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Data-Driven Management of Mountain Meadows in Central Spanish Pyrenees: Enhancing Productivity and Quality via Random Forests Models

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Abstract

Mountain meadows are key components of extensive livestock systems, yet their response to management practices remains poorly quantified. This study assessed the effects of cutting date, fertilization, and stocking rate on forage yield, quality (RFV), and protein yield across three meadow types (extensive, semi-extensive, and intensive) in the Central Spanish Pyrenees. Using Random Forest modeling and simulated scenarios, we evaluated how each factor influenced productivity and nutritive value. Cutting date was the most influential variable. Advancing the harvest improved forage quality (RFV) but reduced yield. Conversely, delaying the harvest increased biomass at the expense of RFV. Protein yield provided a more balanced metric: it remained stable or increased in intensive and extensive meadows but declined sharply in semi-extensive systems when cutting was delayed. Fertilization had a moderate effect, with semi-extensive meadows showing significant yield reductions when fertilizer input was halved, while other systems remained largely unaffected. Stocking rate had the least impact overall, although reduced grazing led to declines in protein yield in semi-extensive and extensive meadows. These findings suggest that cutting date should be prioritized in management decisions, while fertilization and grazing intensity require context-specific adjustments. Random Forest modeling effectively identified trade-offs and guided evidence-based strategies for sustainable mountain meadow management.

Keywords: grassland; optimization; agricultural practices; forage quality

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1. Introduction

Mountain meadows are a key part of livestock farming systems in many European mountain regions, particularly in the Central Spanish Pyrenees [1]. These semi-natural grasslands provide the bulk of forage resources for ruminants, they are grazed in autumn and spring and mowed in late spring or early summer to obtain forage for winter [2]. Beyond their role in sustaining animal husbandry, they also contribute to biodiversity conservation, soil protection, and the maintenance of cultural landscapes [3]. Their persistence is therefore tightly linked to the viability of mountain farming communities and the broader sustainability of highland agroecosystems [4].

Despite their importance, mountain meadows face increasing challenges. Land abandonment, socio-economic transformations, and climate variability are reshaping traditional management practices, often leading to declines in both productivity and forage quality [5].

Farmers in these regions must balance the dual objective of maintaining sufficient yields while ensuring adequate nutritive value to support animal performance [6,7]. Yet, while the ecological and cultural significance of mountain meadows has been widely acknowledged in literature, research explicitly focused on strategies to improve their productivity and quality remains surprisingly scarce [8,9]. Most studies have emphasized biodiversity conservation or land-use change, leaving a critical gap in applied agronomic knowledge for sustaining livestock systems in these environments [10–13].

The productivity and quality of mountain meadows are influenced by a complex interplay of soil properties, climatic conditions, plant community composition, and management practices such as mowing frequency, fertilization, and grazing regimes [14,15]. Traditional agronomic approaches have provided valuable descriptive insights into these factors, but they often rely on linear models that cannot fully capture the nonlinear interactions and context-specific responses typical of mountain agroecosystems [16,17]. This limitation has hindered the development of clear, evidence-based recommendations for improving forage production in such heterogeneous landscapes [8].

In recent years, data-driven approaches and machine learning techniques have emerged as promising tools to address these challenges [18,19]. By integrating diverse datasets and identifying complex interactions, machine learning can provide robust predictions and highlight the relative importance of different drivers of agricultural performance [20]. Among these methods, Random Forest (RF) has gained particular attention due to its predictive accuracy, resistance to overfitting, and ability to quantify variable importance [21]. RF models are especially well-suited to ecological and agronomic systems where multiple interacting factors shape outcomes, making them an ideal choice for studying mountain meadows [22,23].

Although RF has been successfully applied in various agricultural contexts—such as crop yield prediction, soil property mapping, and precision management—its use in mountain forage systems remains limited [24,25]. This underutilization is striking given the urgent need for practical, data-driven insights to support the sustainability of mountain livestock farming. By applying RF models to long-term field data, researchers can move beyond descriptive analyses and generate actionable recommendations for improving both productivity and forage quality in these critical systems [26–28].

Among the diverse drivers of mountain meadow productivity, only three are directly shaped by farmers' management: cutting date, fertilization, and stocking rate [12,13,16]. As the sole controllable variables, their combined consideration provides the practical basis for optimizing forage yield and quality [9,17,29].

This study represents a novel contribution by combining Random Forest modeling with management scenario simulations, an approach not previously applied to mountain meadow systems in the Central Pyrenees, and builds on previous work in which Random Forest models were developed to predict yield and quality parameters of mountain meadows [30]. Here, we extend this approach to explicitly evaluate how management practices can be optimized to enhance both productivity and forage quality. Specifically, we aim to provide evidence-based recommendations for improving the management of mown meadows in the Central Spanish Pyrenees. In particular, we focus on the separate effects of cutting date, fertilization, and stocking rate on forage yield and quality, providing concrete evidence-based insights for local management practices.

2. Materials and Methods

2.1. Data Collection

The study was conducted in the central Spanish Pyrenees (42°30′–42°50′ N, 0°10′–0°40′ E), a mountainous region characterized by diverse topography and varying altitudes.

Fifteen meadows were selected across the Aragón, Gállego, Ara, Cinca, and Ésera valleys. Valleys were treated as blocks to ensure spatial independence and represent the range of management practices. Data were collected over five years (2019, 2020, and 2022–2024). Sampling was restricted to the 100 m^2 central area of each meadow, consistent with the vegetation inventories, to avoid edge effects and ensure representativeness. Within this area, the experimental design followed a randomized block approach with six sampling enclosures (40 × 60 cm; 0.24 m^2) randomly placed as replicates. These enclosures were cut once during the harvest window to obtain fresh biomass, ensuring comparability across meadows and years. In total, 554 samples were collected, each meadow-year combination treated as a replicate.

Management practices were recorded through structured farmer surveys, which included information on (i) livestock type, number, and grazing schedule (used to calculate stocking rate in livestock units, LU); (ii) fertilization type (organic, inorganic, or none), rate, and frequency, with manure and slurry samples analyzed for nutrient content; and (iii) mowing frequency outside experimental cuts.

Vegetation sampling was carried out between 20 May and 10 July, covering the period from flowering onset to the farmers' harvest. In each enclosure, aboveground biomass was clipped at 5 cm height using a battery-powered hedge trimmer. The fresh material was immediately weighed in the field, then frozen and subsequently oven-dried at 65 °C for 48 h to determine the proportion of dry matter (DM).

For forage quality, subsamples were oven-dried at 105 °C for 4 h. Nitrogen concentration (N) was determined by the Kjeldahl method, crude protein (CP) was calculated as [31]:

$$CP = N \times 6.25$$

Relative feed value (RFV) was derived from Acid Detergent Fiber (ADF) and Neutral Detergent Fiber (NDF) according to [32]:

$$RFV = \frac{\left((88.9 - (0.779 \times ADF) \times (\frac{120}{NDF})\right)}{1.29}$$

Protein yield was calculated as crude protein content (%) multiplied by DM yield.

Daily temperature (minimum, maximum, mean) and precipitation data were obtained from AEMET stations (9446, 9789A, 9784P, 9814X, 9838A, 9838B, 9843A) covering the period 2019–2024, from January 1 to harvest.

Flora inventories were conducted during peak biomass using the Braun–Blanquet method [33]. Cover-abundance of each species was visually estimated, and taxonomic identification was carried out to species level. Biodiversity was quantified using the Shannon index [34]:

$$H = -\sum_{i=1}^{S} p_i \times lnp_i$$

where pi is the proportional cover of species i, and S is the total number of species.

Meadows were classified as intensive, semi-extensive, or extensive based on fertilization rate (kg N ha^{-1} $year^{-1}$), grazing intensity (LU ha^{-1} $year^{-1}$ or grazing days), and mowing frequency [2].

Table 1 provides the intrinsic attributes of the studied mountain meadows, including site location and soil characteristics, together with the management factors considered in the experiment (fertilization regime, stocking rate, and cutting date).

Table 1. Meadow characteristics [8].

	Intensive Meadow	Semi-Extensive Meadow	Extensive Meadow
Altitude (m)	602–890	902–1290	1100–1612
GPS Range (approx.)	42.60–42.70 N; 0.10–0.25 E	42.55–42.75 N; 0.15–0.35 E	42.50–42.80 N; 0.20–0.40 E
Slope (%)	9.63 ± 4.13	18.6 ± 4.99	16.1 ± 5.35
Soil type (WRB)	Haplic Regosol	Haplic Phaeozem	Haplic Phaeozem
Clay (%)	30.47 ± 4.87	23.62 ± 4.26	16.29 ± 5.04
Sand (%)	21.01 ± 7.92	40.50 ± 9.49	51.61 ± 9.88
pH	7.71 ± 0.3	6.94 ± 0.29	6.82 ± 0.41
Electric conductivity (dS/m)	0.23 ± 0.05	0.28 ± 0.06	0.21 ± 0.06
Organic matter (%)	3.78 ± 2.12	9.93 ± 3.58	9.25 ± 3.18
Fertilization type	Compound NPK (5-15-15) + urea (46% N)	Composted cattle manure/cattle slurry	Composted cattle manure/None
Fertilization frequency	Yearly	Yearly	Rarely
Nitrogen kg ha^{-1}	66.22 ± 37.77	214.71 ± 136.05	6.17 ± 10.69
Phosphorus kg ha^{-1}	47.04 ± 15.06	305.09 ± 280.11	10.06 ± 11.55
Potassium kg ha^{-1}	69.32 ± 35.29	140.14 ± 145.10	11.57 ± 20.05
Livestock load LU ha^{-1} year^{-1}	0.59 ± 0.10	0.35 ± 0.33	0.20 ± 0.10
Shannon Index	1.82 ± 0.15	2.81 ± 0.31	3.23 ± 0.14
Legume cover (%)	26.25 ± 21.99	24.3 ± 5.95	23.3 ± 5.33
Dominant species	Dactylis glomerata	Arrhenatherum elatius	Festuca rubra
Phenological stage of dominant species at cutting	Flowering	Flowering	Flowering
Cutting date	May-15 ± 16 days	Jun-5 ± 21 days	Jun-13 ± 20 days

2.2. Simulation and Statistical Analysis

All analyses were conducted in Python 3.11 (Jupyter Lab) [35] using scikit-learn v1.3.0 [36] and Optuna v3.2.0 [37]. Random Forest models were developed to predict yield, crude protein content, and RFV, using climate, management, meadow type, and biodiversity as predictors. Model performance was evaluated using k-fold cross-validation (k = 10) on a randomly partitioned dataset (80% for training and 20% for testing). The model's predictive capability and robustness were assessed using standard regression metrics, specifically the coefficient of determination (R^2 and RMSE [38,39]. Hyperparameters were optimized with Optuna, and the final configurations are summarized in Table 2.

Table 2. Random Forest model characteristics.

Model	Yield	RFV	Protein Yield
N estimators	**158**	**198**	**206**
Max depth	**14**	**27**	**16**
Min samples split	**5**	**5**	**5**
Min samples leaf	**1**	**1**	**1**
Random state	**42**	**42**	**42**
R^2	**0.79**	**0.72**	**0.73**
RMSE	**963.62**	**13.86**	**115.34**

Simulation scenarios were designed to assess the sensitivity of forage yield, RFV, and protein yield to farmer-dependent management factors, while controlling for climatic variability. Scenario shifts were defined relative to the observed baseline for each meadow-year: cutting date (actual harvest date), fertilization rate (annual inputs), and stocking rate (LU ha^{-1} year^{-1}). Three factors were modified: (i) cutting date shifts ranging from 5 to 30 days earlier or later, (ii) fertilization adjustments from −100% to +100%, and (iii) stocking rate changes from −100% to +100%. Each scenario was applied to the three Random Forest models, and responses were evaluated accordingly.

Given the non-parametric distribution of the data, we assessed differences among meadow types using the Kruskal–Wallis H test, followed by Dunn's post hoc comparisons when applicable [40]. Within each meadow type, contrasts between baseline management and simulated scenarios (cutting date, fertilization rate, and stocking rate) were evaluated using the Mann–Whitney U test, which is appropriate for non-parametric pairwise comparisons [41]. When multiple scenarios were tested (e.g., several cutting date shifts), comparisons were performed sequentially, and p-values were adjusted using the Bonferroni correction to control for multiple testing [42]. Statistical significance was established at $p < 0.05$ after correction.

3. Results

The environmental and management characteristics of the three meadow types included in the study are summarized in Table 1. Intensive meadows were located at lower altitudes and received synthetic fertilization, while semi-extensive and extensive meadows were situated at higher elevations and managed with organic inputs or no fertilization. Extensive meadows showed the highest biodiversity, as indicated by the Shannon Index, and were also characterized by the latest cutting date, reflecting their lower management intensity and delayed phenological development. Differences in soil texture, nutrient inputs, and species composition reflect contrasting management regimes and ecological conditions.

Figure 1 shows the monthly mean temperature and precipitation patterns recorded in the three meadow types over the 2019–2024 period. Temperature trends were similar across management regimes, with peaks in July and August, while precipitation showed greater variability, particularly in spring and autumn. Intensive meadows exhibited slightly higher temperatures and lower rainfall than semi-extensive and extensive meadows, consistent with their lower elevation.

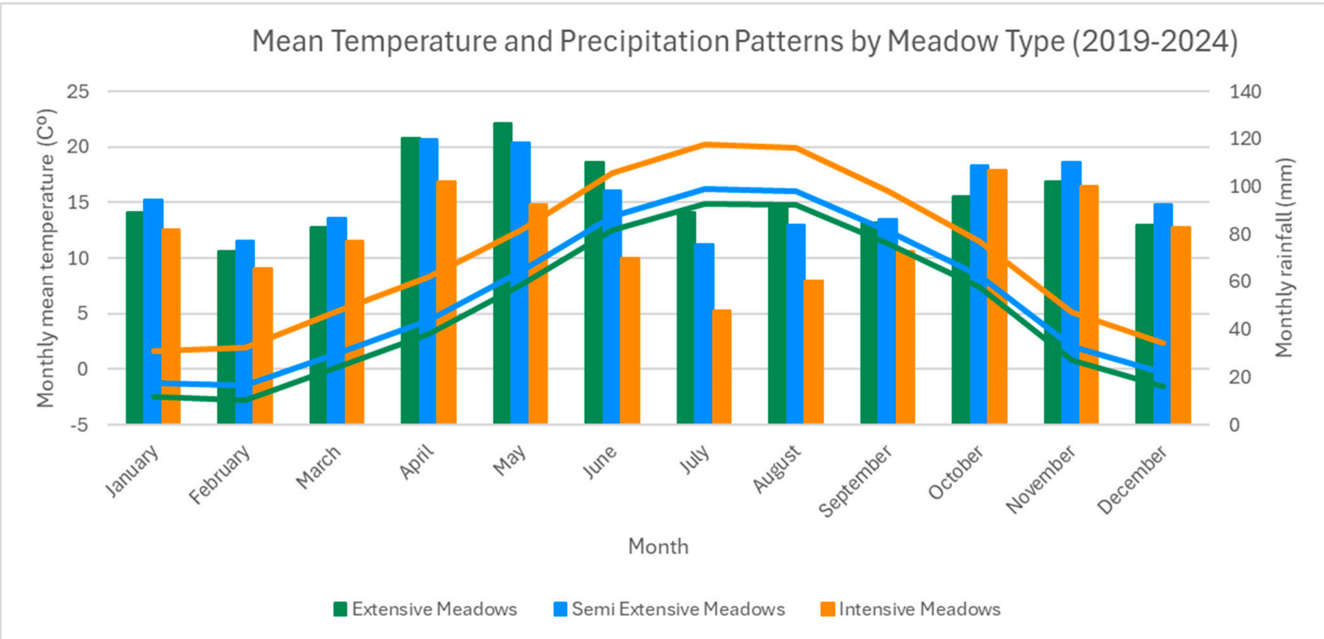
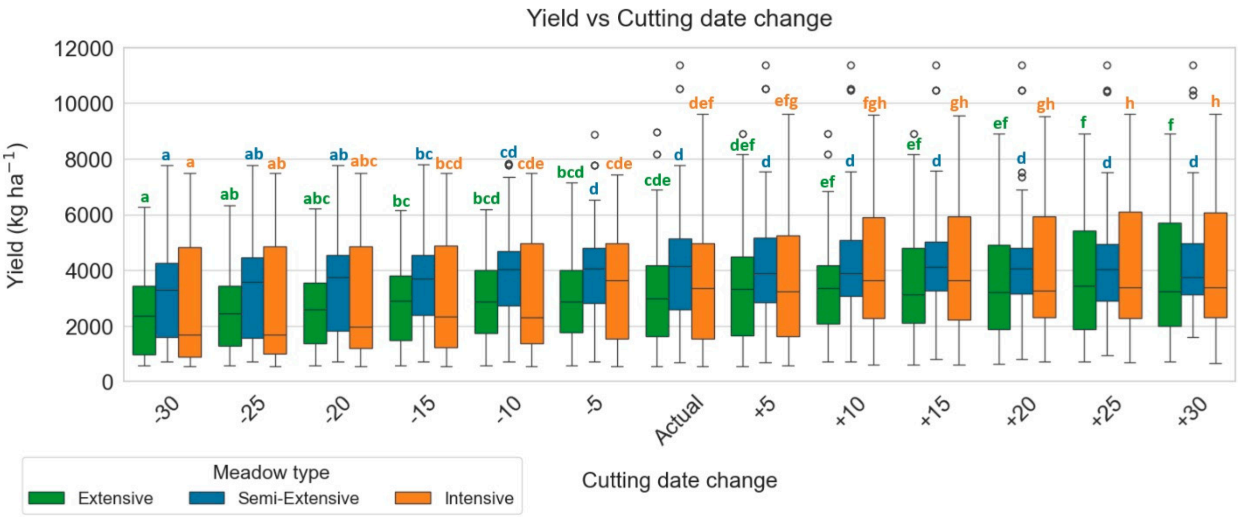


Figure 1. Monthly mean temperature (°C, lines) and precipitation (mm, bars) averaged over the 2019–2024 period for extensive, semi-extensive, and intensive meadows in the Central Pyrenees.

3.1. Cutting Date Delay

As shown in Figure 2a, harvest date adjustments had a clear effect on yield. Earlier cuts consistently reduced yield across all systems. Conversely, delayed cuts increased yield, an effect that was most pronounced in intensive meadows but produced only limited gains in semi-extensive systems. Figure 2b shows significant differences in yield among meadow types, indicating that management intensity influences responses to cutting date.



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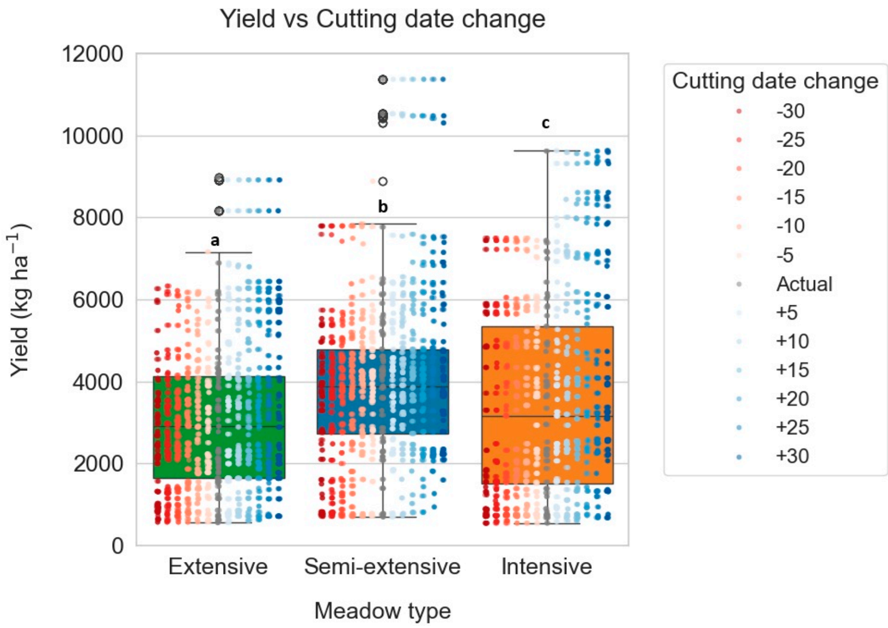

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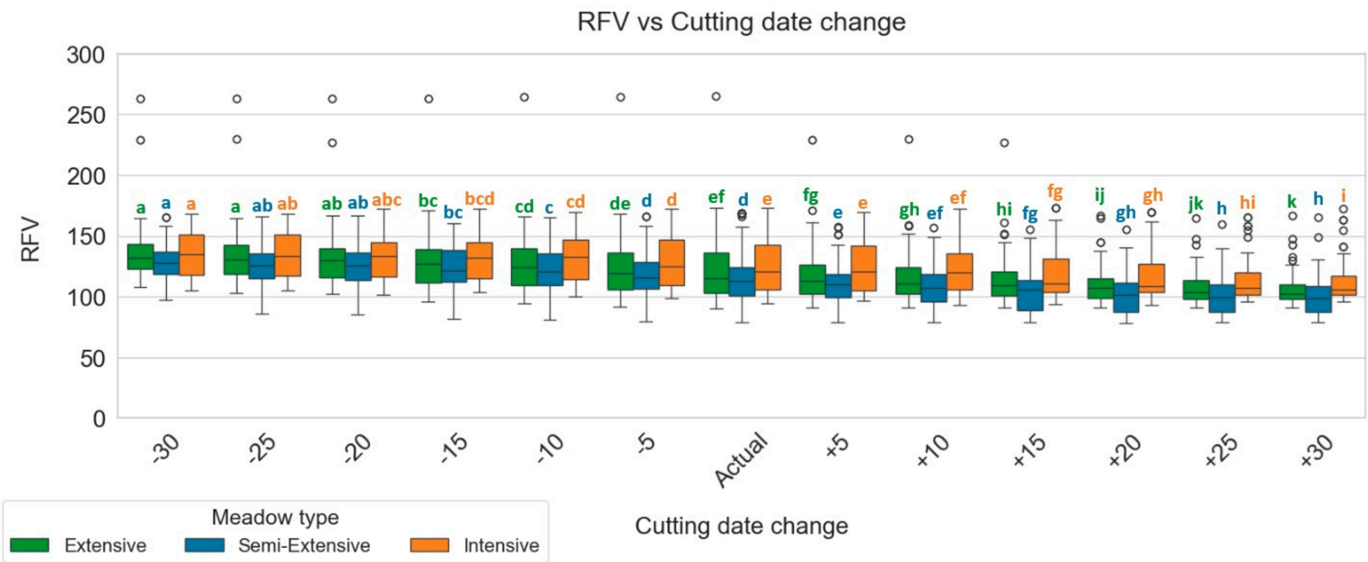
Figure 2. (**a**) Boxplots showing mean yield under specific changes in cutting date (advancing or delaying the actual date by up to 30 days). Colors represent meadow types. Significant differences in yield among cutting dates within the same meadow type were evaluated using the Mann–Whitney U test ($p < 0.05$). (**b**) Boxplots illustrating the distribution of simulated yields by meadow type under different cutting date adjustments. Each point represents a simulated yield for a specific change relative to the actual cutting date. The color gradient indicates the magnitude and direction of the cutting date change. The central line within each box represents the median yield, the box bounds indicate the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual points beyond the whiskers. Lowercase letters (a, b, c, etc.) above the boxplots denote statistically significant differences in median yield between meadow types, as determined by the Kruskal–Wallis H test ($p < 0.05$), followed by Dunn's post hoc test for pairwise comparisons.

Figure 3a shows that forage quality (RFV) changed markedly with cutting date across all management systems. In intensive meadows, advancing the cut generally improved forage quality, while delaying it led to a decline. In semi-extensive meadows, earlier cuts also enhanced RFV, whereas even short delays produced reductions. In extensive meadows, advancing the cut did not consistently improve quality, and delays were associated with clear declines. Figure 3b shows significant differences in forage quality among meadow types, confirming that management intensity influences responses to cutting date.



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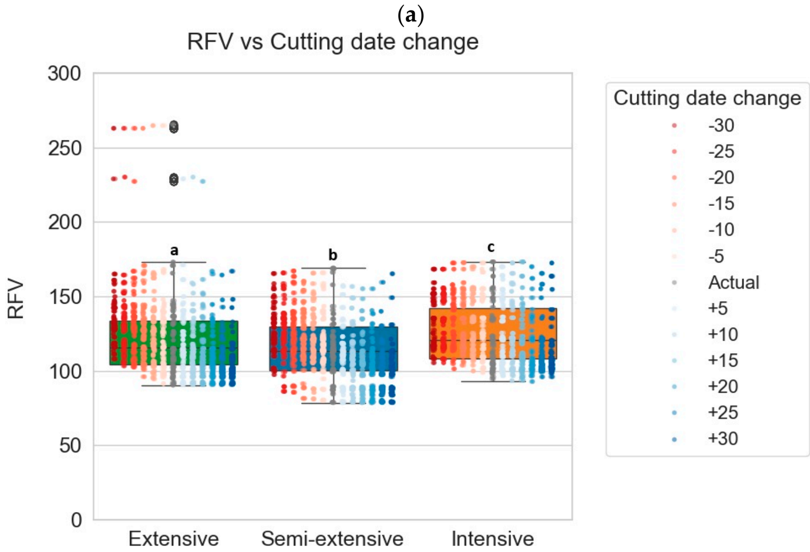

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Figure 3. (**a**) Boxplots showing mean RFV under specific changes in cutting date (advancing or delaying the actual date by up to 30 days). Colors represent meadow types. Significant differences in RFV among cutting dates within the same meadow type were evaluated using the Mann–Whitney U test ($p < 0.05$). (**b**) Boxplots illustrating the distribution of simulated RFV by meadow type under different cutting date adjustments. Each point represents a simulated RFV for a specific change relative to the actual cutting date. The color gradient indicates the magnitude and direction of the cutting date change. The central line within each box represents the median RFV, the box bounds indicate the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual points beyond the whiskers. Lowercase letters (a, b, c, etc.) above the boxplots indicate significant differences in median RFV between meadow types (Kruskal–Wallis H test, $p < 0.05$), followed by Dunn's post hoc test for pairwise comparisons.

Figure 4a indicates that protein yield showed a variable response to cutting date adjustments, with significant differences depending on the system. In intensive meadows, delaying the cut did not result in significant improvements, while in semi-extensive meadows only specific early or late adjustments produced noticeable changes. In extensive meadows, protein yield remained relatively stable, with no significant differences detected across the various cutting date adjustments. Figure 4b shows no significant differences between intensive and extensive meadows. Semi-extensive meadows differed significantly from both, highlighting a distinct response.

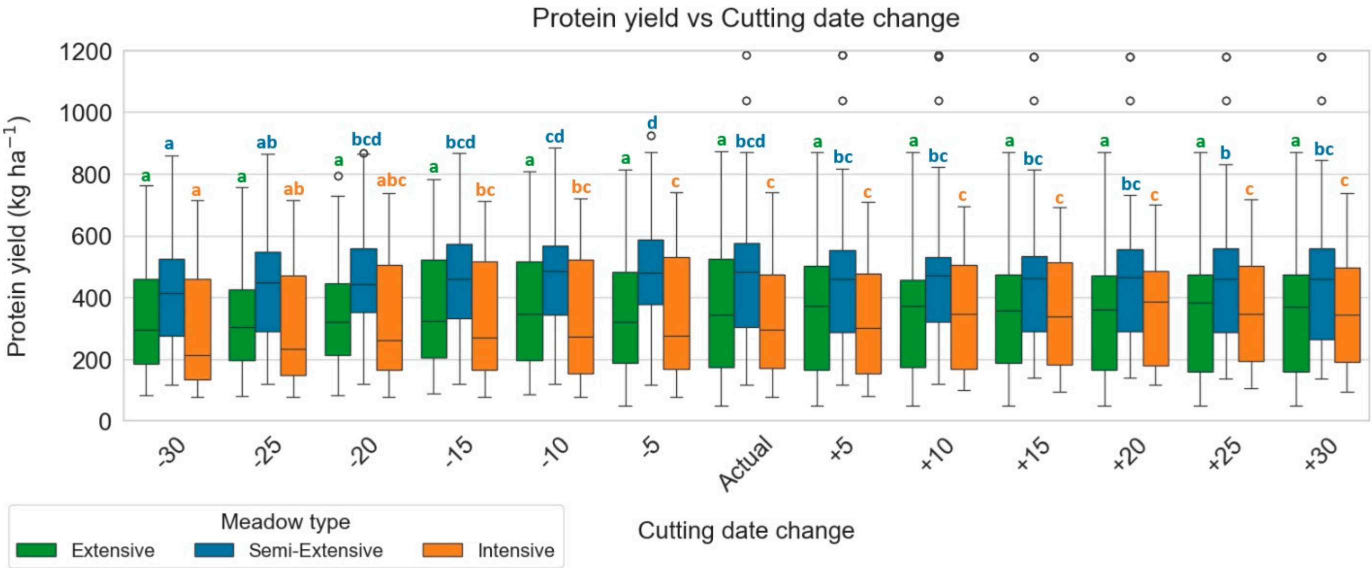

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Figure 4. (**a**) Boxplots showing mean protein yield under specific changes in cutting date (advancing or delaying the actual date by up to 30 days). Colors represent meadow types. Significant differences in protein yield among cutting dates within the same meadow type were evaluated using the Mann–Whitney U test ($p < 0.05$). (**b**) Boxplots illustrating the distribution of simulated protein yields by meadow type under different cutting date adjustments. Each point represents a simulated protein yield for a specific change relative to the actual cutting date. The color gradient indicates the magnitude and direction of the cutting date change. The central line within each box represents the median protein yield, the box bounds indicate the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual points beyond the whiskers. Lowercase letters (a, b, c, etc.) above the boxplots indicate significant differences in median protein yield between meadow types (Kruskal–Wallis H test, $p < 0.05$), followed by Dunn's post hoc test for pairwise comparisons.

Table 3 provides a synthetic summary of the results illustrated in Figures 2a,b, 3a,b and 4a,b, presenting changes in yield (kg ha^{-1}), relative feed value (RFV), and protein yield (kg ha^{-1}) according to cutting date and meadow type.

Table 3. Changes in yield (kg ha^{-1}), relative feed value (RFV), and protein yield (kg ha^{-1}) according to cutting date and meadow type are shown. Values in white indicate no significant differences compared to the baseline (actual management), values in red indicate significantly lower results, and values in green indicate significantly higher results ($p < 0.05$).

	Extensive			Semi Extensive			Intensive		
Cutting Date	**Yield**	**RFV**	**Protein Yield**	**Yield**	**RFV**	**Protein Yield**	**Yield**	**RFV**	**Protein Yield**
−30	−655.74	13.95	−21.31	−797.26	13.08	−61.47	−753.05	9.86	−63.66
−25	−489.07	11.94	−13.3	−675.38	11.44	−36.11	−642.41	9.43	−45.46
−20	−372.95	10.63	−3.7	−578.49	11.17	−10.88	−482.57	7.47	−21.04
−15	−271.75	6.99	5.22	−436.85	8.63	1.81	−388.91	6.52	−11.61
−10	−185.54	4.71	5.28	−163.49	6.66	13.95	−333.32	5.53	−6.66
−5	−186.13	2.12	−2.11	−54.98	3.05	16.36	−142.25	3.48	3.02
Actual	0	0	0	0	0	0	0	0	0
5	216.52	−4.36	13.21	117.72	−5.21	−10.77	178.58	−0.67	−1.23
10	234.12	−6.62	6.74	213.98	−7.19	−9.52	411.13	−2.97	2.86
15	319.13	−8.04	6.09	251.54	−9.97	−8.42	524.83	−6.2	5.46
20	332.49	−12.01	−4.06	261.89	−12.64	−13.92	566.76	−7.82	8.17
25	465.38	−14.73	1.5	297	−15.02	−12.3	736.04	−10.51	11.2
30	599.8	−15.92	5.32	340.5	−15.52	−12.4	747.55	−12.38	10.08

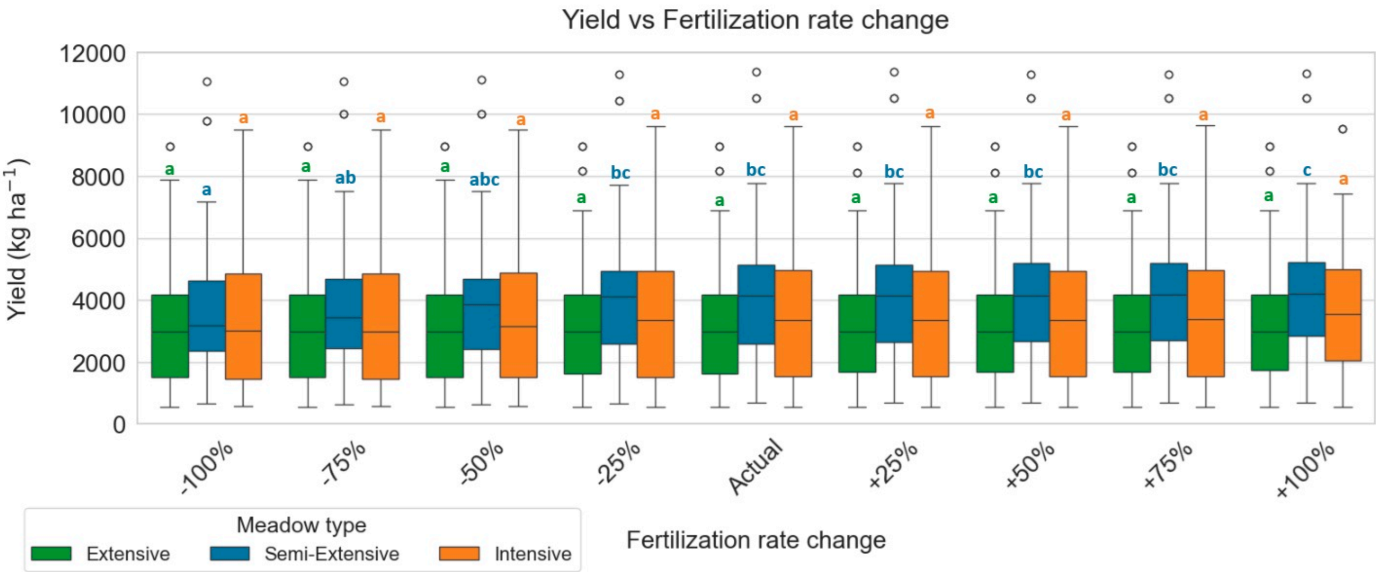
Cutting date emerged as the most influential factor, establishing a clear trade-off between biomass yield and forage quality (RFV) across all three management systems. Advancing the harvest (−30 to −10 days) resulted in significant and consistent losses in both yield and protein yield (exceeding 650 kg ha^{-1} loss at −30 days), while simultaneously optimizing forage quality, particularly in extensive meadows (RFV increased by up to +13.95 units at −30 days).

Conversely, delaying the harvest consistently increased yield, an effect most notable under intensive management; for instance, postponing the cut by +15 days resulted in a yield increase of 524.83 kg ha^{-1}, coupled with a simultaneous reduction of 6.2 RFV units. Protein yield, however, signaled the optimal management window: maximum accumulation was reached at harvest dates slightly post-reference, peaking at +5 days for extensive meadows (+13.21 kg ha^{-1}) and +10 days for semi-extensive meadows (+10.27 kg ha^{-1}). These protein peaks were associated with only slight-to-moderate RFV reductions (−1.42 and −5.07, respectively), thereby evidencing the management equilibrium point. Nevertheless, protein yield declined significantly in all systems when delayed beyond +15 days (Table 3).

3.2. Fertilization Change

Figure 5a shows that fertilizer adjustments did not significantly affect productivity in intensive or extensive meadows. Yields remained stable across treatments. In contrast, significant effects were observed in semi-extensive systems, where eliminating fertilization reduced productivity and higher fertilizer doses enhanced it. Figure 5b shows no significant differences between intensive and extensive meadows. Both differed significantly from semi-extensive meadows.

Figure 6a shows that forage quality (RFV) did not differ significantly within any meadow type across fertilizer doses. Values remained stable. In intensive meadows, reductions in fertilizer did not lead to consistent declines, while in semi-extensive meadows certain increases or reductions in dose were associated with slight variations. In extensive meadows, RFV values were largely unaffected by changes in fertilization. Figure 6b shows significant differences between semi-extensive and intensive meadows. No differences were detected involving extensive meadows.



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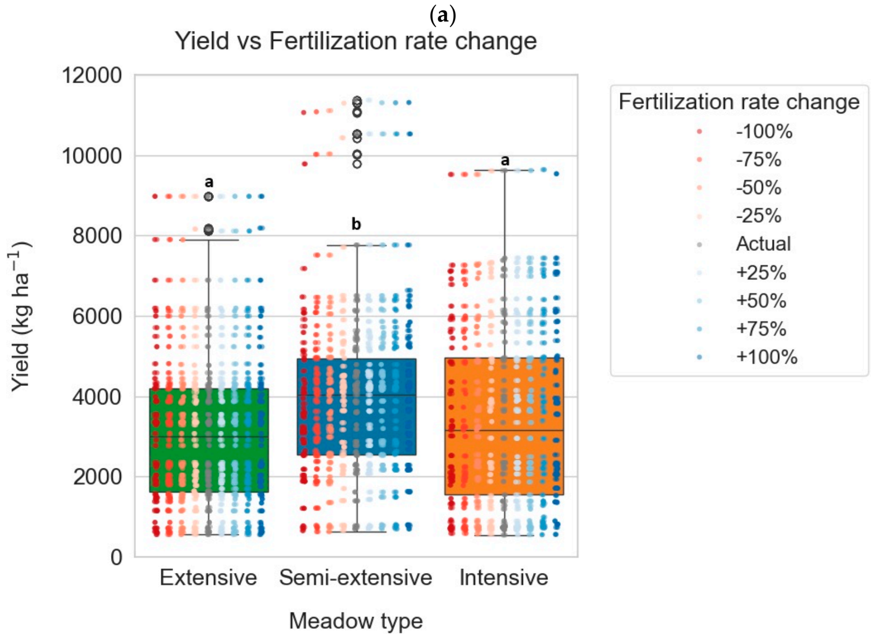

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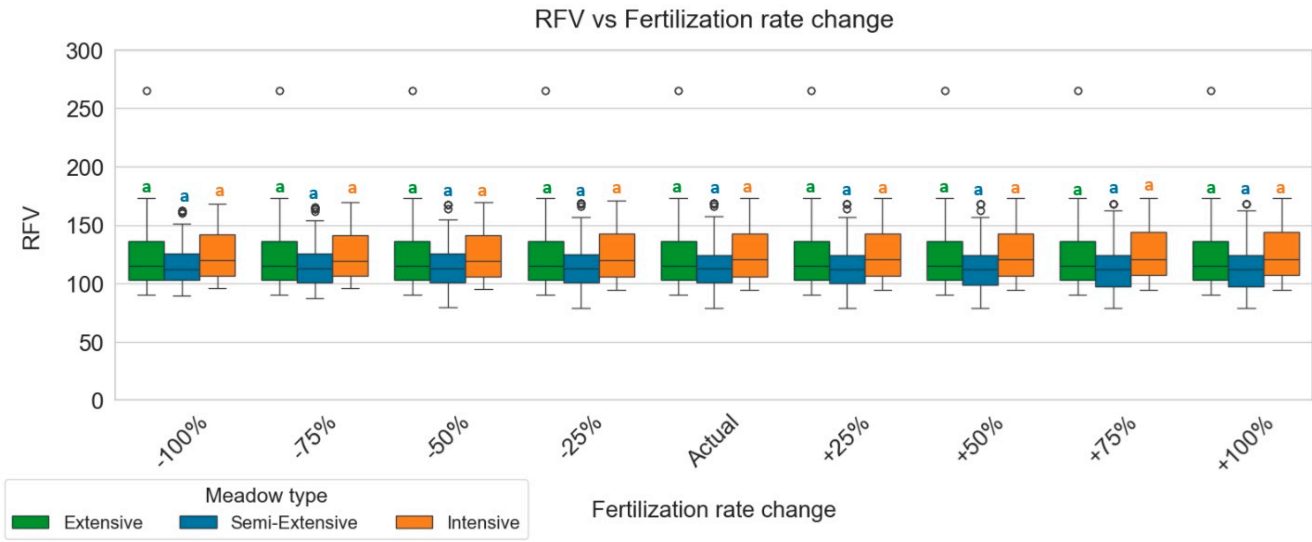
Figure 5. (**a**) Boxplots showing mean yield under specific changes in fertilization rate. Colors represent meadow types. Significant differences in yield among fertilization rates within the same meadow type were evaluated using the Mann–Whitney U test ($p < 0.05$). (**b**) Boxplots illustrating the distribution of simulated yields by meadow type under different fertilization rate adjustments. Each point represents a simulated yield for a specific change relative to the actual fertilization rate. The color gradient indicates the magnitude and direction of the fertilization rate. The central line within each box represents the median yield, the box bounds indicate the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual points beyond the whiskers. Lowercase letters (a, b, c) above the boxplots indicate significant differences in median yield between meadow types (Kruskal–Wallis H test, $p < 0.05$), followed by Dunn's post hoc test for pairwise comparisons.



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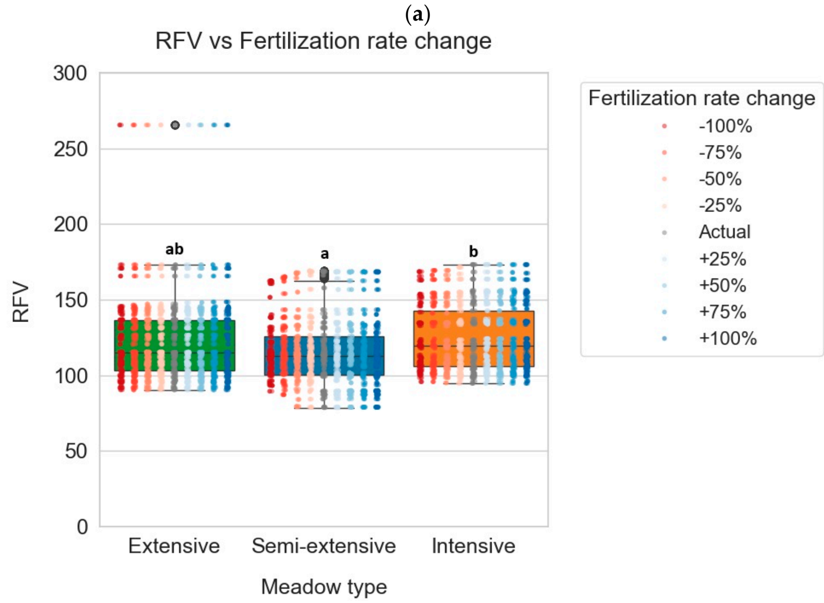

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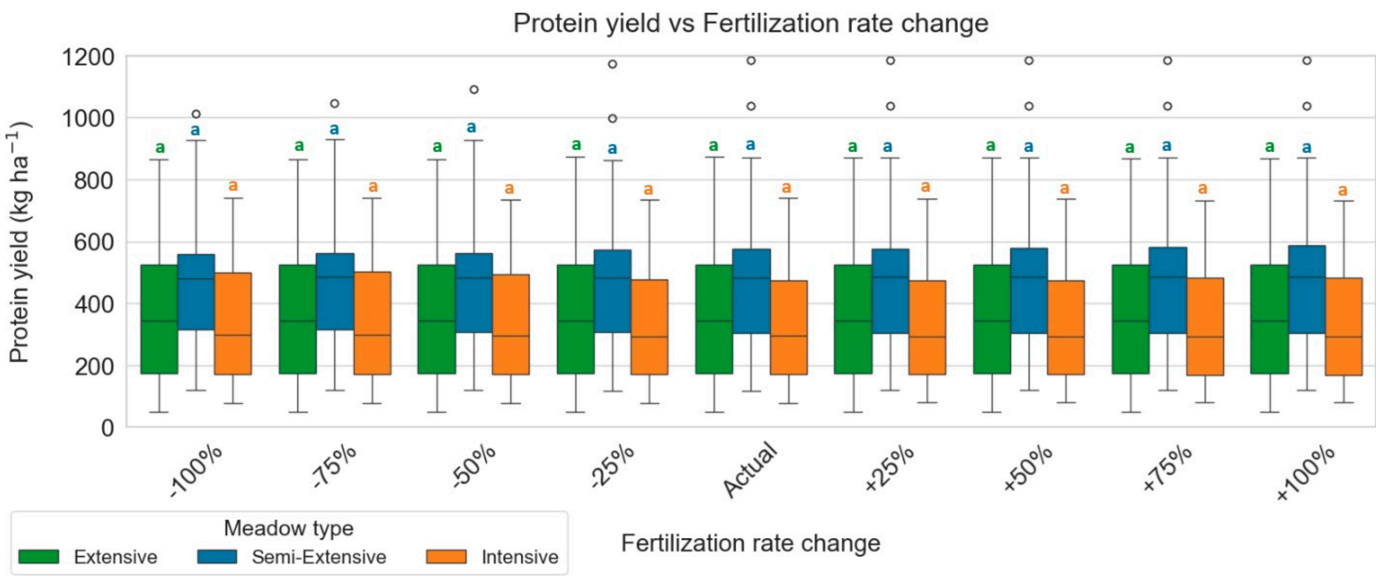
Figure 6. (**a**) Boxplots showing mean RFV under specific changes in fertilization rate. Colors represent meadow types. Significant differences in RFV among fertilization rates within the same meadow type were evaluated using the Mann–Whitney U test ($p < 0.05$). (**b**) Boxplots illustrating the distribution of simulated RFV by meadow type under different fertilization rate adjustments. Each point represents a simulated RFV for a specific change relative to the actual fertilization rate. The color gradient indicates the magnitude and direction of the fertilization rate change. The central line within each box represents the median RFV, the box bounds indicate the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual points beyond the whiskers. Lowercase letters (a, b) above the boxplots indicate significant differences in median RFV between meadow types (Kruskal–Wallis H test, $p < 0.05$), followed by Dunn's post hoc test for pairwise comparisons.

Figure 7a shows that protein yield was unaffected by changes in fertilization rate across all meadow types. In intensive meadows, adjustments in fertilization did not lead to significant changes, while in semi-extensive meadows only slight variations were observed depending on the treatment. In extensive meadows, protein yield was also largely unaffected by fertilization adjustments. Figure 7b shows no significant differences between intensive and extensive meadows. Both differed significantly from semi-extensive meadows.



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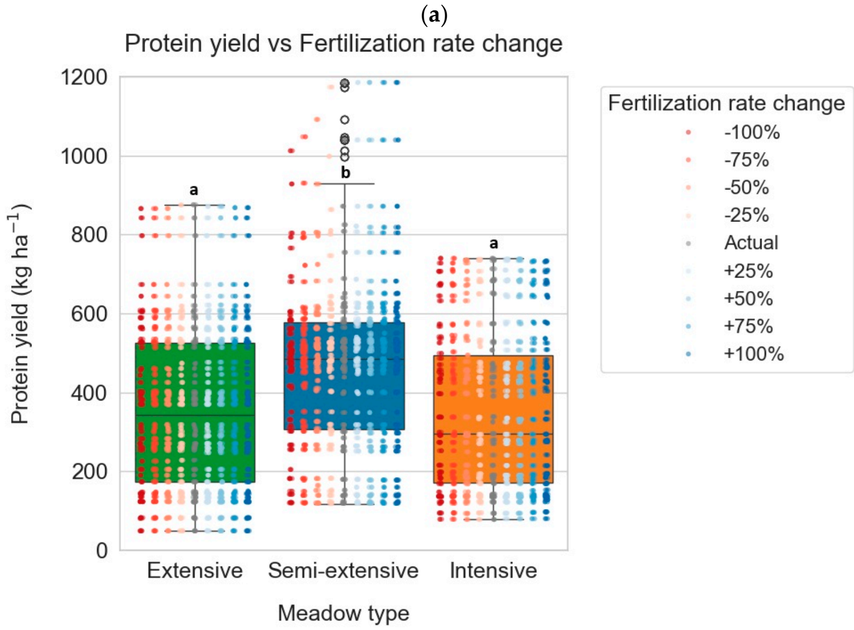

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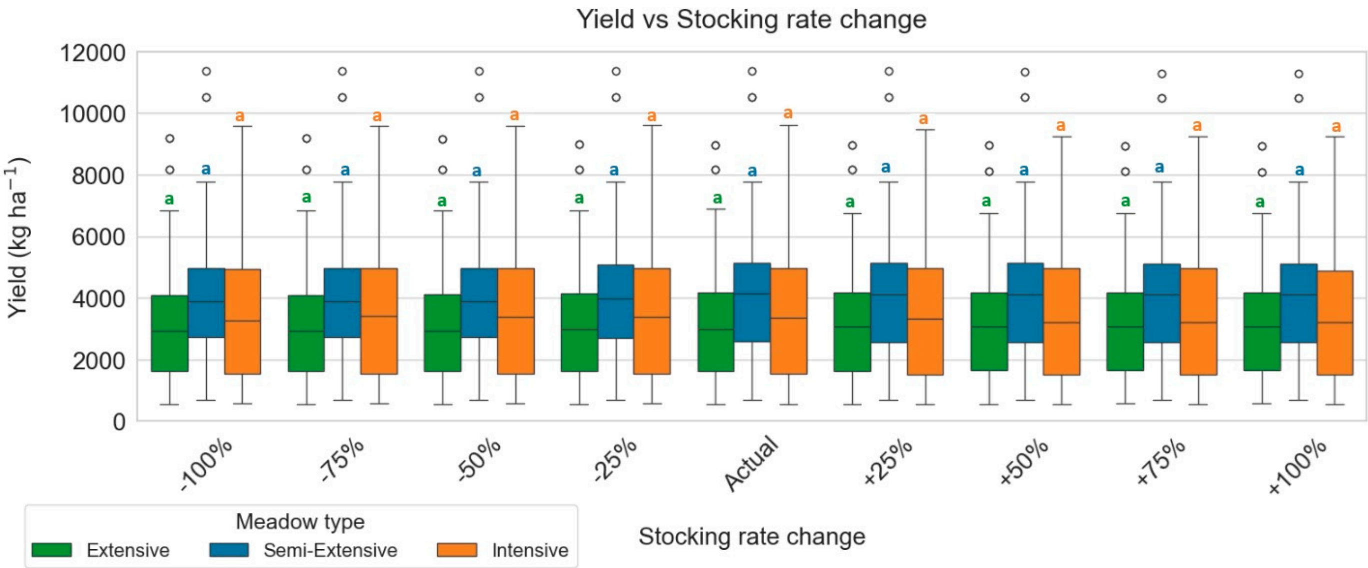
Figure 7. (**a**) Boxplots showing mean protein yield under specific changes in fertilization rate. Colors represent meadow types. Significant differences in protein yield among fertilization rates within the same meadow type were evaluated using the Mann–Whitney U test (p < 0.05). (**b**) Boxplots illustrating the distribution of simulated protein yields by meadow type under different fertilization rate adjustments. Each point represents a simulated protein yield for a specific change relative to the actual fertilization rate. The color gradient indicates the magnitude and direction of the fertilization rate change. The central line within each box represents the median protein yield, the box bounds indicate the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual points beyond the whiskers. Lowercase letters (a, b) above the boxplots indicate significant differences in median yield between meadow types (Kruskal–Wallis H test, p < 0.05), followed by Dunn's post hoc test for pairwise comparisons.

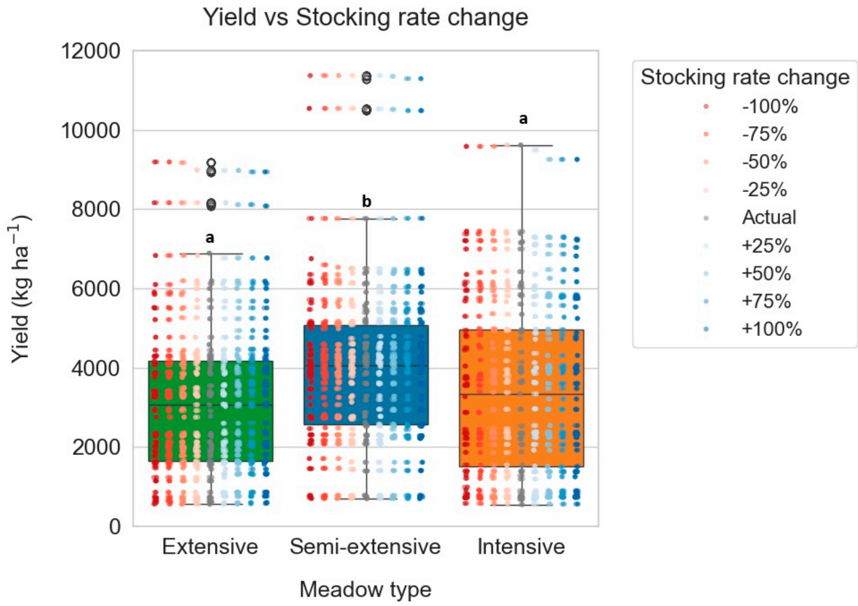
Table 4 summarizes the effects of fertilization rate on yield, relative feed value (RFV), and protein yield across the three meadow types. In extensive meadows, changes in fertilization rate did not produce significant differences in any of the evaluated parameters, with values remaining relatively stable across treatments. In contrast, semi-extensive meadows showed a clear response: eliminating fertilization significantly reduced yield and protein yield, while higher fertilizer doses led to significant increases. Intensive meadows also exhibited sensitivity to fertilization, with reductions under fertilizer withdrawal and progressive improvements as the dose increased. Overall, the results indicate that semi-extensive and intensive systems are more responsive to fertilization adjustments, whereas extensive meadows remain largely unaffected.

3.3. Stocking Rate Change

Figure 8a shows that intensive meadows had relatively stable yields across stocking rates. In semi-extensive meadows, changes in stocking rate produced more evident shifts, while in extensive meadows yields also remained comparatively stable. Figure 8b shows no significant differences between intensive and extensive meadows. Both differed significantly from semi-extensive meadows.



(**a**)



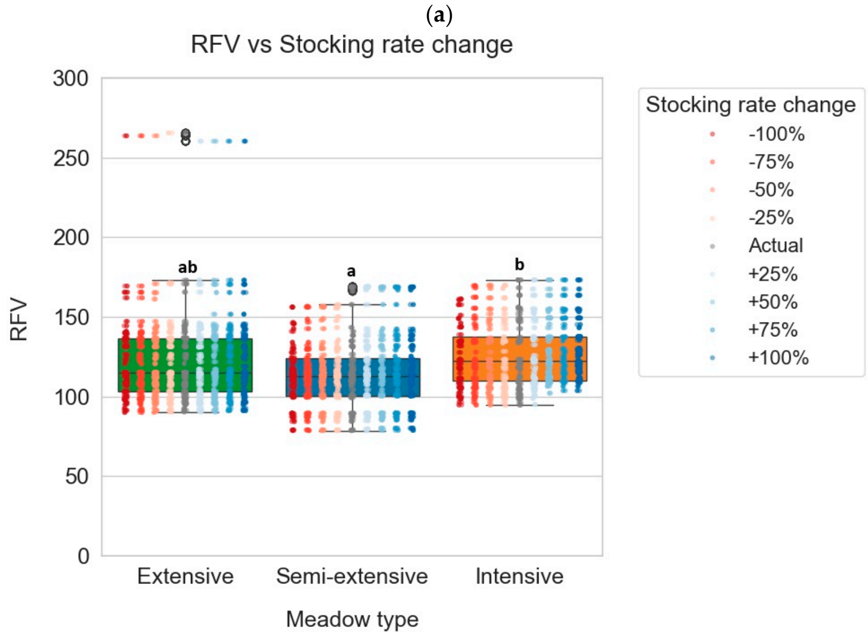
(**b**)

Figure 8. (**a**) Boxplots showing mean yield under specific changes in stocking rate. Colors represent meadow types. Significant differences in yield among stocking rates within the same meadow type

were evaluated using the Mann–Whitney U test ($p < 0.05$). (**b**) Boxplots illustrating the distribution of simulated yield by meadow type under different stocking rate adjustments. Each point represents a simulated yield for a specific change relative to the actual stocking rate. The color gradient indicates the magnitude and direction of stocking rate change. The central line within each box represents the median yield, the box bounds indicate the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual points beyond the whiskers. Lowercase letters (a, b) above the boxplots indicate significant differences in median yield between meadow types (Kruskal–Wallis H test, $p < 0.05$), followed by Dunn's post hoc test for pairwise comparisons.

Figure 9a shows that in intensive meadows RFV improved slightly as stocking rate increased. In extensive meadows, RFV values remained relatively stable across treatments, with no clear response to changes in stocking rate. According to the Kruskal–Wallis test, significant differences were detected between semi-extensive and intensive meadows, whereas no significant differences were found between these two systems and the extensive meadows, as shown in Figure 9b.

(**a**)



(**b**)

Figure 9. (**a**) Boxplots showing mean RFV under specific changes in stocking rate. Colors represent meadow types. Significant differences in RFV among stocking rates within the same meadow type

were evaluated using the Mann–Whitney U test ($p < 0.05$). (**b**) Boxplots illustrating the distribution of simulated RFV by meadow type under different stocking rate adjustments. Each point represents a simulated RFV for a specific change relative to the actual stocking rate. The color gradient indicates the magnitude and direction of the stocking rate change. The central line within each box represents the median RFV, the box bounds indicate the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual points beyond the whiskers. Lowercase letters (a, b) above the boxplots indicate significant differences in median RFV between meadow types (Kruskal–Wallis H test, $p < 0.05$), followed by Dunn's post hoc test for pairwise comparisons.

Table 4. Changes in yield (kg ha^{-1}), relative feed value (RFV), and protein yield (kg ha^{-1}) according to fertilization rate and meadow type are shown. Values in white indicate no significant differences compared to the baseline (actual management), and values in red indicate significantly lower results.

	Extensive			Semi Extensive			Intensive		
Fertilization Rate	**Yield**	**RFV**	**Protein Yield**	**Yield**	**RFV**	**Protein Yield**	**Yield**	**RFV**	**Protein Yield**
−100%	−41.84	−0.02	−0.74	−387.96	1.32	−12.7	−197.03	−0.15	0.64
−75%	−41.78	0.01	−0.54	−273.98	1.25	−10.13	−199.02	−0.09	1.09
−50%	−42.58	0.05	−0.47	−215.5	1.19	−8.24	−96.27	−0.35	1.16
−25%	1.36	0.08	−0.06	−28.57	1.27	−1.54	−18.49	−0.18	0.08
Actual	0	0	0	0	0	0	0	0	0
+25%	9.76	0.02	0.32	6.09	−0.8	2	−4.61	0.33	−0.66
+50%	9.74	0.02	0.36	24.76	−1.3	2.07	−3.46	0.35	−0.85
+75%	9.32	0.06	0.28	27.66	−1.64	3.11	7.81	0.4	−0.77
+100%	20.93	0.06	0.28	61.28	−1.63	3.34	113.34	0.43	0.62

Figure 10a shows that in extensive meadows, reducing stocking rate decreased protein yield, while increases did not exceed baseline levels. In intensive grasslands, no significant changes were detected when either increasing or decreasing the current stocking rate. In semi-extensive meadows, some variation was observed under different grazing pressures, but these differences were not statistically significant relative to the baseline. Overall, reductions in grazing pressure consistently decreased productivity, whereas increases did not enhance protein yield beyond current levels. Figure 10b shows significant differences between semi-extensive and intensive meadows, but none involving extensive meadows.

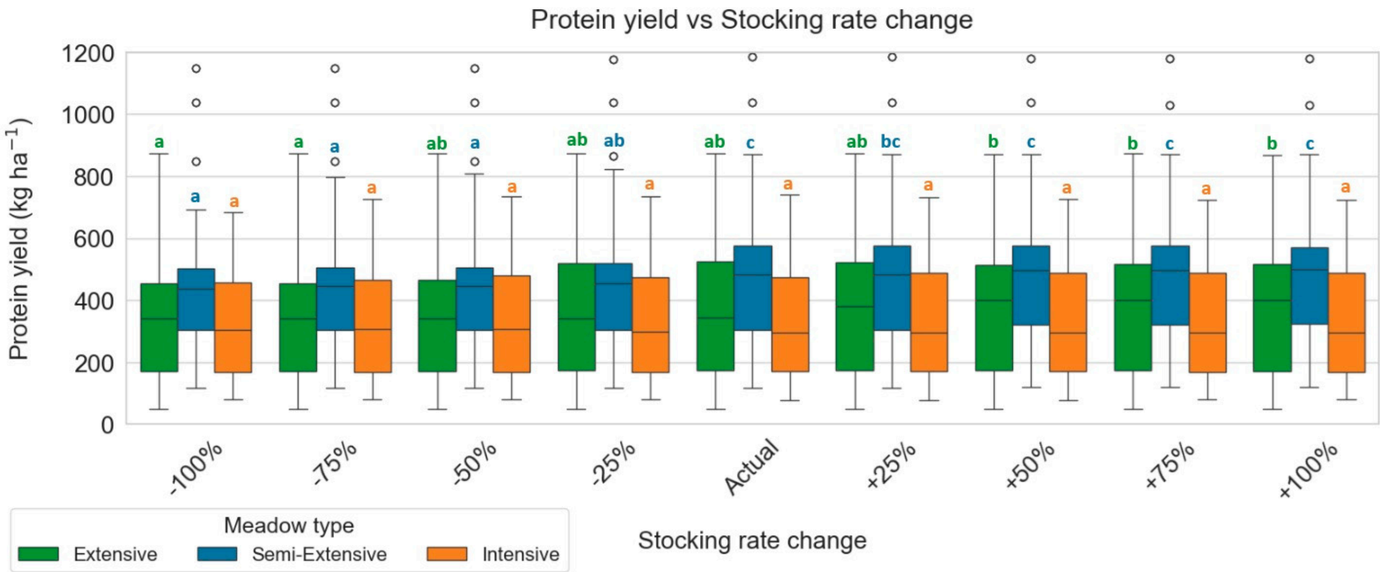
Table 5 shows the effects of stocking rate on forage quality (RFV) and protein yield across the three meadow types. In extensive and semi-extensive meadows, increasing the stocking rate was associated with progressive declines in RFV, while protein yield showed only modest improvements. By contrast, intensive meadows exhibited the opposite trend, with RFV increasing steadily as stocking rate rose, accompanied by clear gains in protein yield. These results indicate that stocking rate exerts contrasting effects depending on management intensity: while extensive and semi-extensive systems experience a trade-off between quality and protein yield, in intensive systems increasing stocking rate improved RFV but reduced protein yield.

Table 5. Changes in yield (kg ha^{-1}), relative feed value (RFV), and protein yield (kg ha^{-1}) according to stocking rate and meadow type are shown. Values in white indicate no significant differences compared to the baseline (actual management), values in red indicate significantly lower results.

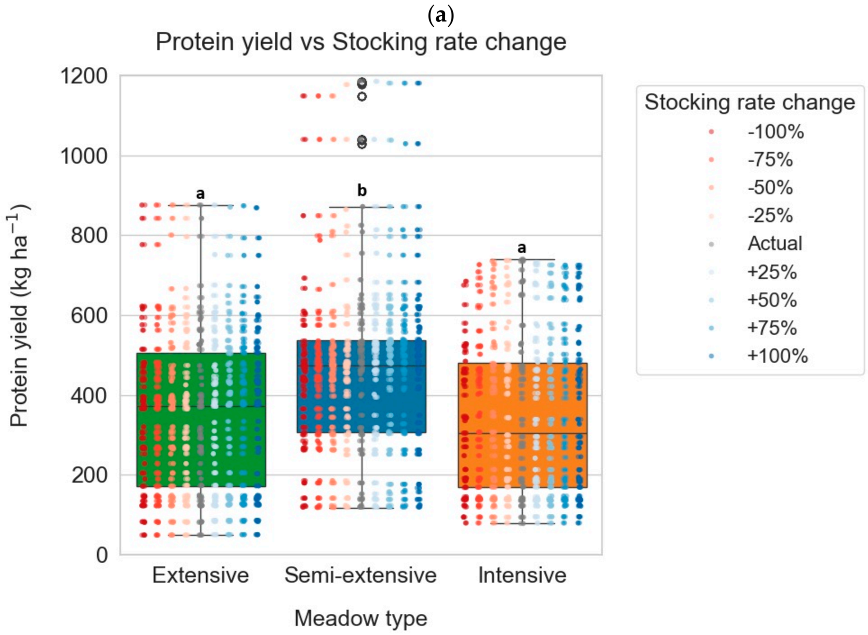
	Extensive			Semi Extensive			Intensive		
Fertilization Rate	**Yield**	**RFV**	**Protein Yield**	**Yield**	**RFV**	**Protein Yield**	**Yield**	**RFV**	**Protein Yield**
−100%	−30.04	−0.56	−14.88	−69.79	−3.1	−37.88	−29.37	−2.31	−26.3
−75%	−30.04	−0.56	−14.88	−50.53	−2.48	−30.76	−14.2	−1.12	−10.09

Table 5. *Cont.*

Fertilization Rate	Extensive Yield	Extensive RFV	Extensive Protein Yield	Semi Extensive Yield	Semi Extensive RFV	Semi Extensive Protein Yield	Intensive Yield	Intensive RFV	Intensive Protein Yield
−50%	−20.58	−0.38	−7.08	−53.05	−2.44	−29.75	4.97	−1	1.16
−25%	−9.56	0.14	−0.79	−37.57	−2.03	−23.55	7.67	−1.02	0.34
Actual	0	0	0	0	0	0	0	0	0
+25%	37.14	0.24	11.48	−2	0.23	−0.66	−14.49	1.78	0
+50%	54.18	0.56	17.26	12.49	0.41	5.61	−60.65	4.99	−1.3
+75%	61.7	0.58	17.65	10.67	0.39	5.7	−65.08	5.66	−1.87
+100%	60.41	0.77	17.16	12.5	0.38	5.84	−73.85	6.04	−2.31



(**a**)



(**b**)

Figure 10. (**a**) Boxplots showing mean protein yield under specific changes in stocking rate. Colors represent meadow types. Significant differences in protein yield among stocking rates within the same meadow type were evaluated using the Mann–Whitney U test ($p < 0.05$). (**b**) Boxplots illustrating the

distribution of simulated protein yields by meadow type under different stocking rate adjustments. Each point represents a simulated protein yield for a specific change relative to the actual stocking rate. The color gradient indicates the magnitude and direction of the stocking rate change. The central line within each box represents the median protein yield, the box bounds indicate the interquartile range (IQR), and the whiskers extend to 1.5 times the IQR. Outliers are shown as individual points beyond the whiskers. Lowercase letters (a, b, c) above the boxplots indicate significant differences in median protein yield between meadow types (Kruskal–Wallis H test, $p < 0.05$), followed by Dunn's post hoc test for pairwise comparisons.

4. Discussion

We used Random Forest because mountain meadow systems involve multiple interacting factors that rarely respond linearly [43]. Traditional linear models often fail to capture such dynamics, whereas Random Forest, by aggregating multiple decision trees, can identify non-linear interactions and quantify the relative importance of predictors without requiring strict parametric assumptions [44]. This makes it particularly suitable for heterogeneous landscapes such as the Pyrenees, where management practices and environmental drivers are strongly intertwined.

As widely reported in previous research, forage yield and quality often display an inverse relationship, with higher production generally associated with lower nutritive value [8,45,46]. This trade-off was also evident in our study, confirming that management decisions must balance productivity with forage quality.

Regarding cutting date, the three meadow types exhibited distinct responses, except for protein yield, where intensive and extensive meadows did not differ significantly. This similarity may be explained by the higher proportion of legumes in intensive systems, which compensate for their lower floristic diversity and sustain protein yield [47,48]. For yield, a general increase was observed with delayed cutting, except in semi-extensive meadows, where production remained stable across a wide window. The absence of significant differences between delaying the cut by 30 days and advancing it by 15 days suggests a 45-day period of yield stability. This resilience may be linked to the high levels of organic fertilization in these systems, which could slow maturation and sustain production [49,50]. In all meadow types, however, advancing the cut by more than 15 days resulted in significant yield reductions. Forage quality (RFV) followed the opposite trend, reaching maximum values with early cuts and declining progressively thereafter, confirming that earlier cutting improves nutritive value but at the expense of yield [45].

Protein yield, which integrates both biomass and crude protein concentration, provided a more balanced perspective. In intensive meadows, protein yield remained stable across a wide range of cutting dates, likely due to the phenological pattern of legumes, which maintain protein levels from flowering to seed set [51]. Extensive meadows showed even greater stability, probably related to their high species diversity, where asynchronous phenologies buffer declines in some species with increases in others [2]. In contrast, semi-extensive meadows were particularly sensitive: protein yield peaked between the current cutting date and a 10-day advancement, while any delay led to significant reductions. This highlights the vulnerability of semi-extensive systems to even moderate delays in harvest.

Fertilization had a smaller impact on forage performance than cutting date. Differences across meadow types were less pronounced: intensive and extensive meadows did not differ significantly in either yield or protein yield, while semi-extensive meadows consistently displayed higher values. This pattern may be related to their location in more humid areas and on more fertile soils, which favor higher productivity. As observed in other studies, the most productive systems tended to show lower forage quality, although differences with extensive meadows were not significant [8,30].

Yield response to fertilization was negligible in intensive meadows, suggesting that production is more constrained by climatic conditions than by nutrient availability. A similar lack of response was observed in extensive meadows, likely due to their complex floristic composition, which confers resilience and reduces dependence on fertilization. In contrast, semi-extensive meadows exhibited significant yield reductions when fertilization was decreased by at least 50%. This suggests that while a minor reduction (e.g., −25%) could maintain comparable yields (−28.57 kg ha^{-1}, not significant), a 50% reduction would lead to significant losses (−215.5 kg ha^{-1}). For forage quality (RFV), no significant differences were detected in any grassland type, indicating that quality is more strongly linked to cutting date than to fertilization [52,53]. Similarly, protein yield did not vary significantly with fertilization, suggesting that yield gains and quality declines offset each other, resulting in stable protein yield across treatments.

Stocking rate was the management variable with the least overall effect. As with fertilization, semi-extensive meadows showed significantly higher yield and protein yield than intensive and extensive systems, between which no significant differences were observed. In contrast, forage quality was significantly lower in semi-extensive meadows compared to intensive ones but did not differ from extensive systems. This pattern is consistent with the role of stocking rate as an indirect form of fertilization, since higher grazing pressure increases nutrient inputs through animal excreta [7,17,54].

Within each meadow type, no significant differences were detected in yield or forage quality when stocking rate was modified, suggesting that production and quality can be maintained regardless of grazing intensity. However, differences emerged in protein yield. In both extensive and semi-extensive meadows, reducing stocking rate led to significant declines. In extensive systems, this result is expected, as grazing represents the main nutrient input, and its reduction directly limits protein production [29]. The absence of a similar effect on total yield may reflect compensatory mechanisms in biomass accumulation. In semi-extensive meadows, where organic fertilization is already high, the decline in protein yield is less likely to be nutrient-driven and may instead be related to the stimulatory effect of grazing on plant regrowth [54]. Intensive meadows did not show this response, possibly due to their lower floristic diversity, which reduces the capacity for compensatory growth under different grazing pressures [55].

While these simulations offer valuable insights, the limitations of the modeling approach must be considered.

Despite the robustness and predictive accuracy of the Random Forest model used in this study, several limitations must be acknowledged. As a non-mechanistic, data-driven approach, Random Forest does not incorporate physiological or ecological processes explicitly, which restricts its interpretability in terms of causal mechanisms [56]. Moreover, the model's structure does not account for potential multicollinearity among input variables, meaning that highly correlated predictors may obscure individual effects or inflate variable importance measures [57]. While Random Forest is well suited for capturing complex, nonlinear relationships, its reliance on empirical patterns limits extrapolation beyond the observed data range and may reduce reliability under novel management scenarios or climatic conditions [58]. Therefore, predictions should be interpreted with caution and complemented by mechanistic insights or field validation when informing management decisions.

Taken together, these findings highlight that semi-extensive meadows are the most sensitive system, consistently showing distinct responses to management changes. While intensive and extensive meadows appear more resilient to adjustments in fertilization and grazing, semi-extensive systems require more precise and adaptive management strategies.

A practical implication of these findings is that advancing the cutting date is generally advisable across all meadow types, although the optimal margin differs: approximately 10 days in semi-extensive meadows, 15 days in intensive systems, and up to 20 days in extensive ones. Delays, by contrast, are consistently penalized with reductions in forage quality and protein yield. These differences can be explained by the baseline cutting schedules and the ecological characteristics of each system. Extensive meadows, traditionally harvested later in the season, retain a wider margin for improvement when cuts are advanced. Intensive meadows, despite being cut earlier, also benefit from earlier harvests, likely due to the predominance of grass–legume mixtures in which grasses senesce rapidly under these conditions. Semi-extensive meadows, however, show the narrowest adjustment window, with only a 10-day advancement improving outcomes. This suggests that their current cutting dates are already close to the agronomic optimum, leaving less room for improvement. In this sense, semi-extensive systems represent a central situation, while intensive meadows offer some scope for optimization and extensive meadows the greatest potential for gains through earlier cutting.

5. Conclusions

Advancing harvest improves forage quality (RFV) but reduces yield, while delaying it increases biomass and protein yield at the expense of nutritive value. Protein yield, which integrates both dimensions, proved especially useful for evaluating trade-offs: intensive and extensive meadows maintained stable protein levels across a wide range of cutting dates, whereas semi-extensive meadows were highly sensitive to delays, with even moderate postponements leading to significant declines.

Fertilization had a smaller impact than cutting date. Intensive and extensive meadows showed limited responses to dose changes, whereas semi-extensive meadows were more dependent on nutrient inputs. In contrast, semi-extensive meadows responded more strongly: reducing fertilization by 50% led to significant yield losses, suggesting that these systems are more dependent on nutrient inputs. However, the results also indicate that halving fertilizer doses may still maintain acceptable yields, offering a potential strategy for cost reduction without compromising productivity.

Stocking rate was the least influential factor overall. Yield and forage quality remained stable across grazing intensities, but protein yield declined when stocking rate was reduced in semi-extensive and extensive meadows. This reflects grazing as both a nutrient input and a stimulant for regrowth. Intensive meadows showed no significant response, possibly due to their lower floristic diversity and reduced capacity for compensatory growth.

In summary, management strategies in mountain livestock systems should prioritize cutting date adjustments to balance yield and quality. Fertilization and stocking rate play more context-dependent roles, with semi-extensive meadows emerging as the most productive but also the most sensitive to management changes. Random Forest modeling was effective in identifying these trade-offs, offering a robust framework to support evidence-based decision-making in complex agroecosystems. Nevertheless, future research should validate these model-based insights through controlled field experiments explicitly manipulating cutting date, fertilization, and stocking rate, to ensure that simulated responses are consistent with actual agronomic outcomes.

Author Contributions: Conceptualization, A.J., A.U. and R.R.; methodology, A.J. and R.R.; formal analysis, A.J., A.U. and R.R.; investigation, A.J. and R.R.; resources R.R.; writing—original draft preparation A.J., A.U. and R.R.; writing—review and editing, A.J., A.U. and R.R.; project administration, R.R.; funding acquisition, R.R. All authors have read and agreed to the published version of the manuscript.

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