110. Optimizing variable N application to living grass coverage estimated in late autumn or early spring

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Abstract

A field experiment was conducted in 2022–2023 and repeated in 2023–2024, estimating plant coverages using digital processing of autumn and spring aerial images to determine fertilizer rates. Three fixed and two variable manure and mineral N rates were applied in early spring and after the first cut. Dry matter yield (DMY) and agronomic efficiency (AE) were evaluated over two seasons. A low or variable N rate based on spring coverage led to DMY and AE comparable to high N rates. Autumn coverage in the second season improved slurry application decisions, offering a valuable tool for grassland management.

Keywords: forage yield, image analysis, machine learning, nitrogen, proximal sensing, slurry rate recommendation, winter damage

Introduction

Local directives and guidance are clear in livestock-dense regions in Norway, demanding a reduction of manure spreading. This practice is not recommendable but used due to economic reasons during late autumn and winter (Prasad *et al.*, 2022). Its effects are often associated with nitrogen (N) and phosphorus (P) runoff and losses, additionally causing negative environmental consequences (Miller *et al.*, 2011). In grassland production, nutrient use efficiency depends on plant density, soil nutritional status and turnover, amount of applied nutrients, cutting regime and weather conditions. In cold temperate regions, harsh winters could affect the sward growth when the season starts, resulting in uneven plant coverage across the field.

N input rates are determined after soil sampling and chemical analysis and adjusted according to yield and economic response (Valkama *et al.*, 2016; Wachendorf *et al.*, 2004), which is highly resource demanding and time consuming. Therefore, sampling and decision-making technologies are required to ease this task and increase sampling precision. Imaging tools contribute to determine grassland plant coverage and other aspects of grassland status (Borra-Serrano *et al.*, 2019; Rueda-Ayala *et al.*, 2019b). At the Norwegian Institute of Bioeconomy (NIBIO) an automatic colour image processing tool was developed for estimating plant coverage on images acquired on grassland fields. This study aimed at (i) validating the imaging tool capabilities to generate accurate fertilizer dose recommendation for ley grass based on estimated plant coverage at late autumn or early spring, and (ii) comparing dry matter yield (DMY) and agronomic efficiency (AE) of non-perennial grasslands to either fixed (even) or site-specifically adjusted N fertilizer dose.

Materials and methods

Experiment description and image acquisition

A ley grass experiment was conducted in the growing season October 2022–September 2023 and repeated in the season 2023-2024, at the NIBIO Særheim research station (Klepp Stasjon, Norway, lat. 58.76 N, long. 5.65 E). Grass sward damage was induced once on 20 October 2022 by rotary harrowing (high suppression) or mowing at a cut hight of 1 cm (low suppression) on randomly distributed subplots within three repetition blocks. In this way, low, high and no suppression levels of varying plant coverage (due to plant kill and growth reduction) across all fertilizer treatments were produced. Colour images were acquired over the experimental field, using a UAV-mounted camera (21 megapixels resolution). Aerial scouting was carried out on 31 October (in 2022 and 2023), 28 February 2022 and 20 March 2023. Georeferenced orthomosaics of the whole field were reconstructed for each sampling season with the software AgiSoft PhotoScan (AgiSoft, 2018).

Image analysis and fertilizer dose recommendation

The Grasision® image analysis tool was developed by NIBIO under the Norwegian research council's Milestone-project 'FORNY2020, Nr. 300567'. The tool uses machine learning (ML) algorithms to segment complex sward grass structures and estimate pixel coverage of living plants, dead plants and bare soil from grassland colour images taken by means of cameras mounted on unmanned aerial vehicles (UAV) or tractors (Rueda-Ayala and Höglind, 2019; Rueda-Ayala *et al.*, 2019a,b). Segmentation of grass-sward structures was applied to tiles derived from the aforementioned orthomosaics. Gaussian mixture models and nearest centroid classifier, vegetation indices, such as the color index of vegetation extraction (CIVE) and excess green index (ExG) were the ML techniques used, following the procedure described in (Rueda-Ayala *et al.*, 2019a). Additionally, the tool was designed to recommend grassland renovation based on research data (Rueda-Ayala and Höglind, 2019).

The decision-making for renovation part from Grasision was modified to recommend variable slurry application rate, and to export a site-specific fertilizer application map. Fertilizer doses were recommended assuming that a low living plant coverage requires low fertilizer amounts, while high plant coverage requires higher amounts, and bare soil areas should not receive any fertilizer to avoid wasting nutrient resources. Consequently, five manure application treatments were applied, including three of fixed doses at whole plot (45m × 7.5m) level, and two variable rates adjusted site-specifically along 5 subplots (9m × 7.5m), totalling 45m the plot length. Variable rates were based on the estimated plant coverage (Figure 1a, b) and recommendations mapped (Figure 1c). The three fixed treatments were evenly applied on each treatment plot, regardless of plant coverage variation. Used doses were: zero, 0 kg N/ha; low, 60 kg N/ha applied at growing season start (April) and 45.5 kg N/ha after the first cut (June); high, 120 kg N/ha applied in April and 91 kg N/ha in June. Requirements of N were firstly calculated on the basis of soil analysis. The variable rate (autumn) used the doses zero, low, and high, based on October imagery. The variable rate (spring) used doses zero, low, and high, according to estimated coverage on February/March imagery. At both dates, a part of the N came from cattle slurry (first application: low N, 26 kg N/ha; high N, 52 kg N/ha) and the other from mineral sources (correspondingly 34 and 68 kg N/ha, from N 27-0-0). Slurry had a 4.1% dry matter content, 2.7 kg total N/t, 0.33 kg P/t, 3.3 kg K/t, 0.28 kg S/t, pH 7.6 and 1000 kg/t volume weight. The slurry was applied with a precision spreader and doses were adjusted on the manure N-content calculated from chemical analyses and the NIBIO Nitrogen animal manure calculator (Husdyr N-Kalkulator, https://lmt.nibio.no/husdyrn/). After cut 1, N applied from slurry was 13 kg N/ha for the low rate, and 26 kg N/ha for the high rate; and the rest from mineral sources, i.e., 32.5 and 65 kg N/ha (N 27-0-0). After cut 2, all N rates were only from mineral sources, i.e., 24.5 kg N/ha for the low rate, and 49 kg N/ha for the high rate. Phosphorous and potassium (K) deficiencies were avoided due to high application rates on all plots, according to soil analyses.

Data collection and analysis

The field was cut three times in 2023 (May 31, August 2 and October 21), and in 2024 (June 12, July 31 and September 23). Dry matter yield was determined after drying samples at 60 °C for 48 h. The AE index (Congreves *et al.*, 2021) was used as an indicator of how efficiently N was used to produce harvestable forage matter. This index was calculated as the difference between yield from fertilized plots and the treatment *zero* divided by the amount of N applied: $AE=(Yield_t-Yield_0)/kg\ N$. Total forage DMY per year was calculated by adding yields of all three cuts. A linear mixed-effects model, fitted by the restricted maximum likelihood approach (REML) was applied using the statistical software R, version 4.4.1 (R Core Team, 2024) and the package 'nlme' (Pinheiro *et al.*, 2023). Total DMY per year and AE were the response variables. Fertilizer treatments, year and their interactions were analysed as fixed. The N applied and estimated living plant coverage were used as covariables. Spatial heterogeneity due to the sward suppression and resulting coverage variability was incorporated into the model with the function 'varIdent', to estimate their effect on yield variance (σ). This variance structure was formulated with different spread per stratum, allowing each suppression level to model its own yearly variance. Spatial correlation was tested using the geocoordinates of each subplot's centroid; each centroid was nearly 7.5m distant from each other. The calculated variogram showed no correlation of neighbouring yield measurements even up to 60 m length. For yield analysis, the repetition blocks were assigned as random, using a random intercept structure. Regarding AE, sward suppression treatments were the random intercept, including a random slope defined by the N applied dose. Marginal means adjusted with the Tukey HSD ($\alpha=0.05$) method and their corresponding 95% confidence limits (CL) were used to explore differences in model predictions for the fertilization treatments.

Results

Plant coverage achieved by suppression effectively ranged between <10% to >90%. The fertilizer doses were applied according to the coverage estimated at late autumn and spring (Figure 1); the consequent yield results are shown in Figure 2. Living plant coverage as an indicator to define the fertilizer dose showed a positive relation with DMY. Nearly 30 kg DMY/ha (CL=20–42; $P<0.001$) were produced per percentage point increase in plant coverage, on average. Total DMY (t/ha) averaged by fertilizer treatment and year was bigger with increasing fertilizer dose. Nearly 23 kg/ha (CI=15–32) per applied kg N were attributable to increasing N dose ($P<0.001$). However, since only three levels were tested, the estimated coefficients in this analysis should be taken with care. The calculated variogram showed no correlation of neighbouring yield measurements even up to 60 m length. Variability in the baseline DMY across suppression treatments was substantial (SD=0.833), with a small variation in the N dose effect (SD=0.06). This high variation indicates that other events might have played a stronger effect on DMY. This fact is also indicated by the high residual variation (SD=2.06). The random intercept and slope were negatively correlated ($r=-0.99$), suggesting that high suppressed plots exhibit weaker effects of N rate. The fixed rates high 2023 and 2024 and low 2023 highest DMY (Figure 2). The variable rates spring 2023 and variable autumn 2023 and 2024 ranked second with 11.6, 10.3 and 9.6 t DMY/ha, respectively. The lowest DMY was for the no fertilizer (zero) 2023 and 2024 (7.3 and 3.8 t DMY/ha, respectively). On average 2.4 t DMY/ha (CL=2.1–2.7) were lost from 2023 to 2024 on all fertilizer rates.

Plant coverage did not influence the AE, thus this covariable was not accounted for in the model. The REML analysis showed significant effects only for the fixed low N rate ($P<0.001$) and variable spring 2023 ($P=0.002$). The AE was significantly higher when the fertilizer treatment was low on both seasons (Figure 3), being 29.5 kg DMY/(kg N) (±27–32) in 2023 and 28.6 kg DMY/(kg N) (CL=26–31) in 2024 (Figure 3), compared with all other treatments, which on average was 16.4 kg DMY/(kg N) (CL=8.6–21.4). Variability in the baseline AE across suppression treatments was high (SD=0.59), with a minimal variation in the N dose effect (SD=0.008). As for DMY, this variation

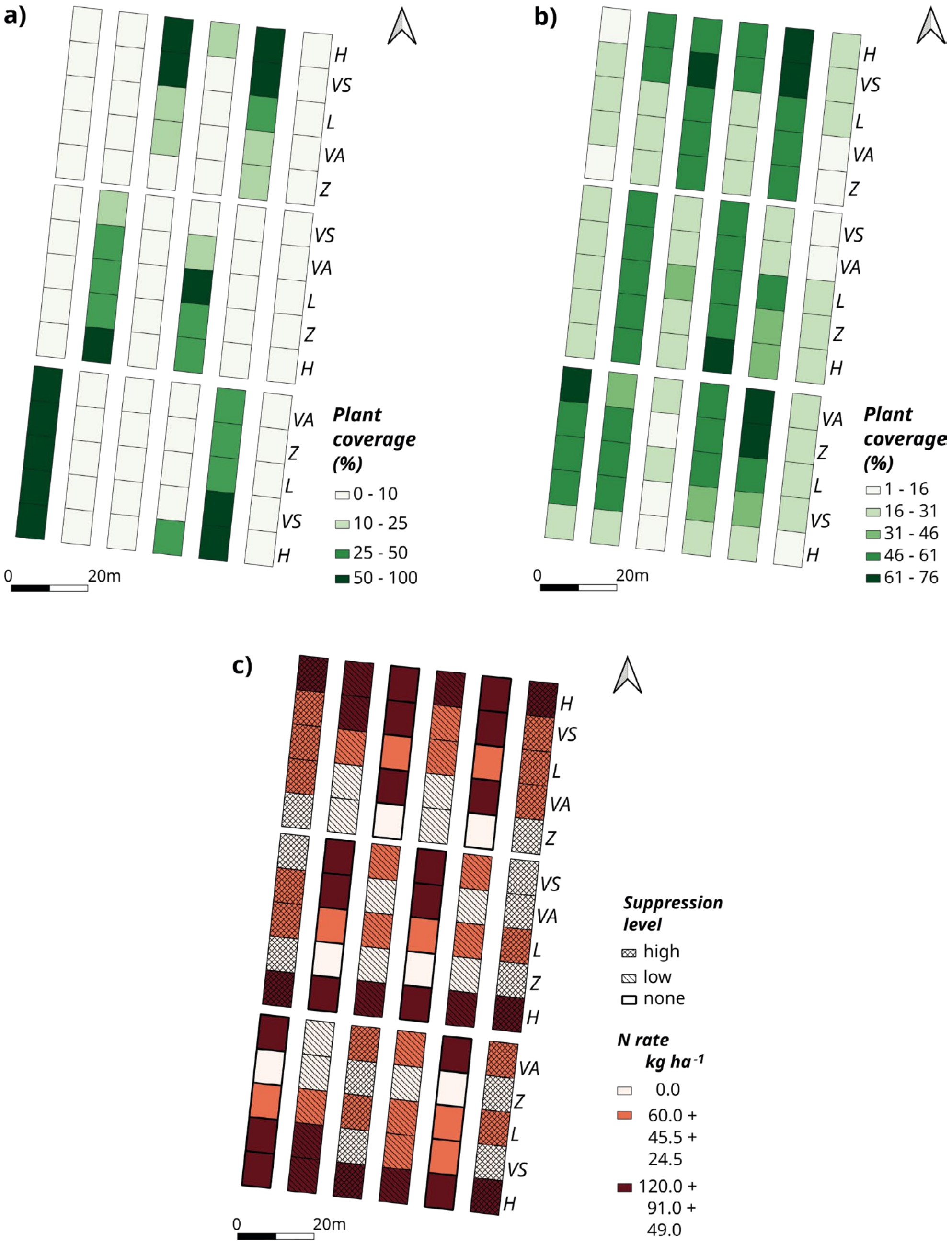

Figure 1. Sample maps of estimated living plant coverage on 31October 2022 (a) and February 28th, 2023 (b), with distribution of the fertilizer plots (Z= zero, L= low, H= high, VA= variable autumn, VS= variable spring). Panel (c) shows the sward growth suppression levels used (high, low and none) and actual N rate applied per from slurry (0, 60, 120) and mineral sources after first cut (45.5; 91) and second cut (24.5; 49).

might be attributable to other causes than those evaluated in this experimental setup. The random intercept and slope were also negatively correlated (*r*=–0.99), meaning that high suppressed plots exhibit weaker effects of N rate. The residual variation was also high (SD=1.8).

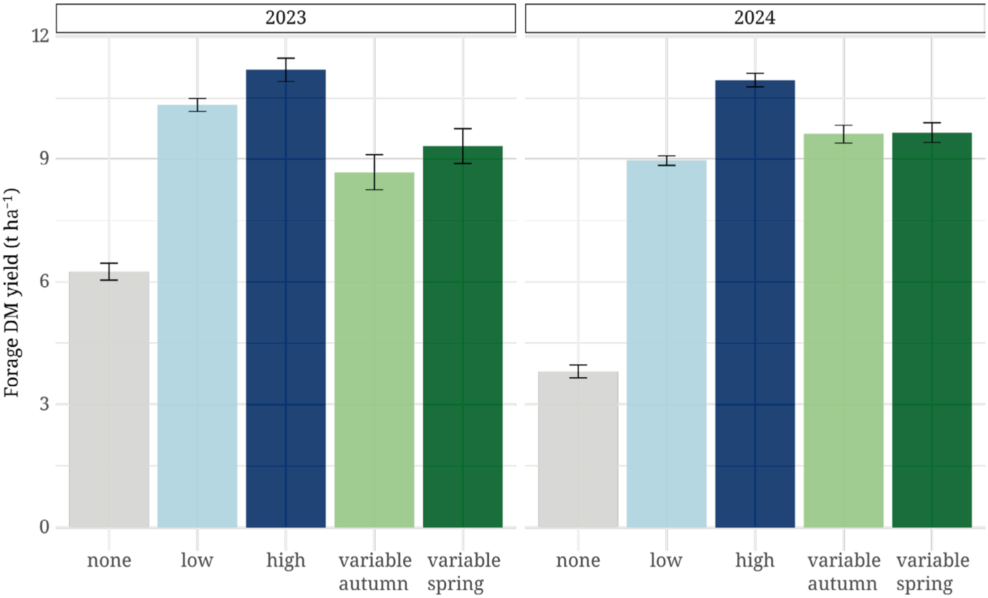

Figure 2. Forage DM yield averaged per fertilization treatment and year. Thin black lines indicate standard errors and if not overlapping, statistical differences were found.

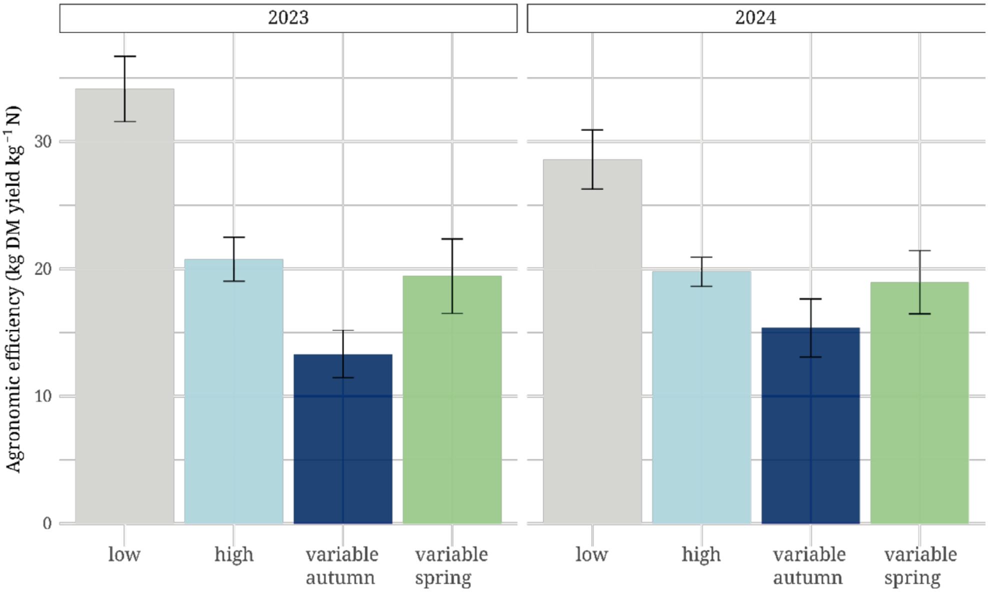

Figure 3. Agronomic efficiency (AE) index (kg DMY/(kg N)) averaged per fertilization treatment and year. Thin black lines indicate standard errors and if not overlapping, statistical differences were found.

Discussion

These results do not necessarily highlight benefits of using an image-based variable fertilizer rate to increase DMY and agronomic N use efficiency. The unusually long drought in 2023, which occurred early in the growing season, followed by abundant rainfall immediately after, affected DMY productivity. Forage DMY and AE decreased from 2023 to 2024 across all fixed N rates. Uneven grass growth, both naturally occurring and artificially induced through suppression, may have masked actual yield losses and resource use inefficiencies. In contrast, when variable rates based on autumn or spring image analyses were implemented, DMY and AE remained relatively stable from 2023 to 2024, although DMY seemed more affected. Possibly, extending the monitoring period and comparing results with plant N content analyses would reveal true yield and agronomic N use efficiency stabilization over time.

Overall, the effects of site-specific fertilizer management based on ground coverage to determine appropriate nutrient rates and improve use efficiency require further investigation, particularly in grasslands and ruminant-based farming systems. Beyond yield effects, future assessments should also consider forage nutritive value, comparing in-biomass nitrogen with the amount supplied. Additionally, given the challenges associated with manure surplus in livestock-dense regions, manure budget estimates should be incorporated into fertilization strategy evaluations at both farm and regional levels.

Conclusions

This study showed the feasibility of using image analyses to generate plant coverage-based variable-rate fertilizer recommendations for perennial grasslands. However, site-specific N fertilizer rate adjusted to the plant coverage either in the autumn before the growing season or in the early spring did not result in higher dry matter yield or better agronomic N use efficiency than fixed application rates in the two-year field experiment. Further analyses from more fields and more than two-year period are required for better understanding the field plant cover heterogeneity and N fertilization effects on grassland yield, field supply and environmental implications. More aspects, such as forage quality and the total amount of manure used per field should also be taken into consideration.

Acknowledgements

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