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Comparing economic effects of remote herbage mass estimation in small-scale farms in mountain regions

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This study uses a cost-benefit analysis to compare the economic effects of using three digital technologies for herbage mass estimation: Rising Plate Meter (RPM), Unmanned Aerial Vehicle with Structure from Motion (UAV SfM) and Portable Light Detection and Ranging (UAV LiDAR) systems in small-scale farms in mountainous regions of southern Germany. The results show that, at the current state of technology, digital herbage mass estimation leads to comparatively high costs, coming to a large extent from labor and depreciation costs. Despite of the relatively high annual costs, the costs associated with the use of the RPM could be compensated on all investigated farm types by improving their pasture utilization by only 5%. By contrast the costs of a UAV LiDAR could not be compensated on the current state of technology. However as soon as the technical developments and positive changes in the legal framework are implemented, the costs of the UAV-based technologies studied will decrease significantly. This will lead to their wide dissemination in pasture-based production systems.

Keywords
pasture-based production systems, small-scale, precision agriculture, cost-benefit analysis

Growing population forces our agricultural production systems to be revised to be able not to stress the planetary boundaries and at the same time to achieve the goal of food security in all parts of the world (Campbell et al. 2017, Willet et al. 2019). The required sustainable agricultural practices can be implemented with the help of a variety of approaches, including the creation of protected natural areas, sustainable ecological intensification, the diversification of sustainable farms and organic farming (Garnett et al. 2013, Garbach et al. 2017, Tilman et al. 2011). Organic farming is superior to conventional farming in many aspects, particularly regarding its environmental impacts (Mondelaers et al. 2009). Examples of this are lower nutrient inputs into the groundwater, rivers and lakes, lower ecotoxicity of the production processes and higher biodiversity on ecologically managed land (Gamage et al. 2023). However, the challenging issue in organic farming is that yields are often significantly below those of conventional farming. That is why organic farming often requires almost twice as much area to achieve a defined yield level (Tuomisto et al. 2012). As a result, critics argue that organic farming does not produce enough food to meet important humanitarian goals, such as feeding the world's growing population.

Most livestock farms use a high proportion of concentrated feed (CF) in the daily animal feed ration. This leads to a food-feed competition (Makkar 2018, Kelly 2019). Trade-offs occur due to large conversion losses from food provision via animals compared to producing food for direct human consumption. Moreover, the production, processing, and transport of feed account almost for 50% of the

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greenhouse gas (GHG) emissions from livestock worldwide (FAO 2023). Additionally, the significant contribution of methane emissions from enteric fermentation in the digestive systems of ruminant animals should be mentioned regarding livestock housing systems (Olesen et al. 2006, Rotz 2018). That is why there is a growing trend towards vegetarianism and veganism, with appeal for diets without meat or/and animal products (Schader et. al 2015, Muller et al. 2017).

However, when talking about pasture-based livestock systems, the importance of ruminants (mainly cattle) in turning human-inedible feeds, such as grass, into high quality food for human beings must be considered (Ploll et al. 2020). This is particularly important, as two-thirds of agricultural land worldwide (ca. 3.4 billion ha) are grassland that cannot be used for arable production systems, mostly due to its location (soil quality, altitude, precipitation). From the position of sustainable agricultural production and nutrition, it is beneficial to use these areas with ruminants. This is confirmed by various studies dealing with scenario calculations for the possible development of agricultural and dietary systems in the future and their impact (Steffen et al. 2015, Schader et al. 2015, Muller et al. 2017, Kleen and Guatteo 2023).

In the scenario of “Food not Feed”, Schader et al. (2015) argued that an adequate diet (with 3,028 kcal/person and day) for the growing population in 2050 could be achieved even with an improvement of 19 to 46% of the environmental impact of agricultural systems. Only 5% of the energy will come from animal husbandry in this case. However, in the “Food not Feed” scenario, poultry and pig stocks should be dramatically reduced, while all ruminant species would be slightly to sharply (4 to 44%) increased and are fed by grass for the most part. Muller et al. (2017) suggest a similar strategy extended by some more key points: grassland-based feed systems, decrease in food waste and meat consumption as well as increase in organically managed agricultural land. Thus, land consumption would hardly increase, and the negative environmental impacts would drop sharply.

More positive effects from pasture-based livestock systems include well-functioning cycles of nutrients and organic material (Mader et al. 2002), reduction of net GHG emissions from livestock production systems due to the carbon sequestration in the soil (Zhang et al. 2023), provision of further essential ecosystem services such as maintaining biodiversity, water balance and cultural landscape as well as providing animal welfare benefits (Hennessy et al. 2020).

The issue of how organic pasture-based livestock production systems can be made efficient, consistent, and sufficiently developed to meet the demands of society and increasing consequences of climate change still awaits satisfactory solutions.

Digitalization or automatization of some processes could be one solution. Profitability of pasture-based farms depends on the efficient pasture utilization that can be achieved through regular herbage mass (HM) estimation (O’Donovan 2000) to allocate sufficient pasture area and meet the daily nutritional demands of grazing animals (Hanrahan et al. 2017). Precise allocation of livestock to the available herbage on the pasture would reduce losses and save CF which in turn could mitigate the food-feed competition. There are destructive (herbage cut, removal and weighting) and non-destructive methods of HM estimation. Destructive methods are very time and labor consuming, as many samples should be collected to make a good HM estimation on rotationally grazed paddocks (O’Donovan 2002). That is why more and more attention is paid now to alternative (non-destructive) methods such as rising plate meter and remote sensing by aerial imaging (McSweeney et al. 2015, Obanawa et al. 2020, Sun et al. 2021).

In this study, we emphasize the pressing need for further research on the cost-benefit analysis of remote herbage mass estimation. Previous research has demonstrated the feasibility of using rising plate meter or UAV-based sensing to estimate herbage mass remotely. However, more comprehensive studies are necessary to establish and compare economic effects of using these methods (Ghajar and Tracy 2021). Moreover, it is important to consider the individual properties of pastures and needs of farms or regions to achieve the best economic effect.

In our study we have analysed organic pasture-based dairy farms in the South of Baden-Wuerttemberg (Germany), to serve as a basis for discussing the following hypothesis: Digital technologies (rising plate meter or UAV-based remote sensing) for an automated herbage mass estimation can enable an economically meaningful, modern grazing and herd management and thus increase forage performance in small-scale organic pasture-based dairy systems. In selecting the farms for our study, we deliberately focused on organic farms as representative of the agricultural landscape in our project region the South of Baden-Wuerttemberg.

Material and Methods

Data acquisition from pasture-based dairy farms in South Germany

All relevant operational and economic data were quantified and collected in close cooperation with the farm managers of 23 professional farms which are legally obliged to keep records. These records contain all business transactions based on documents. This accounting serves the information of the entrepreneur and is the basis for calculating tax liability. Information about livestock was centrally recorded via the HI animal database, that is an animal identification and information system, conducted by the Bavarian State Ministry for Food, Agriculture and Forests. Animal performance data (e.g. milk yield, age at first calving, reproduction rate) were taken from the State Inspection Associations' reports for individual farms. An average of data sheets from three financial years (2018–2021) is used for the data presented in Table 1. Plant production data (e.g. pasture yield and composition of grasses/herbs/legumes) was collected by our partners with a RPM, quadrat sampling as well as transect surveys.

Table 1: Basic data characterizing small-scale pasture-based model farms in three mountainous grassland regions based on the analysis of 23 organic farms in South Baden-Wuerttemberg

Model farm		**„Valley“**	**„Hill“**	**„Mountain“**
Average characteristics of pastures within model farms	Pasture yield			
	% of steep paddocks			
	% of extensive pasture			
Farms	number	9	5	10
Precipitation	mm/a	1,347	1,300	1,595
Grassland area	ha	53	60	63
Paddock size	ha	5.25	2.38	4
Pasture yield	dt DM/ha	72	61	49
Grasses: Herbs: Legumes	Yield percentage (%)	74:20:6	46:31:23	50:45:2
Crude protein content	%	12.3	13.8	14.5
Energy content	MJ/kg DM	6,1	6,0	5,5

Model farm		„Valley“	„Hill“	„Mountain“
Herd size	heads	43	50	40
Milk yield	kg ECM/cow	7,302	5,902	5,819
Concentrated feed	t/cow	9.37	11.9	6.57
Forage performance	kg ECM/cow	5,263	3,426	4,243
Grazing hours	h/cow/a	2,291	1,880	1,896
Breed[1)]		HF:50%; BV: 50%	VW: 75%; HF: 25%	BV: 25%; HF: 25%; VW: 50%

[1)] HF: Holstein; BV: Braunvieh; VW: Vorderwälder.

Sample description

The non-representative convenience sample encompasses 23 organic dairy farms with pasture feeding in South Germany (Baden-Wuerttemberg). The farms are operated according to the criteria of organic farming under Council Regulation (EC) No. 848/2018 or according to the guidelines of the Bioland (Bioland 2022) and Naturland (Natruland 2022) farming associations. According to Kiefer et al. (2014), success factors for pasture based dairy production are forage performance und grazing hours. These two factors as well as peculiar topographic and climatic properties (e.g. share of steep paddocks and the annual precipitation) that can influence management decisions were used to cluster 23 farms and develop model farms that represent farm organisations in three landscape locations that could be found in mountain regions in Baden-Wuerttemberg. The model farms “Valley”, “Hill” and “Mountain” have common operative and economic characteristics with typical farms in these three locations (Table 1). It is typical for these three regions that grassland yield decreases from the “Valley” through the “Hill” to the “Mountain”. In contrast, the percentage of steep paddocks and extensive pasture areas rise. The model farms in these three locations have a grassland area between 50 ha and 70 ha with a grassland yield between 45 and 85 dt DM/ha and year depending on the region cluster. The average milk yield is between 5,500 and 7,300 kg ECM/cow and year and the forage performance is between 3,500 and 4,700 kg ECM/cow and year. The farms use between 6.57 dt to 11.9 dt of CF per cow and year. Additional production-related characteristics of the farms can be taken from Table 1. All farms deliver their milk to the same dairy in the region. As a result, there are no differences in milk prices (Table 3). The variety in the milk contribution margin between the different model farms could be explained largely by the differences in the milk yield. This data forms the basis for cost-benefit analysis.

Technologies

In our study we analysed three types of technologies for remote automatic herbage mass estimation: Rising Plate Meter (RPM), unmanned aerial vehicle with structure from motion (UAV-SfM) technology and portable light detection and ranging (UAV-LiDAR) systems (Table 2). SfM uses time-delayed images for 3D information, while LiDAR sensors use infrared laser pulses for real-time, accurate environmental images.

Table 2: Characteristics of different technologies for herbage mass estimation/prediction

Feature/Parameter	RPM	UAV-SfM	UAV-LiDAR
Coefficient of determination (R2) Mean and standard deviation	0.68–0.93 0.79 +/- 0.1	0.65–0.81 0.72 +/- 0.07	0.34–0.67 0.55 +/- 0.15
Root Mean Square Error (RMSE) Mean and standard deviation	335–522 kg/ha 409 +/- 81 kg/ha	290–957 kg/ha 642 +/- 273 kg/ha	589–1010 kg/ha 806 +/- 172 kg/ha
Spatial resolution	-	0–2 cm	0–10 cm
Controllability	requires an operator	remote controlled by an operator	
Legal basis (in Germany)	-	- flying license - UAV liability insurance - flight only at sight distance - special permission for flying above some plots or in some areas	
Load	no limitation	with limitation	
Max. application time/Flight time	< 1 Day	up to 27 minutes	
Costs	low	moderate	very high
Flexibility	moderate	high	
Data collection	- easy to use - time-consuming	- specific training is needed - legal restrictions on some plots are possible - time-saving	
Data processing	- rapid and easy	- specific knowledge of how to use Software is necessary	
		- time-consuming	- fast

Source: Schellberg 2008, Dandois et al. 2013, Wang et al. 2017, Borra-Serrano et al. 2019, Grüner et al. 2020, Harder et al. 2020, Higgins 2019, Lussem et al. 2020, Obanawa et al. 2020; Klingler et al. 2020, Murphy et al. 2021, Sun et al. 2021, Togeiro de Alckmin 2021, Lyu et al. 2022, Zhao et al. 2022, Hütt et al. 2022, EASA 2023, Riegl 2023, Bazzo et al. 2023

RPM is the easiest to use and best-established tool for non-destructive herbage mass monitoring (Sanderson et al. 2004). It is widespread in intensive pasture-based dairy systems meanwhile, for example in Ireland and New Zealand (O'Brien et al. 2019). However, especially for heterogeneous or difficult-to-reach areas the herbage mass estimation process with RPM could be very time-consuming and labor-intensive as it requires a correspondingly high sample number and spatially uniformly distributed sampling (Murphy et al. 2020, Hart et al. 2020). That is why more attention was devoted to alternative methods in recent years, such as data collection with unmanned aerial vehicles (UAVs) (Zhang and Kovacs 2012, Bareth and Schellberg 2018, Libran-Embid et al. 2020, Lyu et al. 2022) as they are easy to use and technically efficient for collecting imagery data at different temporal and spatial resolutions (up to some millimetres (Zheng et al. 2020)) also in inaccessible areas (Table 2).

Satellite remote sensing is another alternative that seems promising for effective pasture management (Ali et al. 2016, Wang et al. 2019, Schwieder et al. 2020, Chen et al. 2021, Bazzo et al. 2023). However, most of the high spatial resolution (< 10 m) satellite systems, that are needed to calibrate and evaluate estimation models in agricultural landscapes that are fragmented and have a small average field size, are operated on a commercial basis. Thus, the cost of image acquisition (over 1,000 euro per acquisition depending on the spatial resolution) (Sozzi et al. 2018) for rapid revisit times may become a limiting factor. In addition, meteorological conditions (cloud cover limiting visibility) can severely limit the usefulness of satellite imagery. Experience has shown that there can be several weeks without satellite data or with poor quality images due to weather conditions

(Whitcraft et al. 2015, Bazzo et al. 2023). As the aim of using remote sensing technologies is to provide the farmer with timely data for management decisions, satellite approaches were excluded from our study due to their relative impracticality (at the current state of the art) compared to other technologies.

Rising plate meter (RPM)

We focused on an RPM named Grasshopper® (True North Technologies, Shannon, Co. Clare, Ireland). The RPM measures compressed sward height with the help of an ultrasonic sensor. Precision of this tool is supported by integrated GNSS and Bluetooth systems. Special software that can be installed on a smartphone or tablet and calibrated to the particular region (type of pasture) relates an average compressed sward height of the plot to the dry matter yield (McSweeney et al. 2019). The accuracy of herbage mass estimation varies depending on the growing conditions. Accuracy of estimation can be affected by grassland management regime, growth state of plants, species composition and season (McSweeney et al. 2019). For intensive grasslands, accuracy of up to 90% can be achieved (Murphy et al. 2021). For extensive grasslands the results are less satisfying, and algorithms are needed to be further improved (Hart et al. 2019, Stumpe et al. 2021). Data collection and processing for HM estimation is outlined in Figure 1. Each measurement point is displayed on the plot map in the App, various parameters are recorded, and the herbage mass is estimated with the help of an equation.

Unmanned aerial vehicle with SfM system (UAV-SfM)

Recently, UAV-based remote sensing has received more attention as a means of application in grassland monitoring (Wijesingha 2020, Obanawa et al. 2020). UAV remote sensing systems consist of a platform, a sensor system, a ground control, a data processing system, and one operator (Sun et al. 2021). UAVs can be equipped with different types of imaging and non-imaging sensors. In our study, we have analysed the following combination of UAV and sensors: DJI P4 multispectral (DJI, Shenzhen, China) with multispectral sensor and RGB camera. Due to this combination of sensors, information is collected with 5 cameras covering Blue, Green, Red, Red Edge, and Near Infrared bands (with wavelength ranges from 450 nm up to 1,400 nm) – all at 2 MP with global shutter, on a 3-axis stabilized gimbal. DJI P4 multispectral has a flying time of up to 27 minutes and a take-off mass of 1,487 kg. Further characteristics are described in Table 2.

Data processing and analysis include generation of 3D point clouds and orthomosaics from RGB images with the help of an SfM algorithm (using the Agisoft Metashape software, St. Petersburg, Russia) with a further rasterization (Figure 1). Rasterization is performed through creation of digital surface models (DSM) and digital terrain models (DTM). By subtracting DTM from DSM a canopy height model is calculated, which is further used for prediction of herbage mass with allometric equations (Cunliffe et al. 2016).

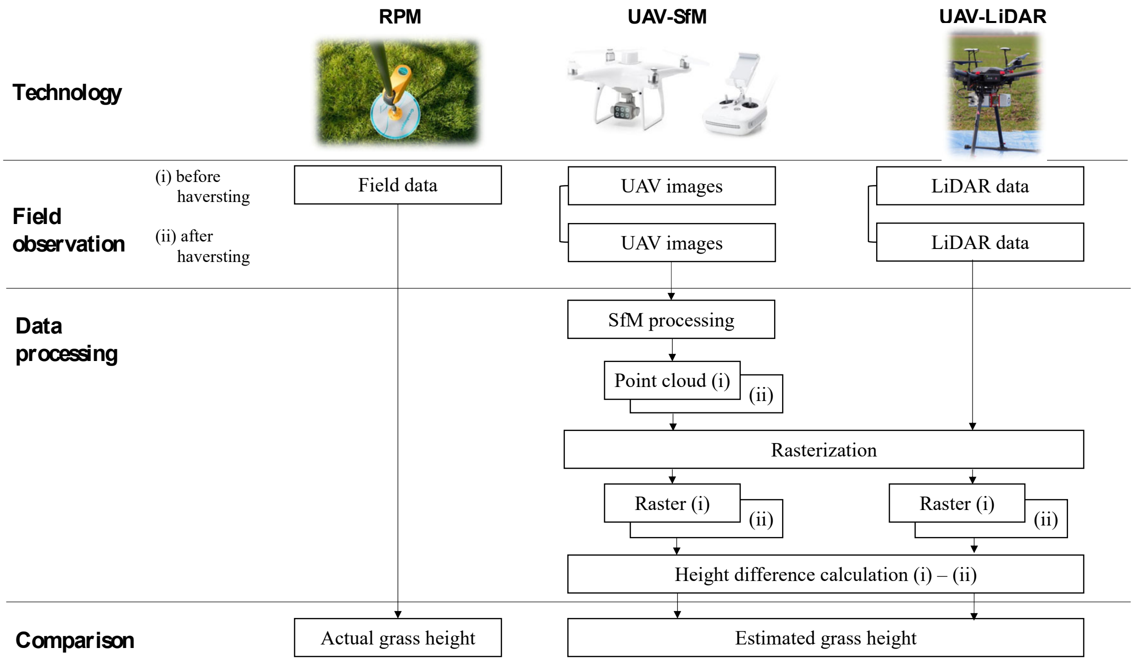


Figure 1: Outline of the measurement procedure (based on Obanawa et al. 2020)

Unmanned aerial vehicle with LiDAR sensor (UAV-LiDAR)

Another promising remote-sensing technology for biomass estimation is LiDAR (ten Harkel et al. 2019, Zhang et al. 2021). Compared with UAV SfM LiDAR sensor is an active sensor that directly generates 3D point clouds (Hütt et al. 2022) which makes data processing not so time- and computer-intensive. Thus, UAV LiDAR can provide more accurate results in a shorter time (Ganz et al. 2019). For our study we used the following combination of UAV and LiDAR sensors: a Riegl miniVUX-1 UAV LiDAR scanner mounted on a DJI Matrice 600 pro UAV (Hütt and Bareth 2022). Further characteristics of UAV LiDAR are presented in Table 2.

At the current state of the art, depending on the type of pasture (its morphological characteristics) and prediction algorithm different ranges of precision are achievable. In this case, precision can be described by the Coefficient of Determination (R^2) and Root Mean Square Error (RMSE) reported in three representative studies (Table 2). The metrics both show that the best results are achieved with the RPM (R^2_{mean} = 0.79; $RMSE_{mean}$ = 409 kg/ha) (Klingler et al. 2020, Murhpy et al. 2021, Togeiro de Alckmin 2021). With the UAV-based technologies (SfM and LiDAR), an average coefficient of determination of only 0.72 and 0.55 can be achieved (Dandois et al. 2013, Wang et al. 2017, Borra-Serrano et al. 2019, Grüner et al. 2020, Lussem et al. 2020, Zhao et al. 2022). It should be noted that the UAV-LiDAR technology is not yet as advanced as the other two technologies.

Cost-Benefit Analysis

In order to economically compare three digital technologies for automatic herbage mass estimation, a cost-benefit analysis was performed. This methodical approach can help to inform, how data-driven decisions align with an organization’s objectives, optimize resource allocation, and maximize the overall value derived from technology investments (Maretto et al. 2023).

To perform cost-benefit analysis, the full costs (acquisition and ongoing costs, such as hardware and software, installation, maintenance, training, etc.) for the RPM, UAV SfM and UAV LiDAR technologies were recorded or calculated (Table 3). The assumptions for the calculations were made based on the results of practical experiments in DiWenkLa-Project, literature, expert discussions with companies, service providers and other research projects. Possible benefits of the use of digital technologies, such as reduction of CF intake and/or increase of forage performance were determined and integrated into a spreadsheet-based calculation model for the three model farms. The farms have different types of pastures in relation to their morphology and topography (Table 1). Heterogeneity of pastures as well as the slope of paddocks have a direct impact on the automatic herbage mass estimation with their digital technologies analysed in this study (Hart et al. 2020). With a grazing duration of 185–205 days per year, the whole pasture area in our project region should be monitored approximately 19 times within the vegetation period, to provide adequate herbage mass estimation. This intensity of 19 times is based on the assumption that a pasture is used three times during a growing season and that monitoring is carried out every seven to ten days.

Depending on the status quo of pasture utilization of every farm, accuracy of technology and management adjustments that a farmer will do after digital herbage estimation, different levels of pasture utilization could be achieved. To account for this, four scenarios were developed: Scenario 1 (70% pasture yield utilization); Scenario 2 (75% pasture yield utilization); Scenario 3 (80% pasture yield utilization) and Scenario 4 (85% pasture yield utilization). As an adaptation strategy for a better pasture utilization, additionally to the reduction of CF intake, an increase in animal stock was calculated. These two adaptation strategies seem to be more realistic in practice. Improved pasture management can improve grassland quality as well (Beukes et al. 2019). This study considers crude protein and energy content in status quo pastures in three locations for feed quantity calculations. However, it does not consider potential qualitative effects of remote herbage mass estimation technologies in cost-benefit analysis or scenario calculation, as these are sensitive to individual farm managers' decisions.

Cost-benefit analysis was performed based on the common assumptions: 4% interest on capital resources, 17.5 € hourly wage, 6 years depreciation period and 470 €/t for CF. Hardware costs for UAV SfM and UAV LiDAR consist of the costs for UAV with sensors, iPad and additional batteries. Software costs for UAV SfM cover one-time activation of SAPOS (the German satellite (real-time) positioning service) and license for AgiSoft. For the data processing from UAV LiDAR activation of SAPOS, software POSpac, RIProcess, RIPrecision and LASTool are needed. To apply these digital technologies, a farmer needs to pay for training and additionally calculate with two hours for RPM and 16 hours (two full working days) for installation and test-phase for UAV SfM and UAV LiDAR. Moreover, a flying license for UAV SfM and UAV LiDAR needs to be obtained.

Table 3: Overview of important assumptions for the cost-benefit analysis for RPM, UAV SfM and UAV LiDAR

Parameter	Unit	RPM	UAV SfM	UAV LiDAR
Acquisition costs in Euro				
Hardware	Euro	1,495	7,593	72,594
Software	Euro	-	3,250	20,065
Installation costs	Euro	35	280	280
Training	Euro	20	2,000	2,000
Data protection	Euro	-	65.99	65.99
Flying license	Euro	-	25	25
Ongoing costs in Euro/a				
Software	Euro/a	-	-	2,000
Field observations	min/ha	7/13.05/19.1[1)]	10	5
Data processing	min/ha	-	20[2)]	3
Training (appr. 2 hours/a)	Euro	-	220	220
Maintenance service	Euro	-	129	129
Additional parameters				
Milk contribution margin	Euro/kg ECM	0.25/0.22/0.21[1)]	0.25/0.22/0.21[1)]	0.25/0.22/0.21[1)]
Milk price	Ct/kg ECM	51.67	51.67	51.67

[1)] For model farms "Valley" /" Hill"/ "Mountain" (Table 1) (own observations; Hart et al. 2020).
[2)] Data processing takes approx. 1 hour/ha; but we have assumed that a farmer does not need to sit in front of the computer all the time, that is why we have reduced the processing time to 60%.

Ongoing costs consist mostly of labor costs for data collection (field observations) and data processing. Time for data collection with RPM differs in the three typical farm regions because of the difference in the average slope of paddocks and share of extensive pasture. The steeper the fields and the higher the proportion of extensive pasture, the more time-intensive is data collection. Data processing with UAV SfM takes approximately one hour per ha. But for our study we have estimated that a farmer does not need to sit in front of the computer all the time, that is why we have reduced the processing time to 60%.

To assess the effect of fluctuations on results of our cost-benefit calculation model in selected variables, a sensitivity analysis was carried out. The following variations were assumed: an increase in milk yield by 10% and 20%; increase in pasture area size by 10%, 20% and 30%; wage increase by 10%, 20% and 30%; reduction of hardware costs by 10%, 20% and 30%; reduction of time required for the use of technology (e. g. data collecting and data processing) by 10%, 20% and 30%.

Results

The results show that, at the current state of technology, digital herbage mass estimation leads to comparatively high costs in ct/kg ECM (from 0.7–3 ct/kg ECM for yield estimation with RPM to 7.6–9.7 ct/kg ECM for UAV LiDAR (Figure 2A)). This is true at least for small non-agglomerated parcels and/or extensive pastures with a high proportion of steep plots.

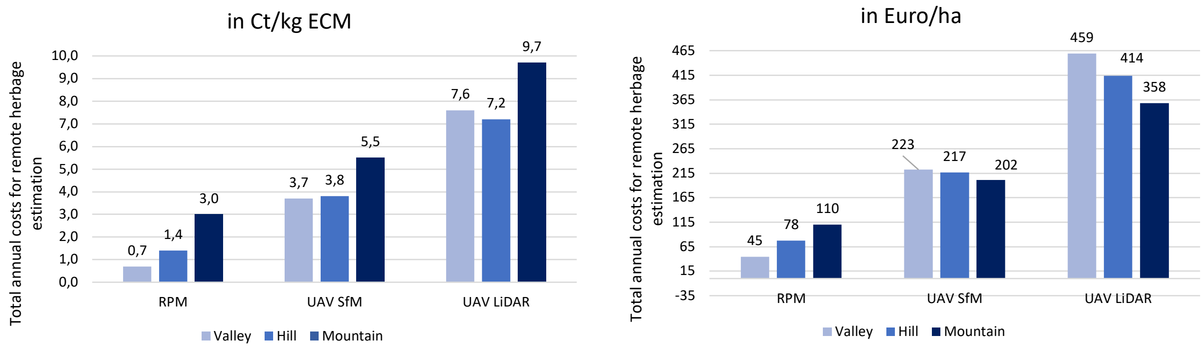
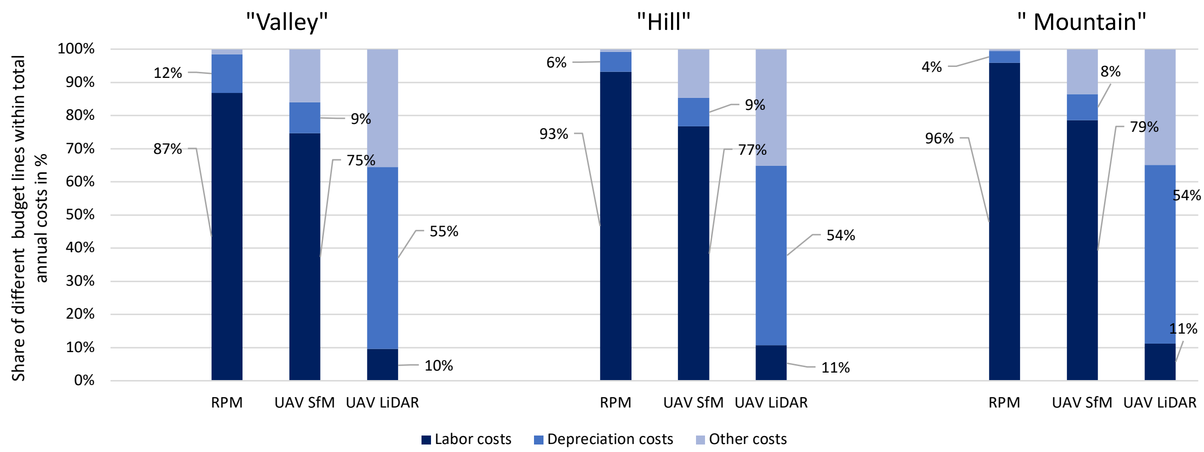


Figure 2A: Total annual costs for remote herbage estimation for different digital technologies and different model farms

Ongoing costs play a major role in the annual costs for the use of RPM and UAV SfM (Figure 2B). Up to 95% of the ongoing costs come from the labor costs for in-field data sampling as well as data evaluation. The high labor intensity of the digital pasture yield estimation is also linked to the fact that farmers must measure their grazing paddock approximately every seven to ten days, depending on the intensity of pasture use during the grazing period. In comparison, high accuracy of yield prediction in crop systems could be achieved with only three measurements per vegetation season (Ali et al. 2022). In case of the UAV LiDAR, depreciation costs account for more than half of the annual costs.



* Other costs include installation costs, licence costs for software, service costs and training costs.

Figure 2B: Share of different budget lines within total annual costs for analysed technologies of remote herbage mass estimation in the depreciation period for different model farms

The results show that the largest economies of scale in the use of digital technologies for automatic pasture yield estimation occur with changes in the wage rate and the time required to use the technology. The costs of all three technologies are around 16% lower for farms that have the same structures as in our clusters but have a 20% higher average milk yield. These are, for example, the farms in "Valley" regions with a milk yield of approx. 7,500 kg ECM/year instead of 6,310 kg ECM/year. As the digital biomass estimation allows for better pasture utilization, the potentially higher CF costs could be overcompensated due to this technology for farms with higher milk yield (compared to the "status quo"). An essential cost reduction is observed by a reduction of the time required for the use of the RPM or UAV SfM. Up to 28% cost savings would be allocated to farms with up to 30% lower proportion of steep and very steep areas and/or areas with high pasture heterogeneity (including nature conservation areas). The importance of the "time intensity" parameter is reflected in the strongly negative effect of an increase in the wage indicator, which is to be expected in the future. Rather larger farms will benefit from the reduction of hardware costs that will use UAV LiDAR technology (in comparison with "status quo"), as the share of depreciation costs in the total annual costs using UAV LiDAR is up to 55%. By contrast, depreciation costs by RPM and UAV SfM correspondingly account for only 3% to 12% and 8% to 10%. Thus, the larger the farm (e.g. pasture area), the higher the costs for data collection and data evaluation for the use of the RPM and the UAV SfM.

Table 5a: Annual costs of the use of different technologies for remote automatic herbage mass estimation per year

	RPM	**UAV SfM**	**UAV LiDAR**
"Valley"	2,189 Euro	10,914 Euro	22,510 Euro
"Hill"	4,266 Euro	11,912 Euro	22,776 Euro
"Mountain"	7,030 Euro	12,909 Euro	22,926 Euro

Table 5b: Possible benefits of better pasture utilization through the use of the three analysed semi-automatic remote herbage mass estimation technologies on different model farms.

<table>
<tr><th>Benefits</th><th>Valley</th><th>Hill</th><th>Moun-tain</th><th>Benefits</th><th>Valley</th><th>Hill</th><th>Moun-tain</th></tr>
<tr><th colspan="4">70% pasture utilization</th><th colspan="4">80% pasture utilization</th></tr>
<tr><td>Decline in concentrate feed costs, in Euro/farm/a</td><td rowspan="5">Status Quo</td><td>n/a</td><td rowspan="5">Status Quo</td><td>Decline in concentrate feed costs, in Euro/farm/a</td><td>12,194</td><td>7,720</td><td>13,843</td></tr>
<tr><td>Concentrate feed reduction, in kg/a</td><td>n/a</td><td>Concentrate feed reduction, in kg/a</td><td>25,944</td><td>16,425</td><td>29,453</td></tr>
<tr><td>Additional profit for the increase in livestock [1)], in Euro/farm/a</td><td>n/a</td><td>Additional profit for the increase in livestock [1)], in Euro/farm/a</td><td>6,090</td><td>n/a</td><td>n/a</td></tr>
<tr><td>Potential increase in livestock, heads</td><td>n/a</td><td>Potential increase in livestock, heads</td><td>6</td><td>n/a</td><td>n/a</td></tr>
<tr><td>Additional milk, in kg ECM/farm/a</td><td>n/a</td><td>Additional milk, in kg ECM/farm/a</td><td>26,376</td><td>n/a</td><td>n/a</td></tr>
</table>

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Benefits	Valley	Hill	Mountain	Benefits	Valley	Hill	Mountain
75% pasture utilization				**85% pasture utilization**			
Decline in concentrate feed costs, in Euro/farm/a	6,671		8,555	Decline in concentrate feed costs, in Euro/farm/a	17,716	13,007	
Concentrate feed reduction, in kg/a	14,194		18,203	Concentrate feed reduction, in kg/a	37,694	27,675	
Additional profit for the increase in livestock*, in Euro/farm/a	n/a	Status Quo	n/a	Additional profit for the increase in livestock*, in Euro/farm/a	10,150	1,920	Increase in milk yield is necessary
Potential increase in livestock, heads	n/a		n/a	Potential increase in livestock, heads	10	1	
Additional milk, in kg ECM/farm/a	n/a		n/a	Additional milk, in kg ECM/farm/a	43,960	4,770	

[1] It is assumed that the infrastructure for the extension of the livestock population is in place and that no further investment is necessary.

Table 5a gives an overview of the total annual technology costs in the different model farms. The total annual costs increased from the “Valley” to the “Mountain” model farms for all three types of technologies. However, the largest difference is observed for the use of RPM, which results in 2,189 euro/a for the “Valley” model farms compared to 7,030 euro/a for the “Mountain” model farms. On the other hand, the difference in the use of UAV LiDAR is only about 400 euro/a between the “Valley” and “Mountain” model farms. Table 5b shows the results of the calculation of possible benefits that could be achieved by using remote herbage mass estimation technologies. For example, depending on the initial accuracy of pasture use and the progress achieved in pasture use through the technologies, savings in CF costs of up to 13,000 euro/a can be achieved for different model farms.

Thus, the results of our cost-benefit analysis with several scenarios show that the costs associated with the use of the RPM could be compensated in all model farms even by improving their pasture utilization by only 5%. For example, at “Valley” locations, the annual costs of 2,189 euro/farm and year can be overcompensated by saving CF costs of 6,671 euro/farm and year. Even in “Mountain” regions the decline in CF-costs (8,555 euro/farm and year) is higher than the annual costs of the use of the technology (7,033 euro/farm and year). By contrast, to compensate the costs of a UAV SfM, a reduction of the CF use must be combined with further adaptation strategies. These could be, for example, a change (or increase) in the herd size (Table 5b). However, to avoid further investments, stable and working capacities must be available. The costs of a UAV LiDAR could not be compensated on the current state of technology, as considerable changes in grazing management, which enable a significantly improved pasture utilization (min. + 25%), are needed.

Moreover, an increased pasture utilization from 5% up to 15% and adjusted forage performance to the race-specific values (up to 6,500 kg ECM/cow and year) in “Valley” regions could save from 14 t up to 37 t of CF per farm yearly (Table 5b) and contribute to the reduction of “food-feed” competition. In case of free stable capacities, additional cows could be fed with a surplus of herbage mass (due to the increased pasture utilization) that results in milk additionally produced. Depending on the region and accuracy of pasture utilization, up to 43,960 kg ECM per farm could be produced additionally every year according to our model calculations.

Discussion

The aim of our study was with the help of cost-benefit analysis to compare economic effects of remote herbage mass estimation tools in small-scale farms in mountain regions. Cost-Benefit Analysis is a widely used method for evaluating for example the economic feasibility of a decision to use a particular technology by comparing the costs and benefits associated with it. With our study we could show that digitalisation in small-scaled pasture-based production systems have the potential to improve traditional farming practices by introducing technology-driven solutions. However, our study has some limitations within empirical evidence about the costs and the economic performance of the use of digital technologies on real world farms. Due to the lack of experiments with the use of technology directly by farm managers on the farm in real conditions, we have assumed a labor intensity for the use of technology based on the experiments with qualified personnel but on real farm pastures. In reality, this labor intensity could be higher due to the lack of experience and know-how of a farm manager. It is also possible that the time spent on data collection could be lower due to better orientation on own pastures and paddocks compared to the external personnel.

Our results show that the economic sensibility of optimizing grazing management through a precise herbage mass estimation depends on the farms' individual management and production system: the more annual feed coming from pasture, the more reasonable would be the decision to invest in such digital technologies. The use of RPM and UAV SfM could already be economically appropriate on several organic pasture-based dairy farms in order to increase forage performance. However, those farms which have an up to 30% lower proportion of steep and very steep areas and/or areas with a high heterogeneity (among other things nature conservation areas) will benefit in the first place. These landscape characteristics increase the time required for data collection when using the RPM. In the case of the UAV SfM, the time for data processing will be reduced the more homogeneous the pasture is. Up to 28% lower costs would be incurred by these farms. By contrast, UAV LiDAR is a technology of the future. Further research is needed since the accuracy of the algorithms for herbage mass estimation with the aid of a LiDAR sensor compared to the RPM and UAV SfM are not yet sufficiently precise. This technology is currently only being tested to be used in grassland but offers great potential through rapid data collection and data processing (compared to RPM and UAV SfM).

Generally, measuring the pastures with the UAV could be a very promising technology, because of the time saving and possibility to fly over different paddocks independent of their topographic features. But there are a few technical limitations. The charge capacity of a battery is about 25 minutes flying time. After that, the UAV must land again, the battery must be replaced, and the UAV must take-off again. The farmer has to replace the UAV after approximately 1000 flight hours. For the UAV SfM and an operating area of 50 ha, this means an exchange after five or six years. Because of legal reasons, the UAV may only fly at sight distance, which is an area of approx. 8 ha. This also limits user-friendliness of this technology.

A possible alternative could be a service for automatic herbage mass estimation. However, this is not yet common in the field of grassland-based production systems in Germany. There are a few providers theoretically, but the prices are very high (approx. 1,000–1,200 Euro for one-time data sampling and processing of 20 ha pasture) if the farmer has to measure his whole area on average 19 times during the grazing period in regions with three grass cuts. However, these costs vary greatly depending on the transport time, the paddock size, the flight altitude, etc. Nevertheless, experience in other countries (e.g. India, USA) shows that technology and service market are very mobile and if more providers will come in the future, prices may also decrease. Another shortcoming is the necessary IT knowledge of the farmers to be able to evaluate the data correctly with the suitable software. This may also lead to additional high education and training costs.

Despite of some current barriers for the widespread use of digital herbage mass estimation for precise pasture management, our analysis shows that the compensation of the additional costs arising from the use of technologies can be achieved by increasing both the milk yield and the forage performance in combination with a reduction of the use of CF and the purchase of staple food (Beukes et al. 2019). If the farmer will adjust not only his grazing management, but the entire farming system (e.g. also introduces seasonal calving), then he can obtain up to 65% of his annual feed from the pasture in grassland regions and thus drastically reduce his production costs (Kiefer et al. 2014). Due to the rising costs for CF, it could be even more attractive for farmers in grassland regions to invest in digital technologies to improve their grazing management. However, the success is very individual and depends heavily on the particular farm manager.

A high proportion of fresh grass in the daily ration of dairy cattle has some more advantages. Cows that eat a lot of grass are usually healthier than those that mainly receive CF. Grass contains many natural nutrients and fibre that support the digestive system of cows and help keep them healthy (Rinehart 2008). Moreover, pasture-based production systems are characterized by a high animal welfare standard, that is important for organic systems. A diet that contains a lot of grass can also affect the quality of milk produced by cows. For example, the milk of cows who eat a lot of grass can contain higher proportions of Omega-3 fatty acids and other healthy nutrients (Dewhurst and Moloney 2013). Grass-based feeding can also help reduce the environmental impact of animal husbandry. Using grass as a main food source can help reduce the use of chemical fertilizers and pesticides as grass is usually less susceptible to pests and diseases (Sanderson et al. 2004).

The results of our study have implications for food security and they could be useful for a transformation to a sustainable food production system. On the one hand, reduced use of CF means that more crops are available for human nutrition, which contributes to increasing food security overall. On the other hand, a decrease in herbage loss due to the adequate pasture management, provides the production systems with additional feed energy that could be used to produce more output in the same area.

Combining remote sensing technologies with artificial intelligence (AI) could improve accuracy, efficiency, and scalability in estimating herbage mass of pastures. For example, machine learning models, such as convolutional neural networks (CNNs), are trained to recognize and classify vegetation in images captured by drones or other remote sensing platforms. By distinguishing between various plant species and ground cover types, AI models can estimate herbage mass more precisely (Picek et al. 2022). Another example are the AI-based regression models that could be developed to predict herbage mass based on various input variables, such as climate data, soil properties, and remote sensing imagery. These models can learn complex relationships within the data and provide more accurate and dynamic predictions of herbage mass across different landscapes (De Rosa et al. 2021).

In terms of future developments that can and are likely to advance the use of remote sensing technologies in pasture management, the ability of UAV-based technologies to assess grassland forage quality should be mentioned (Oliveira et al. 2019, Wijisingha et al. 2020, Geipel et al. 2021). The integration of data from different sensors, such as hyperspectral and thermal sensors, could provide a more comprehensive understanding of forage quality. Through the development and increasing use of machine learning and AI processes, and the resulting ability to learn from large datasets, the accuracy of forage quality predictions would be increased. This will lead to the ability of this technology to be widely used in practice, as tailoring nutrient management strategies based on UAV-derived forage quality data could include the precise application of supplements to optimise the nutritional content of forage. As a result, the economic benefits of using remote pasture monitoring would be greater.

Conclusion

Even for small-scale farms, the use of digital technologies for automated herbage mass estimation including RPM, UAV SfM and UAV LiDAR could provide a conceivable economically meaningful strategy for modern grazing and herd management. This in turn can increase forage performance in organic pasture-based dairy systems and reduce the use of CF. The most promising technology is the use of UAV with different sensors. However, labor and purchasing costs for technology applications should be reduced. At current time, the labor costs in the use of the drone-based methods account for a large share (up to 80% for UAV SfM) of the costs. On the one hand, this is due to the execution and monitoring of the data acquisition and, on the other hand, due to the high effort required for data processing. Currently, the legal framework requires permanent monitoring of the unmanned aerial system. It is conceivable that these requirements will change in the future, significantly reducing the amount of labor required to monitor flights. In addition, automated charging processes may enable more automated operation of the unmanned aerial systems in the future, which will also have a positive impact on labor costs. Active work is already in progress to reduce the time required for data processing. With the help of specially developed software, the demands on the user for evaluation can be reduced, so that the working time is reduced enormously.

Further technological developments have the potential to significantly reduce the cost of UAVs equipped with different sensors. This is particularly important for the widespread adoption of UAV LiDAR, as depreciation costs for this technology can account for up to 55% of the total annual cost. Reductions in technology costs can come from sensor miniaturization, increased demand in the field and the resulting competition between sensor manufacturers, leading to more affordable options. Another promising future development is the standardization of sensor data formats and UAV platforms, which will improve interoperability between different hardware and software systems. This standardization will streamline data processing and analysis, reducing time and cost.

Moreover, further coupling with weather forecasting models and/or farm management information systems will increase the added value of using such technologies. By leveraging AI techniques, herbage mass estimation can be transformed into a more accurate, cost-effective, and scalable process. However, it is essential to emphasize the importance of data quality and proper model validation to ensure the reliability and robustness of AI-based herbage mass estimation systems. As technology and AI algorithms continue to advance, their integration with herbage mass estimation holds promise for improving pasture management practices and sustainable agriculture.

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