JARS Journal of Applied Remote Sensing

RESEARCH PAPER

UAV LiDAR-based grassland biomass estimation for precision livestock management

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ABSTRACT. We present an approach for grassland management using uncrewed aerial vehicles (UAV) LIDAR data and statistical modeling techniques integrated within a software-based multi-level information system (SMI). The primary objective is to utilize UAV LiDAR data and statistical modeling techniques within an SMI to accurately estimate compressed sward height (CSH) and above-ground biomass for precision farming applications. As a case study, four UAV LiDAR flights were conducted over rotational grazing farmland, and the collected data were processed to a point cloud. A statistical model was developed to estimate CSH values ($R^2 = 0.59$, RMSE = 5.9 cm) using LiDAR metrics of the point cloud data. In addition, destructive sampling of grassland facilitated the calibration process, enabling the modeling of biomass based on the CSH values, specifically expressed as above-ground herbage dry biomass ($R^2 = 0.89$, $\mathrm{RMSE} = 0.2669\ \mathrm{Mg\,ha^{-1}}$). The collected data further enabled the approximation of biomass across the entire area of interest, which covered ~200 ha, utilizing a 2.5×2.5 m polygon grid. The data were subsequently transferred to an SMI, which operates on the same grid and complements the information, thus offering a comprehensive foundation for decision-making, optimizing grazing systems, and efficient resource allocation. We contribute to advancing precision farming and sustainable grassland management.

Keyword: biomass estimation; geospatial information system; grassland management; precision farming; precision livestock management; UAV LiDAR

Paper 230418G received Aug. 31, 2023; revised Feb. 9, 2024; accepted Feb. 12, 2024; published Mar. 14, 2024.

1 Introduction

Climate change poses substantial risks to dairy and meat production, with increased incidence of drought, flooding, and extreme weather events challenging the resilience of these systems.[1] Simultaneously, consumers increasingly demand sustainably produced goods that ensure strict adherence to animal welfare standards.[2] Against this backdrop, grasslands, which constitute a significant portion of agricultural land, emerge as a pivotal element in mitigating climate change effects and ensuring future food security.[3] Precision livestock farming (PLF) has been proposed as an innovative approach to meeting these multifaceted challenges, particularly in managing cattle dairy and meat production more effectively.[4] Within PLF, sensor technologies are becoming indispensable for optimizing grazing management and improving pasture utilization.[5,6]

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In this respect, virtual fencing has been proposed as one major advantage of facilitated grazing.[7] Specifically, detailed geoinformation about the condition of grasslands can facilitate informed management decisions, contribute to developing spatially and temporally flexible virtual fences, and verify compliance with agri-environmental measures.[8,9] Subsequently, software-based decision support tools collect large amounts of available information, break them down, and link them (e.g., through models or optimization methods) for the users.[9–11]

Traditional methods, such as rising plate meters (RPM), have been cornerstones for estimating pasture biomass through the measurement of compressed grass sward heights.[12,13] Despite advances in sensor technology, such as ultrasonic sensors and GPS for data logging,[14,15] these point measurements are, however, not capable of providing the complete spatial coverage needed for precise aboveground standing biomass estimation, and the manual operation of the equipment causes significant labor costs.

Recently, uncrewed aerial vehicle (UAV) remote sensing has been recognized as a cost-effective and non-destructive method for gauging pasture biomass, with studies showcasing its efficacy using various techniques.[16–20] Nevertheless, image acquisition for structure-from-motion is laborious over large areas and demands considerable post-processing. By contrast, LiDAR integrated on UAVs has demonstrated potential for overcoming these limitations, providing high-resolution spatial data efficiently and automatically.[21–24]

The high-resolution, three-dimensional (3D) data captured by UAV-based LiDAR presents not only a quantifiable estimate of aboveground standing biomass. Moreover, pre-grazing sward herbage height and mass are the most important information criteria for efficient grazing management as these determine whether paddocks are stocked (e.g., Claffey et al.[25]). The UAV-based LiDAR information can also provide structural insights into the sward architecture from a height perspective, which is an important measure of the diversity within grassland (e.g., Obermeyer et al.[13]). It would also be possible to assess phenological phases of dominating plant species as these are crucial for herbage quality, as has been shown, for instance, in terms of organic matter digestibility.[26] In addition, studies have tried to derive herbage quality estimates from height measurements (e.g., Bell et al.[27]) since providing sufficient high-quality herbage is particularly important for lactating livestock, affecting the animal performance, welfare, and health.[28] However, in cases of non-uniform botanical compositions, the single sward height assessment is probably a poor predictor of herbage quality.[29]

Despite this previous research, the pragmatic application of UAV LiDAR-derived geospatial information to livestock management remains less understood and underexplored, particularly within dairy farms—a critical research gap that this study addresses. There is a need to develop and examine comprehensive methods that convert UAV LiDAR data into actionable insights for farm management, bridging the gap between technological potential and practical application.

Therefore, this study embarks on the novel inquiry of using UAV LiDAR-based geospatial information for livestock management, supported by a case study from an operational dairy farm. It presents the integration of UAV LiDAR data with on-ground sampling and RPM measurements within a specially developed workflow. The resulting data are then fed into software-based multi-level information system (SMI) that showcases the potential of UAV LiDAR in enhancing management decisions for sustainable dairy farming.

2 Study Site and Research Data Acquisition

2.1 On-Farm Research Site

The study was conducted at an innovative dairy farm[30] in Brandenburg, Germany (52.35° N, 12.68° E), ~60 km west of Berlin (see Fig. 1). The farmland consists of roughly 500 ha of grassland, and around 900 grazing cows (mainly Jersey x Holstein Friesian Crossbreds) are kept outside all year round. The grassland is managed according to rotational stocking with a short duration of grazing per paddock.[31] Integration with the conservation of forage is applied flexibly throughout the grazing season. The farm has been divided into paddocks for this system, and the whole grazing animal herd is kept in one or two paddocks for minimal periods (<1 day). So far, a management decision on stocking is based on weekly paddock-wise measurements using RPMs to determine herbage on offer, similar to the procedures performed in Ireland by Pasturebase Ireland.[32] Cows are milked twice daily.

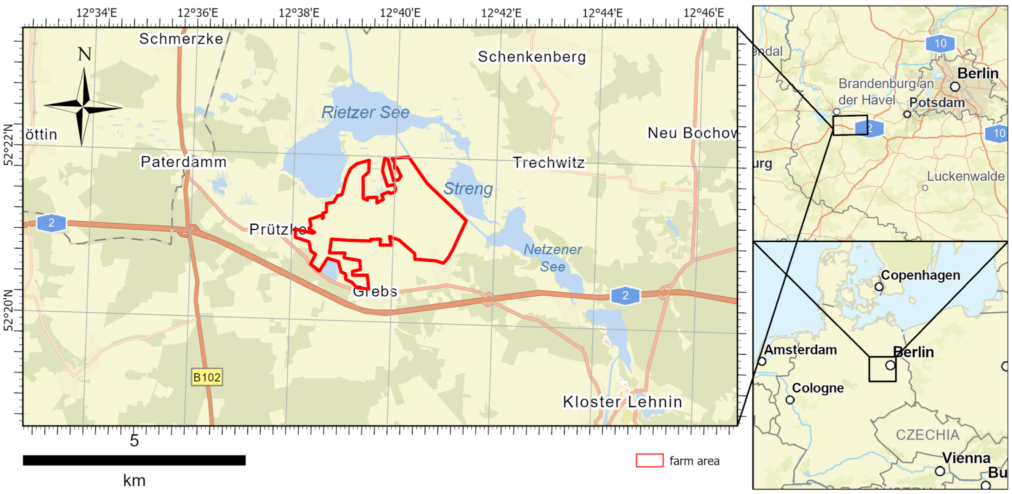


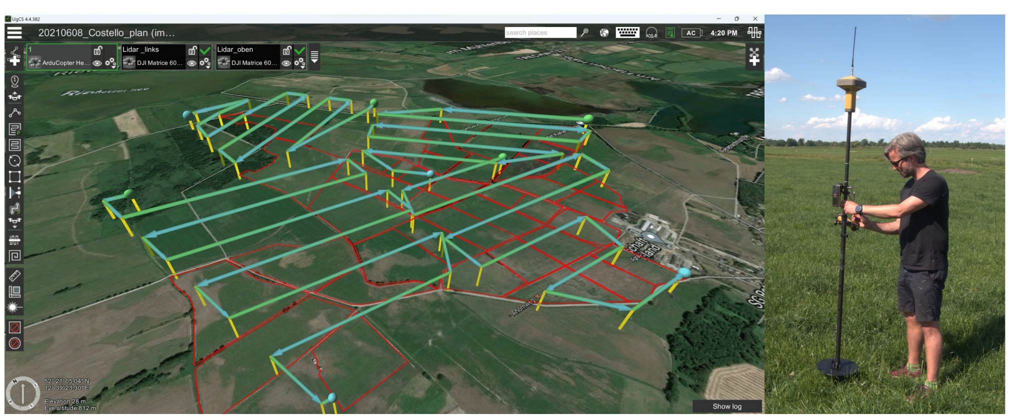
Fig. 1 Location of the study site.

2.2 Compressed Sward Height Measurements

An RPM has a movable plate that compresses the grass surface and measures the distance of the plate to the ground. The determined height is called the compressed sward height (CSH). Through connection with manual calibration cuttings, the CSH can be used to indicate the standing herbage biomass in grassland (e.g., Obermeyer et al.[13]).

To automate the RPM measurements, an RPM DGPS was developed, in line with the work presented by Flynn et al.[15] However, this approach is an improved version as the GPS antenna of the device is directly attached to the RPM measurement area. The device is shown in Fig. 2(b). It consists of a round 3D-printed plastic plate with a diameter of 30 cm and a weight of 200 g that can move along the GPS pole. The size and weight follow those of an older device proposed by Castle.[12] A laser distance meter (Leica Disto) measures the distance between the plate and the device, and the RPM height is then calculated as the distance from the ground. The values are stored in an Android app on a mobile phone and later connected with the point acquired by the GPS. High spatial precision is crucial for successfully connecting UAV remote sensing data with ground measurements. To achieve the needed accuracy, a GR-5 differential GPS (DGPS) (Topcon) in RTK (Base/Rover) mode with RTK correction was used. The DGPS was used to estimate the position of all RPM biomass sampling points and the RPM measurements.

The device was used to measure the RPM height on 383 locations distributed over 17 paddocks. Two of the RPM measurements were excluded as the measured CSH was higher than 60 cm.



(a) (b)

Fig. 2 (a) Screenshot of the flight planning app UgCS with all four UAV LiDAR flights to cover the parts of the farm that were used for rotational grazing (about 200 ha). (b) RPM DGPS device for automated CSH measurements.

2.3 Grassland Herbage Biomass Sampling

Herbage biomass sampling was performed on June 9, 2021. For this, 26 randomly distributed georeferenced points in nine different paddocks were sampled after the UAV flights. The primary purpose of the measurements was to obtain calibration measurements for the CSHs as measured with the RPM. The grass was cut close to ground level in 30×30 cm areas. Grass samples were immediately cooled and later frozen (−18°C). After defrosting, samples were weighed to determine the herbage fresh matter (FM) and subsequently dried (60°C, 48 h) to determine the dry matter (DM) content. The resulting above-ground herbage dry biomass (AGB) was calculated in Mg ha^{-1-1}.

2.4 UAV LiDAR Data

On June 8, 2021, UAV LiDAR data were acquired using a Riegl miniVUX-1UAV LiDAR sensor mounted on a DJI Matrice 600 Pro UAV. The data collection consisted of four UAV flights conducted over a farmland area designated for rotational grazing. Each flight was conducted 80 m above ground level, with a constant speed of 8 m/s. Before the flights, meticulous flight planning was performed using UgCS software [see Fig. 2(a)]. To comply with the German UAV regulations, all flights were conducted within line of sight, necessitating careful selection of take-off points and equipment transportation to these locations. Within the LiDAR coverage area, 60×60 cm plastic plates were deployed as markers, and their positions were accurately measured using the Topcon GR-5 DGPS system configured in Base/Rover constellation with RTK correction.

3 Methods

3.1 Generating and Analyzing UAV LiDAR Point Clouds

The initial step in generating point clouds from mobile LiDAR sensors involves the precise (post-) processing of the trajectory. In this study, the GPS recordings from the UAV collected during the flight were combined with correction data obtained from a GPS Base Station (Topcon GR-5). The GR-5 base station not only logged this correction data during the UAV flights but also transmitted them to the mobile GPS rover, thereby rectifying the positions of the field measurements. This procedure ensured a high level of spatial agreement between the field data and the UAV LiDAR data. The trajectory post-processing was conducted using POSPac UAV (Version 8.4., Applanix, Richmond Hill, Ontario, Canada).

The point cloud was generated using Riegl's LiDAR UAV software environment, RiProcess. This involved integrating UAV orientation and position data with the actual LiDAR measurements. Following the initial point cloud generation, further refinement of the trajectory was performed using RiPrecision. RiPrecision utilizes identical object parts within the point cloud from different overflights to enhance the trajectory accuracy, taking into account LiDAR reference targets. In the final step, the point cloud was divided into strips. To achieve this step, the segments corresponding to each straight UAV flight were aggregated and individually exported, excluding sections associated with UAV turns. A 3D view of the point cloud is shown in Fig. 3.

The individual point cloud strips were subject to further processing using LASTools LiDAR processing software (Version: 210,720, rapidlasso GmbH, Gilching, Germany). This processing involved several steps, including outlier detection, ground point classification, and normalization. To extract valuable information from the UAV LiDAR point cloud for farm management applications, a polygongrid was created for the entire farm area with a grid spacing of 2.5 m, resulting in a total of 535,174 polygons.[33] Each polygon was 6.25 m^2, ensuring that it was small enough to effectively capture variations within a paddock. This polygon size allows for an adequate number of LiDAR points per cell and represents a relevant scale for management considerations. Furthermore, spatial buffers were created with a radius of 1.25 m around each CSH measurement position. Hence, each buffer zone had a size of 4.91 m^2, which falls within the same range as the size of the polygons.

The normalized point cloud was used to calculate LiDAR metrics for each polygon of the polygon grid and each buffer area. LiDAR metrics have been extensively employed to characterize forests (e.g., Pulleti et al.[34] and Shi et al.[35]) and, more recently, have been applied in winter wheat field monitoring.[36] In this study, to capture the vertical structure of the grass the following

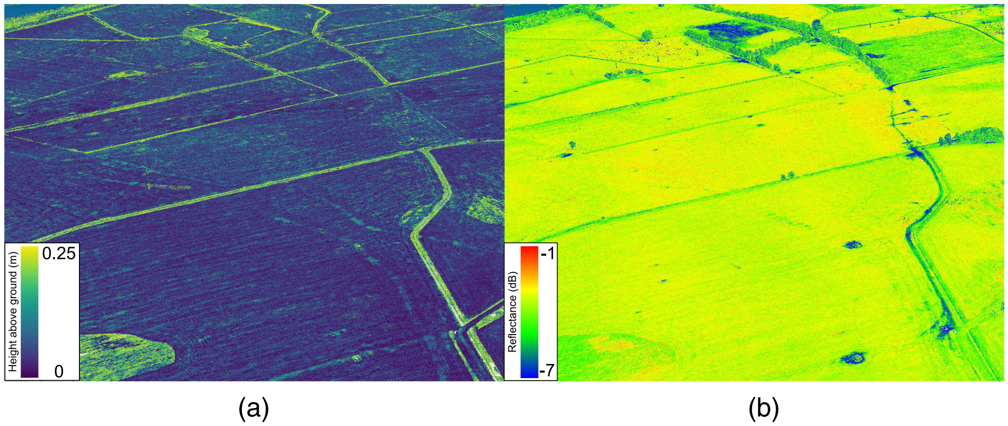


Fig. 3 3D view of the acquired point cloud. (a) The point cloud is colored by height above ground. (b) Reflectance is used for colorization.

metrics were computed for the 381 areas around the RPM measurements and all 534,174 polygons of the polygon grid: the average height, the maximum height, percentiles of the height (50, 75, 90, 95, 99), and the bincentiles (20, 30, 40, 50, 60, 70, 80, 90, 95) of the height.[37] All height metrics were based on the height above ground. In addition, intensity metrics based on the quantity of reflected laser energy were used. The LiDAR intensity is based on laser energy interactions with plant material, related to the density and the structure of the grass, and therefore influenced by the biomass. Specifically, the average intensity and the percentiles of the intensity (50, 75, 90, 95) were calculated. Based on a combination of intensity and height, the height of median energy[38] was calculated. In addition, to incorporate the insights of Xu et al.[22] regarding the significant impact of scan angle on biomass estimation, the scan angle was calculated for each RPM area and polygon area in our analysis. All metrics were then combined to establish a model designed for estimating CSH values.

3.2 Modeling CSH and AGB from UAV LiDAR Point Cloud Metrics

For this study, a customized modeling approach was developed to estimate CSH values from the UAV LiDAR point cloud. The statistical models were established based on the buffer areas to examine the relationship between the LiDAR metrics and the CSH values at the center of each buffer area. To ensure the statistical robustness of the models, a 75/25 split strategy was adopted. This approach allocates 75% of the data for training, allowing the models to learn and identify patterns while reserving 25% for validation to assess the models' predictive performances. This balanced distribution helps mitigate the risk of overfitting and improves the generalizability of the models. Accordingly, the dataset was divided into training (75%, $n = 286$) and validation (25%, $n = 97$) sets, with stratification based on the CSH values. Three modeling approaches were compared: multiple linear regression, partial least squares (PLS), and random forest (RF). The optimization process involved tuning the RF model for the number of variables selected at each split (2, 3, 4) and the number of trees used (100, 200, 400). Similarly, the PLS approach was optimized by exploring the number of components (1 to 10). The optimization aimed to maximize the models' coefficient of determination (R^2) values.

A linear regression (LM) model established a relationship between the AGB estimated from manual calibration cuttings and the CSH values ($n = 26$). This regression analysis provided a means to quantify and understand the correlation between the two variables, allowing for the estimation of the AGB based on CSH measurements. To calculate the AGB for each polygon and aggregate the data spatially, the relationship between calibration cuts and CSH values was used, as was the relationship between LiDAR metrics and CSH values. This combination enabled the absolute and mean AGB to be determined for each paddock while mapping the biomass variability at the resolution of the polygon grid (2.5×2.5 m).

Subsequently, the polygon grid AGB values were aggregated at the paddock level to provide an overall summary of biomass distribution. The AGB value of each polygon was then incorporated into the SMI, enabling a comprehensive analysis and optimization of grazing systems using spatially resolved AGB data.

All statistical analyses were conducted using the R software (Version 4.1.3) with the Tidymodels (Version 1.0.0) and Tidyverse (Version 2.0.0) packages.

3.3 Software-Based Multi-Level Information System

To assist the integration of remote sensing data into modern precision farming activities, livestock grazing, and grassland management, and in particular, the use of virtual fencing technologies, an SMI was developed (see also Sturm et al.[9]). Integrating modern decision-support software tools, such as the developed SMI, can help increase management sustainability within precision farming applications by improving the cost-effectiveness of farming and providing a detailed basis for decision-making.[39]

The general purpose of the SMI is to gather grassland information—such as the AGB—from different sources, for example, those collected through remote sensing operations, and to store, manage, and process the data to the benefit of grassland farmers. More specifically, the SMI is used as an information hub for virtual fencing technology in the collaborative research project GreenGrass.[40] In that context, the SMI provides a user interface that allows the user to plan, adapt, and manage farm-level grassland management (such as virtual or physical paddock planning and fence perimeters), assess and visualize information on grassland condition on the farm or paddock-level, and perform optimization calculations for grazing based on the UAV data layers.

The SMI is designed, in principle, to utilize different types of data, including images, AGB, and grassland flora and fauna species distribution, through a specifically designed data collection framework. Data from different sources, such as UAV-based remote sensing information, agronomic and ecological data, and models, are imported into the SMI database. Subsequently, the SMI provides the necessary data (1) to provide information on grassland conditions and current farm management to the user, (2) to simulate and plan virtual fencing, and (3) to calculate an optimized prioritization for paddocks to be grazed. The user provides all necessary inputs, particularly UAV-based remote sensing data and farm-level management information (see Fig. 4).

4 Results

The model developed to estimate AGB based on the calibration cuts and CSH measured with the RPM exhibited a strong relationship between predicted and observed values, with an R^2 value of 0.89 and an root mean squared error (RMSE) of 0.267 $\mathrm{Mg\,ha^{-1}}$. The scatterplot in Fig. 5 shows the relationship between the predicted and observed biomass values obtained using the established model.

To select the most suitable modelling approach for the CSH values derived from UAV LiDAR data, an evaluation was conducted using the R^2 and RMSE values. The RF algorithm demonstrated superior performance among the evaluated approaches [Fig. 6(b)]. The RF model was optimized with mtry = 4 and trees = 200. The resulting model [Fig. 6(a)] achieved a final

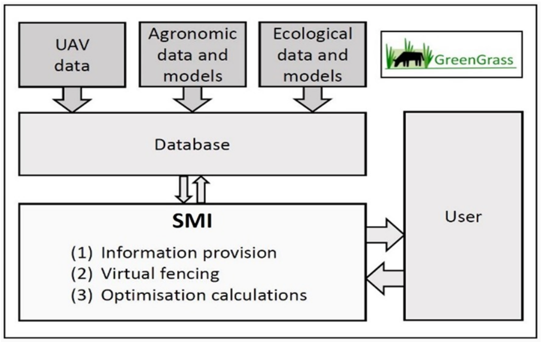


Fig. 4 Principle data workflow within the SMI. Data from remote sensing, agronomic, and ecological models and farm-level data from user inputs are fed into the SMI database. The SMI works with data from the database to provide meaningful output.

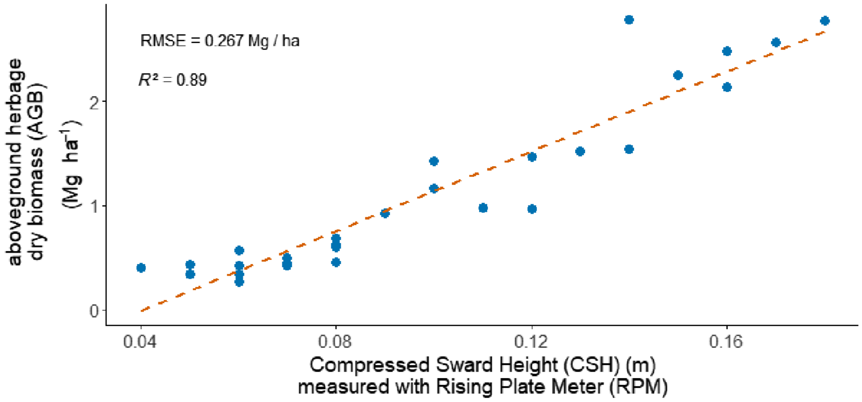


Fig. 5 Scatterplot depicting the relationship between predicted and observed biomass values using the established linear model ($n = 26$). The model achieved an R^2 value of 0.89, indicating a strong correlation between the predicted and observed biomass.

RMSE of 5.9 cm and an R^2 of 0.59. Converting this RMSE to a biomass value using the linear model described earlier, it is equivalent to 0.354 $\mathrm{Mg\,ha^{-1}}$.

The variable importance analysis [see Fig. 6(c)] of the variables used in the RF model revealed that the maximum height and the different percentiles of the height were the most influential variables for CSH estimation, followed by the home variable. The intensity values exhibited relatively lower significance in the model.

The resulting biomass map (Fig. 7) exhibits values ranging from 0 to 3 $\mathrm{Mg\,ha^{-1}}$. Notably, the map highlights areas of high biomass in ungrazed regions.

The results of our study have shown that the integration of the data into the SMI enables users to employ the system, e.g., for the semi-automatic generation of fences. Moreover,

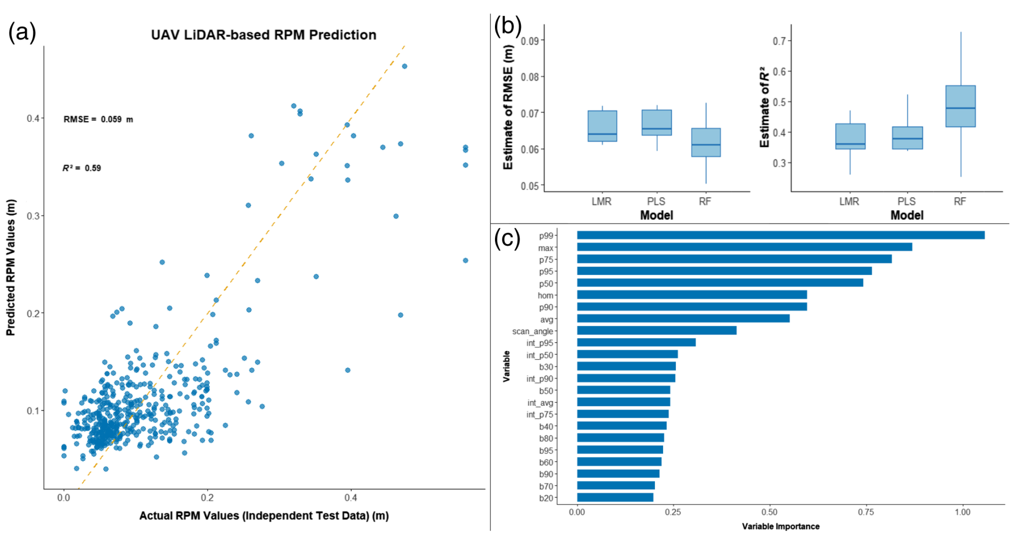


Fig. 6 (a) The scatterplot compares the measured and predicted RPM values from the final RF model. The plotted data points represent the 25% (97) values withheld from the training phase and used for model validation. (b) Boxplot comparison of model performance for estimating CSH. The evaluation is based on 10 data splits into training and validation sets. Three different modeling approaches, LM, PLS, and RF, were assessed using RMSE and coefficient of determination (R^2). The boxplots depict each model's distribution of RMSE and R^2 scores, reflecting their performance across the 10 splits. (c) The bar chart displays the variable importance analysis for the variables used in the RF model. The analysis highlights that the average height above ground emerges as the most important variable for CSH estimation, followed by the home variable. Interestingly, the different height percentiles exhibit varying levels of importance, whereas the intensity values demonstrate relatively lower importance in the model.

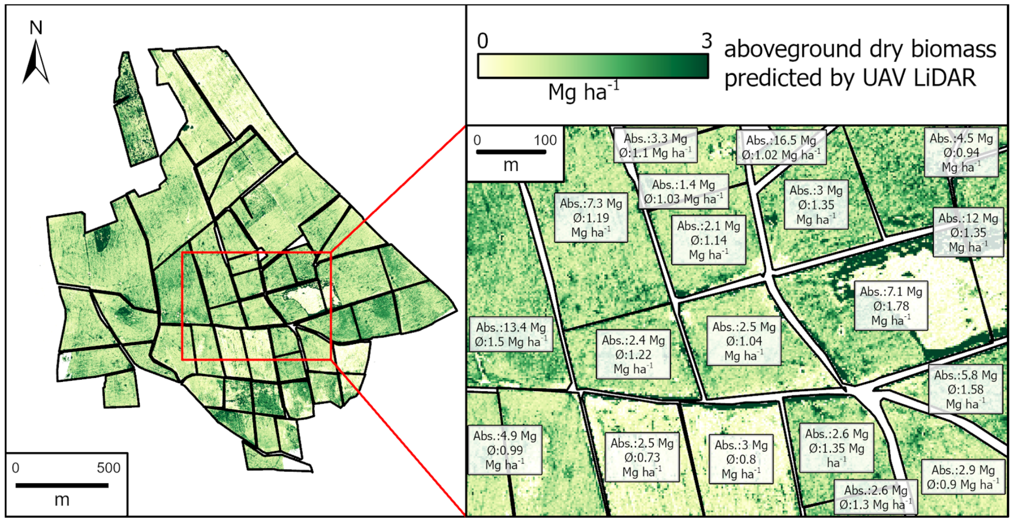


Fig. 7 AGB map of the farmland used for rotational grazing, modeled from the UAV LiDAR dataset.

depending on individual preferences, the grazing system can be efficiently optimized and informed decisions can be made based on a comprehensive dataset.

5 Discussion

The CSH was modeled with an RMSE of around 6 cm, corresponding to about 0.354 Mg ha^{-1}. The measuring uncertainty of the calibration imposes additional inaccuracies in the AGB model cuts of about 0.267 Mg ha^{-1}. These results align with the findings of Zhang et al.,[23] who stated an RMSE of 0.648 Mg ha^{-1} in a similar experiment using UAV LIDAR. However, the biomass estimation accuracy is lower than most photogrammetric UAV-based approaches.[16] On the other hand, if grassland can produce between 8 and 9 Mg ha^{-1} of harvestable herbage biomass under the given conditions,[41] the relative error is small. In addition, grazed grassland is usually more heterogeneous than cut grassland, posing a challenge to accurate herbage biomass estimations integrated over large pasture areas.

UAV-based mapping sensors, such as LiDAR, offer a notable advantage over traditional RPM measurements by providing spatially continuous information.[42] RPM measurements typically capture vegetation structural data at discrete points within a field,[13] resulting in a more limited understanding of the spatial distribution and variability of the biomass. In contrast, LiDAR scanners capture a continuous point cloud of the vegetation structure, allowing a comprehensive and detailed assessment of herbage biomass distribution across the entire surveyed area.[43] This spatial continuity facilitates more accurate and precise biomass estimation of the whole area than previous point-based methods such as RPMs.

Despite its lower accuracy in estimating AGB, UAV-based LiDAR technology for predicting grassland herbage biomass offers significant advantages over photogrammetry approaches. UAV-based LiDAR provides faster and more efficient acquisition of biomass data.[36] Unlike photogrammetry, which relies on passive optical systems and is dependent on favorable lighting conditions, UAV-based LiDAR is an active sensing technology that operates independently of sunlight. This ability eliminates the limitations posed by poor lighting conditions and extends the potential monitoring period, making it a more robust solution for biomass estimation.[44] Furthermore, the efficiency of UAV-based LiDAR enables a rapid coverage of larger areas in shorter time frames, making it suitable for time-critical applications, such as using a system like the SMI. Furthermore, the seamless integration of geospatial data into the SMI system empowers users to make more informed decisions and optimize grazing systems with greater confidence. This accomplishment signifies a noteworthy advance in agricultural technology, streamlining grazing management through the SMI system's semi-automatic fence generation feature. It holds considerable promise for enhancing livestock practices' overall effectiveness and sustainability.[45] Moreover, the estimation of aboveground standing biomass is not only important for grazing enterprises but also extends, particularly, to cut-and-carry approaches, where grass is usually harvested at distinct phenological stages to obtain sufficient high-quality herbage and to optimize regrowth.[46]

The presented data workflow and analysis unveil novel opportunities for data-driven decision-making in agriculture, potentially driving improved livestock management practices, and possibly resulting in enhanced land and resource use (Higgins et al., 2019).[47]

However, there are certain drawbacks associated with using UAV-based LiDAR for biomass information generation. First, UAV LiDAR systems are more expensive than the optical systems used in photogrammetry, and the cost of acquiring and maintaining the LiDAR equipment and the need for skilled operators can pose financial challenges for dairy farms. In addition, this study used the miniVUX-1UAV LiDAR system. In comparison, other studies, such as the work by Zhang et al.,[23] employed the VUX–1 LiDAR system, which boasts a 10 times higher sampling rate. This higher sampling rate of the VUX–1 system allows for more densely sampled point clouds and potentially improves accuracy in biomass prediction.[24] Therefore, the methodology used in this study may have limitations in achieving the highest possible accuracy. Future research with UAV LiDAR systems with higher sampling rates, such as the VUX-1, could address this limitation and enhance biomass estimation accuracy. Another direction could be that of using handheld SLAM LiDAR devices for biomass estimation.[48] They would provide an alternative when UAV flights are prohibited or not possible. Furthermore, this study has not investigated grassland quality. Oliveira et al.[49] recently demonstrated the potential of hyperspectral UAV imaging sensors in providing these quality parameters.

However, despite these challenges, the technology still offers significant advantages over traditional RPM-based methods and UAV-based photogrammetry approaches, particularly in terms of speed, efficiency, and the ability to capture detailed 3D vegetation structures. While the primary focus of our study has been the quantification of biomass using advanced UAV LiDAR technologies, we acknowledge the integral role that grassland quality and optimal harvest timing play in the overarching context of pasture management. The precision data obtained through our methods can serve as a valuable foundation for developing easy and fast procedures that local farmers could adopt to determine the best periods for harvesting. By ensuring that biomass is not only measured accurately but also harvested at its peak nutritional quality, our findings have the potential to contribute to more sustainable and productive agricultural practices. Further research could certainly build upon our work to provide detailed guidelines that combine quantitative biomass data with qualitative assessments of grassland conditions.

Continued research and development efforts are essential to refine the methodology and improve biomass prediction accuracy using UAV-based LiDAR systems, as well as to enhance the profitable use of acquired data. An important future area of research involves investigating quality parameters as key grass traits. Future research could also explore higher sampling rate LiDAR systems or handheld SLAM LiDAR devices for improved accuracy and accessibility. In addition, the potential integration of hyper- and multispectral imaging with this approach could be promising for analyzing and understanding these quality and quantity parameters in greater detail.

6 Conclusion

In conclusion, this study demonstrates the effectiveness of UAV LiDAR technology for precise grazed grassland herbage biomass estimation in precision livestock management. Integrating UAV LiDAR data provides comprehensive spatial coverage, enabling informed grazing management decisions. The SMI showcases the practical application of UAV LiDAR data in optimizing paddock planning and semi-automated fencing, contributing to more sustainable dairy farming practices. UAV LiDAR technology offers valuable insights for data-driven precision livestock management, leading to enhanced productivity and sustainable farming practices.

Code and Data Availability

The datasets generated and/or analyzed during the current study contain geographic locations, which due to privacy concerns cannot be shared publicly. However, non-spatial data is available from the corresponding author upon reasonable request.

Acknowledgments

We would like to acknowledge the assistance of ChatGPT, a language model developed by OpenAI, for providing valuable suggestions and improvements during the writing process. We also appreciate the use of DeepL for translations and Grammarly for language checking. We are grateful for the support of our student assistants, Johannes Isensee, Irek Ireneus, and Tabea Quitzsch, who provided valuable assistance during the fieldwork phase of this study. In addition, we would like to thank the farm owner Paul Costello, and his employees for their support and cooperation before and during the fieldwork. We would like to acknowledge the proofreading services provided by Anne Wegner from write-english.de. This research was supported by the Federal Ministry of Education and Research (BMBF) (Grant No. 031B0734F) as part of the consortium research project "GreenGrass."

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