate forage mass [15]. In a study based on Sentinel-2 imagery, Random Forest and Support Vector Regression models were developed to predict forage mass, crude protein content, and fiber content in pastures. The authors showed that a combination of spectral features, vegetation indices, and meteorological data can be used to support grazing management decisions [16].

In the context of reindeer herding, such methods can be used not only to assess the current state of pastures, but also to move toward predictive management. If data on lichen cover, vegetation height, reindeer density, habitat type, and climatic conditions are combined, the model can identify areas with an increased risk of degradation and recommend changes in grazing regimes [17], [18]. This is especially important for northern pastures, where lichens recover slowly and the consequences of excessive grazing pressure may persist for many years [19], [20]. Study [21] on the assessment of winter forage resources for reindeer showed that UAV data and spatially balanced sampling make it possible to objectively estimate lichen cover and biomass, while such estimates can be linked to the number of "reindeer grazing days" that a given site can support.

Training models on local data is also of particular importance. Even when satellite imagery is used, a universal model may produce substantial errors if it does not account for the specific characteristics of a particular territory, vegetation type, and pasture-use regime [22], [23]. Study [24] demonstrated that the accuracy of machine learning for estimating pasture biomass increases substantially when regular field measurements are added. The authors also emphasize the need for a minimal but systematic amount of ground data for proper model calibration.

For northern pastures, another promising direction is the integration of machine learning with remote snow monitoring data [25]. The winter availability of lichens is determined not only by their biomass, but also by snow cover conditions, the presence of ice crust, and the timing of snowmelt [26]. A study using Sentinel-1 SAR data in reindeer-grazing landscapes showed that radar data can be used to track the onset of snowmelt and the end of the snow season, which can be incorporated into models for assessing forage accessibility and planning grazing routes [27].

Despite the existence of studies devoted to lichen-cover degradation, forage-resource mapping, and bioeconomic modeling of reindeer herding, an applied approach that links statistical assessment of pasture condition with specific management decisions remains insufficiently developed. Of particular importance is the transition from the analysis of individual factors to the formation of a rotational grazing scheme, in which the territory is divided into sectors, some sites are temporarily excluded from grazing pressure, and animal density is adjusted according to vegetation recovery.

Therefore, the aim of this paper is to develop a data-driven framework for rotational reindeer grazing management based on mixed-effects modeling of pasture condition. The dependent indicators include characteristics of lichen cover, such as cover, height, volume, and biomass. The key factors include reindeer density, site-access regime, habitat type, year of observation, and the spatial structure of the data. The proposed approach makes it possible not only to assess the effect of grazing on pasture condition, but also to transform statistical modeling results into practical recommendations for territorial zoning, site recovery periods, and animal density control.

II. MATERIALS AND METHODS

A. Study Data and Preprocessing

The study is based on a long-term dataset describing the condition of reindeer pastures in northern Sweden. The data include observations from pasture plots with different grazing-access regimes, including open and fenced areas, as well as different habitat types. The main pasture condition indicators are lichen cover, vegetation height, vegetation volume, and biomass. The key explanatory variables include mean reindeer density, habitat type, year of observation, grazing-access regime, initial vegetation condition, district, and transect. The dataset has a hierarchical structure, since observations are grouped by districts and transects.

The data were processed in Python. At the preprocessing stage, the main dataset was combined with baseline vegetation indicators, missing values were removed, vegetation indicators were log-transformed, and numerical predictors were centered around their mean values. Such preprocessing was necessary because ecological data are often heterogeneous, spatially dependent, and affected by uncertainty. Similar methodological issues are considered in studies devoted to stochastic and probabilistic data processing [28].

B. Exploratory Analysis and Statistical Modeling

Before model estimation, exploratory data analysis was performed. It included descriptive statistics, correlation analysis, and visualization of the relationship between reindeer density and pasture condition indicators. Scatter plots and correlation matrices were used to identify general trends and possible associations between variables. This stage was considered preliminary, since the effect of grazing pressure may be masked by habitat type, year, enclosure regime, and spatial location.

At the first modeling stage, linear regression with clustered standard errors was used. Clustering was applied at the district level to account for the dependence of observations within the same spatial area. At the second stage, mixed-effects models were applied to account for the hierarchical structure of the data. These models included random effects for districts and transects, which made it possible to separate fixed ecological effects from random spatial variation. The use of structured models for grouped and repeated observations is consistent with approaches applied to panel data, where

hybrid modeling can improve the stability and accuracy of estimates [29].

C. Extended Analysis and Model Evaluation

Additional model specifications were tested to determine whether the effect of reindeer density depends on habitat type, grazing-access regime, or year of observation. Interaction effects were considered to assess whether grazing pressure acts differently in open and fenced plots or across habitat types. A nonlinear effect of reindeer density was also tested, since pasture degradation may not always increase linearly with animal density.

Model quality was assessed using residual analysis, normality checks, heteroscedasticity testing, multicollinearity diagnostics, and information criteria, including AIC and BIC. Preference was given to models that combined statistical reliability, interpretability, and ecological meaning. The use of intelligent data-driven methods for analyzing natural objects is consistent with recent studies in which measurable environmental characteristics are used to classify and interpret complex natural systems [30].

D. Data-Driven Rotational Grazing Framework

The final stage of the methodology involved developing a data-driven framework for rotational grazing management. The framework links statistical modeling results with practical decisions, including assessment of pasture condition, identification of vulnerable sectors, estimation of grazing pressure, and planning of pasture rest periods. The pasture area can be divided into several sectors: some sectors are used for grazing, while others are temporarily excluded from grazing to allow vegetation recovery. The duration of rest periods should be adjusted according to monitoring results, vegetation recovery rates, and spatial differences between districts and transects.

This approach is close to the logic of digital livestock management, where data on animals and production systems are integrated into digital tools for more efficient decision-making [31]. In the context of reindeer herding, such a framework can connect herd density, pasture condition indicators, spatial data, and grazing rotation planning. Thus, mixed-effects models provide a quantitative basis for estimating grazing effects, while the proposed framework transforms statistical results into recommendations for zoning, rest periods, and animal density control.

III. RESULTS AND DISCUSSIONS

The interpretation of the obtained results makes it possible to form a comprehensive understanding of the effect of reindeer density on the condition of pasture vegetation. The preliminary correlation analysis showed a weak negative relationship between reindeer density and lichen cover, with r=−0.115 (Figure 1). This indicates a negative trend; however, more complex statistical models that account for additional factors are required to confirm it.

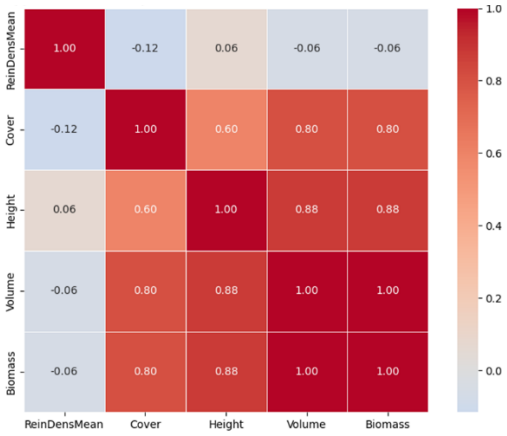

Fig. 1. Correlation matrix: deer density and pasture condition

When building the linear regression model with clustered standard errors (OLS), the significant predictors were the manipulation factor (fencing) and habitat type. Fenced plots and the "»orest and leeward heath» habitat were characterized by substantially higher lichen cover.

The value of R^2=0.193 indicates that the model explains 19.3% of the variation in the dependent variable, Cover_log. This value is relatively low, but such results are common in ecological and social studies. The adjusted R^2=0.165 is slightly lower because it accounts for the number of predictors in the model, which is expected. The F-statistic is 2.509, and Prob(F-statistic) = 0.197. Since the p-value is greater than 0.05, the model as a whole is not statistically significant at the standard 0.05 level. In other words, the combined effect of all variables cannot be confidently distinguished from zero (Table 1).

TABLE I. GENERAL INFORMATION ABOUT THE MODEL

Indicator	Value
Dependent variable	Cover_log
Method	Least Squares (OLS)
Number of observations	241
Degrees of freedom of residuals (Df Residuals)	232
Degrees of freedom of the model (Df Model)	8
Covariance type	cluster (clustered standard errors)
R-squared	0.193
Adjusted R-squared	0.165
F-statistic	2.509
Prob. (F-statistic)	0.197
Log-Likelihood	-335.95
AIC	689.9
BIC	721.3

The coefficient for reindeer density in this model did not reach statistical significance (p=0.480), which may be due to the small number of clusters, as the dataset includes only five districts, reducing the statistical power of the test (Figure 2).

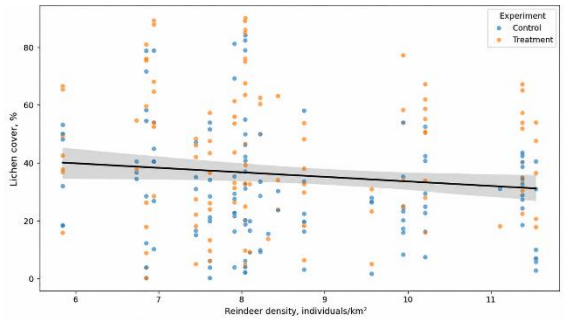

Fig. 2. The dependence of lichen cover on the density of deer

Mixed-effects models provided a more detailed interpretation of the hierarchical data structure. In the model with a random intercept for districts, reindeer density had a marginally significant negative effect on lichen cover ($p=0.057$); an increase of one individual/km² was associated with an approximate 22% decrease in cover. After adding transects as a second random-effect level, the effect remained negative but became less significant ($p=0.094$), indicating that part of the variation was explained by local differences between transects. The temporal effect was also uneven: significant differences were observed for 2010 and 2013, while the 2018 effect disappeared in the two-level model, suggesting a possible slowdown in lichen recovery after 2013.

No significant interactions were found between reindeer density and either fencing or habitat type. This suggests that the negative effect of increased reindeer density was relatively consistent across open and fenced plots and across different habitat types. Therefore, density regulation measures can be applied uniformly across the study area.

The OLS model with clustered standard errors explained about 19% of the variance in Cover_log, but the model as a whole was not statistically significant ($p=0.197$). However, fencing ($p<0.001$) and the "Forest and leeward heath" habitat type ($p=0.024$) were significant predictors. Since residual diagnostics indicated deviation from normality (JB test, $p<0.001$), the OLS results should be treated as preliminary (Table 2).

TABLE II. ADDITIONAL DIAGNOSTIC STATISTICS

Indicator	Value
Omnibus	132.110
Prob. (Omnibus)	0.000
Skewness	-2.123
Kurtosis	11.201
Durbin–Watson	1.978
Jarque–Bera (JB)	856.388
Prob. (JB)	1.09e-186
Condition Number	11.9

Fencing had a stable positive effect on lichen cover, with coefficients of about 0.46–0.48. This confirms that excluding grazing can support lichen recovery. Although the density effect was not significant in all models, the overall results indicate a negative impact of higher reindeer density on pasture condition. This effect appears to be relatively independent of local habitat conditions and can be partly reduced by fenced recovery areas.

Figure 3 shows the relationship between centered reindeer density and log-transformed lichen cover. The regression line indicates a weak negative trend, but the explanatory power is very low ($R^2=0.002$). This means that reindeer density alone explains less than 0.2% of the variation in lichen cover.

The wide confidence interval and large scatter of points show that the density effect is not statistically significant in a simple pairwise regression. Therefore, additional factors must be considered, including habitat type, fencing, year of observation, and spatial structure. This confirms the need for multivariable and mixed-effects models rather than simple linear regression.

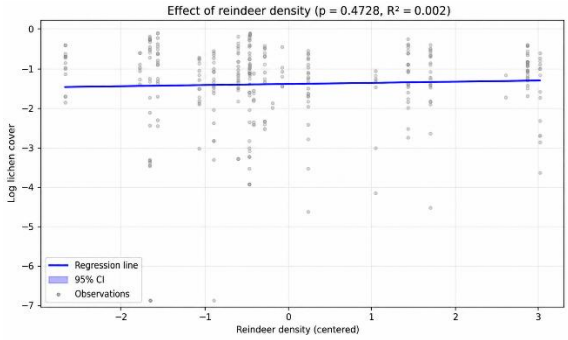

Fig. 3. The effect of deer density

Figure 4 shows the relationship between log-transformed lichen cover and centered reindeer density for two habitat types: Exposed ridges and Forest and leeward heath. Separate regression lines are shown for fenced (Exclosure) and open (Open) plots, with 95% confidence intervals.

In all groups, the regression lines have a negative slope, indicating that higher reindeer density is associated with lower lichen cover. However, the wide confidence intervals suggest that this effect is statistically uncertain, which is consistent with the OLS model result ($p=0.480$).

Fenced plots show higher lichen cover than open plots across both habitat types, confirming the positive effect of grazing exclusion ($p<0.001$). The Forest and leeward heath habitat also demonstrates higher lichen cover than Exposed ridges, which agrees with the significant positive habitat effect ($p=0.024$).

The slopes are visually similar across groups, indicating no significant interaction between reindeer density, fencing, and habitat type. Therefore, the negative effect of reindeer density appears to be relatively consistent across different pasture conditions, supporting the use of uniform density management measures across the study area.

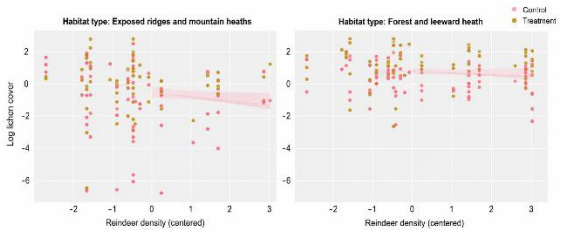

Fig. 4. Dependence of lichen coverage on deer density by habitat type

Figure 5 shows the random district effects, expressed as deviations from the fixed intercept. The zero-effect line represents the overall mean.

Districts 16 and 30A show positive effects (+0.302 and +0.231), indicating above-average lichen cover. In contrast, districts 30B, 17, and 30C have negative effects, indicating

lower-than-average cover. The difference between the highest and lowest district effects is about 0.64 log units, which corresponds to an approximately 1.9-fold difference in lichen cover. The between-district standard deviation is 0.274, confirming substantial spatial heterogeneity in pasture conditions.

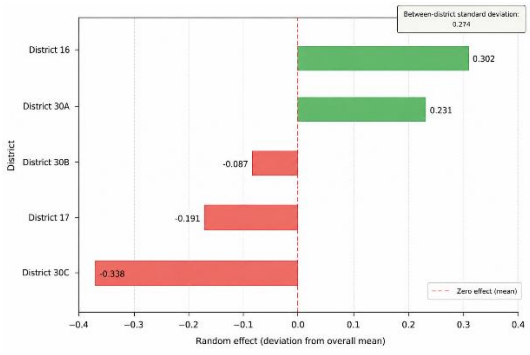

Fig. 5. Differences between districts (random effects)

Figure 6 presents the same district random effects with 95% confidence intervals, allowing the reliability of between-district differences to be assessed. Only districts 16 and 30A show statistically significant positive deviations from the overall mean. For the remaining districts, the differences are not significant because of wide confidence intervals, likely due to fewer observations or high within-district variability.

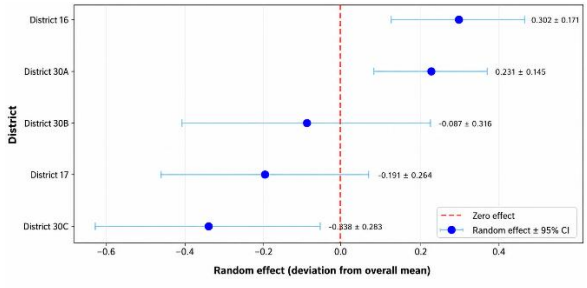

Fig. 6. Random effects of areas with 95% confidence intervals

Figure 7 shows boxplots of log-transformed lichen cover by district. The red dashed line indicates the overall mean (-1.386).

District 30C has the lowest median cover and the highest variability, suggesting strong internal heterogeneity. Districts 17 and 30B show intermediate values, while districts 16 and 30A have the highest lichen cover. This pattern is consistent with the positive random effects observed for districts 16 and 30A.

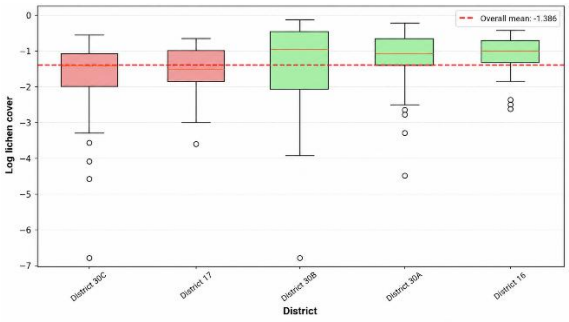

Fig. 7. Distribution of lichen coverage by area

Spatial analysis revealed clear between-district differences in lichen cover. The standard deviation of random effects was 0.274, and the total range reached 0.64 log units, corresponding to almost a twofold difference in cover. The highest lichen cover was observed in districts 16 and 30A, while the lowest was found in district 30C. These results confirm the need to account for spatial structure using mixed-effects models or clustered standard errors. Ignoring district-level differences may lead to biased effect estimates and overestimated predictor significance.

IV. CONCLUSION

The obtained results provide practical implications for sustainable reindeer pasture management. Fencing was found to be the most reliable measure for supporting lichen recovery, as fenced plots showed consistently higher lichen cover than open plots. However, full grazing exclusion over large pasture areas is often economically and practically difficult. Therefore, a rotational grazing system with fenced sectors can be considered a more realistic management strategy.

The proposed approach involves dividing a large pasture area into several sectors, for example, 3–5 units. Some sectors are used for grazing, while others remain temporarily excluded from grazing to allow vegetation recovery. According to the observed dynamics, positive recovery was most evident after 12–15 years, while the effect weakened by 2018. This suggests that a rest period of about 10–15 years may be suitable before a sector is returned to grazing use.

The results also indicate that reindeer density should be controlled within each sector. Although a precise density threshold was not identified, the consistently negative coefficient suggests that even moderate increases in density may negatively affect lichen cover. Therefore, during active grazing periods, animal density should not exceed the long-term regional average, while recovery sectors should remain fully protected.

The negative effect of reindeer density did not significantly depend on habitat type, which means that the rotational scheme can generally be applied across different pasture conditions. At the same time, more productive habitats, such as forest and leeward heath, may support more frequent use, whereas less productive areas may require longer recovery periods.

Regular monitoring every 3–5 years is necessary to adjust grazing schedules and density limits according to actual vegetation recovery. Special attention should be paid to transect-level variation, since local differences within districts were substantial. A pilot implementation with 2–3 sectors is recommended before scaling the framework to larger territories.

Overall, rotational grazing with fenced recovery sectors represents a data-driven and ecologically justified approach. It can help combine traditional reindeer herding with long-term conservation of lichen-dominated pasture ecosystems.

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