agronomy

MDPI

Review

Measuring Herbage Mass: A Review

Varthani Susruthan [1,2], Daniel J. Donaghy [1,*], Paul R. Kenyon [1], Nicholas W. Sneddon [1] and Andrew D. Cartmill [1]

[1] School of Agriculture and Environment, Massey University, Palmerston North 4442, New Zealand; v.susruthan@massey.ac.nz (V.S.); p.r.kenyon@massey.ac.nz (P.R.K.); n.w.sneddon@massey.ac.nz (N.W.S.); a.cartmill@massey.ac.nz (A.D.C.)

[2] Department of Biosystems Technology, Faculty of Technology, University of Jaffna, Kilinochchi 42400, Sri Lanka

* Correspondence: d.j.donaghy@massey.ac.nz

Abstract

The accurate measurement of herbage mass is essential for feed budgeting and the management of sustainable and profitable grazing systems. There are many techniques available to estimate herbage mass in pastoral systems, and these vary in accuracy, cost, and time taken to implement. In situ and remote sensing techniques are both associated with moderate to high error, as herbage mass is affected by a number of dependent and independent factors, including sward composition, soil structure, chemical characteristics and moisture levels, climatic conditions, and grazing management, which must be considered in the development of an accurate local calibration model for precise estimation of herbage mass. This review provides an overview of commonly used herbage mass assessment techniques and describes their limitations, synergies, and trade-offs, and also covers the integration of new technologies which have the potential to monitor pastures at scale. This review highlights the need for further research and to integrate new technologies for accurate and precise measurement of herbage mass, noting the lack of calibration with in situ methods, the need for development of new protocols for assessment, variance in equipment and software compatibility, and the need to evaluate the effectiveness of methods/techniques on a variety of livestock operations for extended periods.

Keywords: herbage mass estimation; livestock grazing system; pasture production

check for updates

Academic Editor: Gianni Bellocchi

Received: 26 August 2025
Revised: 21 September 2025
Accepted: 22 September 2025
Published: 24 September 2025

Citation: Susruthan, V.; Donaghy, D.J.; Kenyon, P.R.; Sneddon, N.W.; Cartmill, A.D. Measuring Herbage Mass: A Review. *Agronomy* **2025**, *15*, 2264. https://doi.org/10.3390/agronomy15102264

1. Introduction

Pastoral grazing systems (varying from intensive irrigated pastures to extensive rangeland) can provide a sustainable and cost-effective means of enhancing the productive capacity of livestock [1,2]. The profitability of pastoral farms depends on pasture quality, production (pasture grown per hectare), and efficient utilisation (pasture consumed per hectare) [1–5]. The quality and quantity of pasture are essential to maintain farm animal production, which is one of the key challenges associated with grazing systems [4]. This may vary with sward composition, season, plant growth stage, and age of regrowth [4,5]. On the other hand, efficient pasture utilisation is a cornerstone of sustainable and profitable livestock farming to ensure that the resource is used to its full potential [1]. However, this remains a fundamental challenge in planning and decision-making in grazing systems [6].

Pastoral grazing systems have varying dynamics, which are influenced by plant species morphological and functional characters, edaphoclimatic factors, sward composition, and pasture and livestock management practices. Due to these varying dynamics, farm managers are advised to monitor herbage mass (HM) production. However, multiple parameters must be taken into account to select an appropriate technique; for example, plant morphological characteristics, growth rate, HM production capacity, and availability of labour, time, and finance are key factors when choosing the most appropriate technique for estimating HM [6,7].

Different techniques for estimating HM are available, and these are often classified based on technique/method; however, accuracy and ease of application vary between techniques. The whole-plot direct sampling method can be used to accurately and reliably measure HM [8,9], while plot sub-sampling is a direct method for estimating HM while minimising interference with the entire sward [8]. These direct methods, while accurate, are time-consuming and challenging at scale, i.e., in large paddocks with a wide variation in pasture HM. Indirect methods of HM measurement minimise the physical removal of herbage, reduce the cost of measurement, and allow for HM estimates to be made from large areas relatively quickly [8]. Indirect methods include using a rising plate meter (RPM), electronic capacitance probe, or a simple pasture ruler, which can be used to estimate the HM after appropriate calibrations are undertaken [10,11].

There are substantial opportunities to use technology to improve utilisation of pasture and thereby improve the profitability of pasture-based systems, through increased accuracy and frequency of pasture monitoring [12–15]. Remote sensing and geographical information systems are increasingly being used to estimate grassland production and validate modelling and forecasting efforts, to support informed decision-making [16–18].

In general, no single method is the most appropriate for measuring HM under all situations [6,9]. However, actual and predictive HM values, for example, uncompressed and compressed plant height, vegetation density, canopy structure and ground cover, plant maturity, botanical composition, visual obstruction measurements, or remote sensing data, can be used to develop a more accurate regression relationship [9,19,20]. Over the past 50 years, more sophisticated and user-friendly techniques and tools have been developed, but few of them have been widely adopted. Possible reasons for this include the fact that these techniques and tools are frequently associated with moderate to high experimental error, and results vary according to the techniques, user, and many other factors. Therefore, the present review paper briefly discusses a variety of HM measurement techniques, their appropriate use, their limitations and trade-offs, and synergies.

2. Techniques to Estimate Herbage Mass

Herbage mass can be directly measured or estimated at different points in the paddock using appropriate techniques or tools termed in situ HM measurements, whereas remote sensing can be used to capture the spatial heterogeneity of vegetation across the paddock at a different scale. Figure 1 illustrates the hierarchical order of various HM assessment tools and techniques. In situ techniques are often used to first calibrate remote sensing instruments. Selecting an appropriate method or technique to estimate HM depends on various factors such as sward characteristics, climatic variations, soil characteristics, and statistical and financial limitations. Table 1 outlines a range of techniques and methods that can be used to measure or estimate HM, along with comments on the synergies and trade-offs of each.

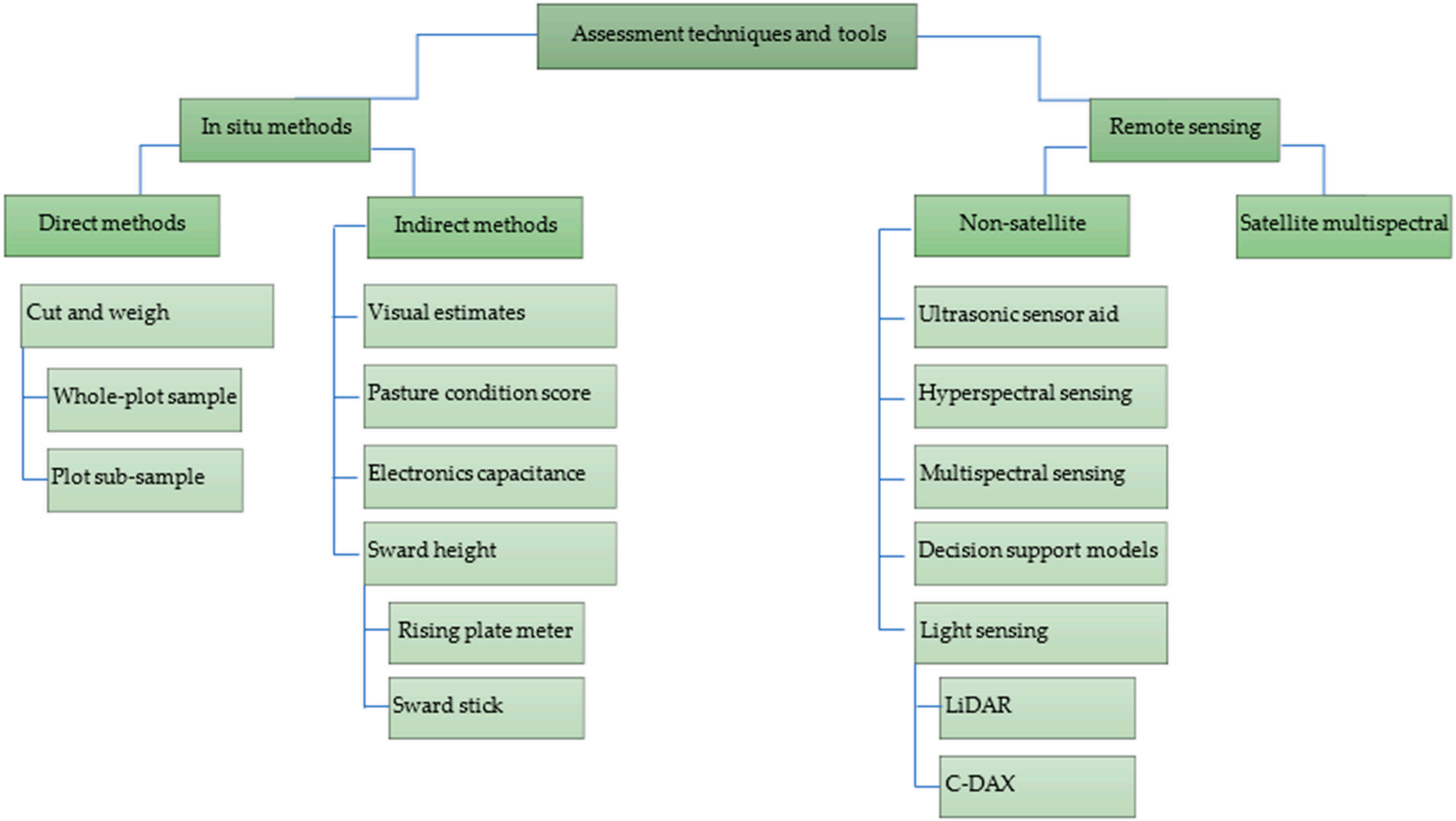

Figure 1. A graphical illustration of the classification of in situ and remote sensing methods for herbage mass measurements.

Table 1. Outline of various measurement techniques used to measure pasture herbage mass that were most relevant to temperate grasslands.

Assessment Techniques and Tools	Measure	Accuracy	Calibration	Destructive or Non-Destructive	Synergies	Trade-Offs	References
Cut and weigh	Weight	High	No	Destructive	Direct method, and accurate for a particular sampling point	Expensive, time-consuming, and labour-intensive Accuracy reduces when generalising to a large area	[21–24]
Visual estimates	SSH and density	Highly variable	Yes	Non-destructive	Quick method, low expense, can assess a large area and is more suited for simple sward	Preliminary training is essential, variation among operators	[8,25,26]
Pasture condition score tool	SSH and density	Low	Yes	Non-destructive	Provide timely resource management recommendations	Variation among operators in scoring	[27,28]
Electronic pasture probe	SSH	Low	Yes	Non-destructive	Quick and simple method for homogeneous vegetation canopies	Readings are affected by moisture in the vegetation, sward type, and ratio of living to dead material	[8–10,23,29]
Sward stick	SSH	Low	Yes	Non-destructive	Simple and suitable for recording the sward surface architecture, and best for hill counties	Less accurate with stemmy material and very tall or lodged grass, time-consuming and labour-demanding	[7,9,10,22,30]
Rising plate meter	CSH	Moderate	Yes	Non-destructive	Quick and cost-effective Suitable for pure or mixed pastures	Regular calibration is essential, different calibration relationships for various seasons, different species composition and labour demand	[7,8,10,22,31,32]

Table 1. *Cont.*

Assessment Techniques and Tools	Measure	Accuracy	Calibration	Destructive or Non-Destructive	Synergies	Trade-Offs	References
Decision support models	Farm records	-	Yes	Non-destructive	Quick and computer-based method	Complex to use and needs training and demonstrations	[33–35]
Light sensing (C-DAX)	SSH	Moderate	Yes	Non-destructive	Provides fast, accurate estimates and relatively low cost among other advanced methods, no cloud cover challenges	Require different seasonal calibrations specific to the region	[36,37]
LiDAR	SSH	Moderate	Yes	Non-destructive	Less time and multiple measurements can be obtained from the same place	Relatively expensive, and poor ability to measure in windy conditions	[38]
Ultrasonic sensor aid	SSH	-	Yes	Non-destructive	Quick response, small instrument, low power consumption and automation	Low accuracy and not suitable for high levels of biomass and sward height	[24,39]
Hyperspectral sensing	SA	-	Yes	Non-destructive	Rapid, reliable approach for near real-time quantitative assessment and accurate	Expensive and needs more studies	[40,41]
Multispectral sensing	SA	-	Yes	Non-destructive	Reasonable accuracy and affordable	Lack of long-term studies	[40,42]
Satellite multispectral	SA	-	Yes	Non-destructive	Large aerial coverage, less time and remote sensing	Cloud cover challenges and needs more studies	[40,43]

Where CSH = compressed sward height; SSH = sward surface height; SA = spectral absorption; "-" = denotes where data were not published as part of the studies or more scientific evidence was needed.

2.1. In Situ Measurement Techniques

(a) Cut and weigh technique

This is the most direct method to measure HM and is highly accurate for the area in which the pasture is harvested. It can also provide an accurate estimate of post-grazing residuals in trampled land [23]. However, in practice on farms, using this technique to estimate HM is unlikely due to it being time-consuming, and it therefore does not allow for relatively quick day-to-day management decisions [22].

Due to the complete removal of herbage from the quadrat, this direct method is considered destructive, and it prevents further measurements in the harvested areas. Similarly, this method does not account for the effects of urine and faeces on the pasture or the effects of trampling or selective grazing, which may cause an overestimation or underestimation of allocated pasture [6]. Lastly, this method is not recommended in shrublands where the spatial variability is very large due to the plant structure, and accuracy reduces when extrapolating to large areas [21].

The number of samples, size, shape, and frame material are based on statistical, agronomic, ecological, practical, and financial considerations [7]. In this method, cutting height is dependent on the grass species, animal grazing habits, industry/sector, and management practices [8]. The size of quadrats depends on the growth habits of grass species and sward uniformity. The number of samples needed to obtain a reliable estimation of total herbage depends on the area size and needs to be representative of the sampling area [7,8].

A strip-cut technique can be undertaken by using a cutting tool/machine that covers more of the existing variation in the sward than using other quadrats [7]. The strip-cut technique means the sampling area length is longer than it is wide. The width of the strip depends on the width or diameter of the cutting machine (handheld power-driven tools, clippers, and lawn or hedge trimmers), while the length can be determined by any type of measuring device. It is a more accurate technique than quadrats in terms of implementation at a paddock scale; however, it is hard to obtain spatial variability data [7], and like the quadrat technique, it is work-intensive. Additionally, cutting machines often need frequent sharpening due to proximity to abrasive soils and other debris [8]. The Danish harvester [7] and Haldrup machines (Haldrup GmbH, Germany) are commonly used harvesters which can reduce work intensity.

(b) Visual estimates

Visual estimation is a quick method for estimating HM; however, preliminary training and/or calibration are essential to ensure accurate estimation of the actual HM by eye [8,25]. The appropriate calibration procedure can transform visual estimates into actual estimations of HM [25]. However, without proper training and calibration, high observer variation in estimation is a considerable drawback of this method [8]. It is more likely to be successful if photographic standards of known yields are used as references during the estimations [26]. This technique is less complicated for experienced operators and more suited for monospecific or simple mixture pasturelands [7].

(c) Pasture condition score tool

The United States Department of Agriculture Natural Resources Conservation Service developed the pasture condition score system to monitor and assess pasturelands [27,28]. This technique is commonly used in rangeland conditions; however, it is not commonly used in New Zealand (NZ). Ten indicators of vegetation and soil status are rated on a scale of 1 to 5, and their aggregate score is used to provide management recommendations and inform resource utilisation [28,44]. The ten indicators include percent of desirable plants, plant cover, plant diversity, plant residue, plant vigour, percent legume, uniformity of use, livestock concentration areas, soil compaction, and erosion [27]. However, variation among operators in scoring (like those of visual estimates) and visually scoring some indicators, such as soil compaction, indicate the need for rapid and objective methods that account for spatial variability [44].

(d) Electronic pasture probe

Electronic instruments such as electronic capacitance meters (Alistair George Manufacturing, Waihi Beach, New Zealand) and sonic sward sticks have been developed to improve the speed and accuracy of HM measurement [9]. An electronic capacitance meter uses a single rod probe and an electronic system that accumulates readings from various sites within a pasture plot to estimate HM [9]. The system measures the capacitance of the air–herbage mixture based on differences in the dielectric constants [9,10]. However, readings are affected by moisture in the vegetation, sward type, season of growth, and ratio of living to dead material [8,22,23], and adjustment on the calibration equations is often needed to obtain a more precise estimation [9,10]. The sonic sward stick (Mk 1 version) utilises an ultrasonic rangefinder to measure sward height [45] from the flight time of an ultrasonic pulse bouncing off the surface of the plants [9]. However, the relationship between sonic height and HM does not always have a proportional relationship due to the multiple reflections from all surfaces, crop geometry (size, angle, and surfaces of leaves), leaf surface, and density of plants [45–47].

(e) Sward stick method

A sward stick, also known as a pasture ruler, is the simplest instrument to estimate HM by measuring the uncompressed canopy height (or 'standing height') of the plant [9]. The sward stick relies on a positive relationship between HM and uncompressed canopy height [9,10] and is considered a good method for recording the architecture of the sward surface [30], particularly in short pastures such as *Lolium perenne* L. and *Trifolium repens* L. [7]. It is quick, user-friendly, and durable [48]. Numerous previous studies, presented in Table 2, revealed the different regression equations, coefficient of determination (R^2) values, and error levels for different swards and seasons (unique to the country) using sward sticks. These calibration equations can be readily employed in these swards with a quick mathematical estimate by inputting the average sward height. For a more detailed analysis, individual height measurements can be efficiently processed using a spreadsheet. However, for more accurate estimations, there is a need to develop different seasonal calibration equations, which may be site/location-specific.

Table 2. Regression models found in the bibliography for herbage dry matter mass (*y*) estimation using the sward stick reading (*x*).

Country	Pastures	Regression Equation	Season/Month	I	R^2	cv	Error	S.E.	Reference
Japan	Bahia grass pasture (*Paspalum notatum*)	y = 294 x − 2205	May	10	0.92	0.237	481 **	-	[49]
		y = 192 x − 1091	June	50	0.92	0.179	306 **	-	
		y = 176 x − 1378	July	50	0.97	0.120	166 **	-	
		y = 232 x − 1460	August	10	0.93	0.184	270 **	-	
		y = 164 x − 286	September	50	0.91	0.168	361 **	-	
		y = 366 x − 2378	October	10	0.89	0.256	842 **	-	
	Centipede grass pasture (*Eremochloa ophiuroides*)	y = 269 x − 893	June	50	0.88	0.200	338 **	-	
		y = 359 x − 1657	July	10	0.98	0.106	318 **	-	
		y = 422 x − 1451	August	50	0.84	0.264	1172 **	-	
		y = 283 x − 424	September	50	0.97	0.093	341 **	-	
		y = 510 x − 1450	October	10	0.97	0.109	443 **	-	
		y = 314 x + 540	November	10	0.57	0.354	1275 **	-	

Table 2. *Cont.*

Country	Pastures	Regression Equation	Season/Month	I	R^2	cv	Error	S.E.	Reference
New Zealand	Plantain (*Plantago lanceolata*) mix	y = 124.4 x + 1647.8	Early spring	168	0.66	-	21 *	6.93	[20]
		y = 152.6 x + 1609.5	Late spring	192	0.49	-	26 *	11.26	
		y = 161.1 x + 1188.1	Summer	72	0.74	-	23 *	11.54	
		y = 109.9 x + 843.3	Autumn	144	0.59	-	20 *	7.75	
		y = 129.4 x + 1418.5	Mean	576	0.50	-	29 *	5.44	
	Chicory (*Cichorium intybus*) mix	y = 118.5 x + 1553.3	Early spring	168	0.54	-	25 *	8.53	
		y = 142.6 x + 1465.8	Late spring	192	0.54	-	25 *	9.48	
		y = 119.1 x + 1534.8	Summer	72	0.56	-	26 *	12.5	
		y = 104.6 x + 814.2	Autumn	144	0.62	-	27 *	6.89	
		y = 112.5 x + 1453.8	Mean	576	0.46	-	30 *	5.05	
	Combined plantain and chicory	y = 121.1 x + 1603.9	Early spring	168	0.59	-	27 *	5.48	
		y = 144.0 x + 1569.8	Late spring	192	0.51	-	26 *	7.29	
		y = 135.1 x + 1396.7	Summer	72	0.64	-	25 *	8.56	
		y = 104.7 x + 854.0	Autumn	144	0.61	-	24 *	4.94	
		y = 118.4 x + 1460.1	Mean	576	0.47	-	30 *	3.69	

Where cv = coefficient of variation; I = number of observations; R^2 = coefficient of determination; error = * RPE = relative predication error (%), ** S.D = standard deviation (kg dry matter/ha); S.E = standard error; x = sward stick reading (height of the plant); y = herbage dry matter mass; "-" = denotes where data were not published as part of the study.

However, the sward stick is unsuitable for very tall or lodged grass and is less accurate with stemmy material and after grazing [7,30]. Multiple measurements have been reported to improve the accuracy of this method in post-grazed and uneven swards [50]. It can also be relatively more expensive than other indirect methods; for example, in projects involving many recorders, communal training is required to achieve consistency between operators [30], and the application at a large farm scale can be challenging in relation to accuracy and consistency when compared to more automated tools.

(f) The rising plate meter method

The RPM method is a commonly used on-farm tool to estimate HM [51]. This established method measures compressed height, which reflects both sward height and density [10,52,53], and converts this to HM via a calibration equation [7,20,31,54–57], and it often shows a positive linear relationship [58]. Rising plate meters measure compressed pasture heights at intervals of 0.5 cm to 1 cm, from a round or square plate of a standard dimension and weight.

The accuracy of an RPM is also affected by factors including pasture type [8], species diversity [31,59], herbage moisture content [8,59], the ratio of green to dead material [8], plant maturity [31], soil type and fertility [53], season [8,53], and geographic region [58]. This instrument has been used to measure pure grass sward/mixed pastures, legumes, and forbs with varying degrees of success (Table 3). These studies demonstrate that the RPM is an effective tool for measurement of different swards; however, its accuracy may vary depending on region and season. Similar to the sward stick, trained operators and regular calibration can also improve estimation accuracy [60].

In addition, similar to a sward stick, the equation can be applied to estimate HM in various ways, including as a direct mathematical calculation and/or combined with applications which will improve the calculation. Recent advancements in RPMs provide highly efficacious grassland management [54]. The RPM, with micro-sonic sensor, digital data capture capabilities via Bluetooth communication, linked to a smart device application, integrated mapping, and decision support tools, ease the HM estimation [54].

Table 3. Regression models found in the bibliography for herbage dry matter mass (*y*) estimation using the rising plate meter reading (*x*).

Country	Pastures	Regression Equation	Season/Month	i	R^2	cv	Error	S.E.	Reference
New Zealand	High-sugar ryegrass and clover	y = 34.9 + 136.6 x	Summer Autumn Winter Spring	50	0.84	-	4.16 *	-	[61]
	Perennial ryegrass and clover	y = 150.4 + 132.5 x			0.76	-	5.23 *	-	
	Tall fescue and clover	y = 139.4 + 118.5 x			0.81	-	3.95 *	-	
	High-sugar ryegrass, clover, herbs	y = 450.5 + 105.3 x			0.86	-	2.90 *	-	
	Perennial ryegrass, prairie grass, clover, herbs	y = 381.4 + 99.1 x			0.80	-	3.40 *	-	
	Tall fescue, lucerne, prairie, grass, clover, herbs	y = 610.6 + 83.5 x			0.80	-	2.90 *	-	
New Zealand	Chicory	y = 86 x + 235	Summer	244	0.73	-	664 **	-	[31]
	Plantain	y = 94 x + 455		135	0.70	-	711 **	-	
	Ryegrass-based	y = 218 x + 48		135	0.73	-	772 **	-	
New Zealand	Plantain mix	y = 86.3 x + 1884.7	Early spring	168	0.63	-	22 *	5.09	[20]
		y = 107.4 x + 1753.6	Late spring	192	0.54	-	25 *	7.12	
		y = 129.9 x + 1204.4	Summer	72	0.61	-	27 *	12.3	
		y = 100.3 x + 843.0	Autumn	144	0.68	-	18 *	5.78	
		y = 100.4 x + 1511.1	Mean	576	0.54	-	28 *	3.86	
	Chicory mix	y = 84.2 x + 1677.6	Early spring	168	0.52	-	21 *	6.28	
		y = 91.3 x + 1660.2	Late spring	192	0.55	-	25 *	6.04	
		y = 72.9 x + 1768.6	Summer	72	0.57	-	25 *	7.50	
		y = 76.3 x + 869.4	Autumn	144	0.66	-	26 *	4.61	
		y = 77.7 x + 1561.3	Mean	576	0.48	-	30 *	3.36	
	Combined plantain and chicory	y = 84.4 x + 1794.6	Early spring	168	0.57	-	24 *	4.03	
		y = 95 x + 1752.4	Late spring	192	0.52	-	26 *	4.63	
		y = 83.7 x + 1716.1	Summer	72	0.53	-	29 *	6.59	
		y = 75.5 x + 1019.8	Autumn	144	0.63	-	24 *	3.41	
		y = 83.8 x + 1596.7	Mean	576	0.49	-	27 *	2.53	
Colombia	Ryegrass and kikuyu	y = 79.7 x + 319.7	Summer	825	0.85	-	-	0.53	[62]
Corvallis	Grass-based	y = 87.7 x − 305.5	Spring	350	0.64	-	-	-	[63]
	Legume-based	y = 110.3 x − 405.7		350	0.81	-	-	-	
	Grass-based	y = 65.1 x − 32.9		350	0.72	-	-	-	
	Legume-based	y = 61.0 x − 79.2		350	0.81	-	-	-	
	Herb-based	y = 79.1 x − 403.5		350	0.84	-	-	-	
Ireland	Perennial and hybrid ryegrass	y = −227.6 + 233.3 x −5.35 × ^{2}	Spring, Summer, and Autumn	1640	0.59	-	19.8 *	-	[57]
		y = −446.5 + t + m + 263.9 x − 6.6 × ^{2}		1640	0.70	-	17.9 *	-	
		y = 111.8 + t + m + 8.9 d + 118.7 x		1640	0.68	-	19.2 *	-	
Austria	Grass-based	y = (x − 40) × 25	Spring, Summer, and Autumn	3796	0.73	33.7	-	-	[64]

Where cv = coefficient of variation; Herbs = (plantain +chicory); I = number of observations; m = month; d = percentage of dry matter (DM) content; R^2 = coefficient of determination; error = * RPE = relative predication error (%), ** S.D = standard deviation (kg DM/ha); S. E = standard error; t = type of ryegrass; x = rising plate meter reading (height of the plant); y = herbage DM mass; "-" = denotes where data were not published as part of the study.

It is important to note that few calibration equations are currently available to estimate the HM using RPM in diverse pasture swards, comprising more than five species. The calibration of an RPM for HM estimation can often differ between sward types, as they are influenced by factors including the density of the sward [32], composition [31], and morphology of the dominant plant [32]. Much like other indirect measuring tools, the RPM method has limitations. Several studies have shown that using RPMs may not be representative of the pasture for various reasons, including a poor relationship between HM and post-grazing residuals (2.5–5.0 cm) [9,22] and the effect of hoof indentions and trampling [23]; in addition, stemmy materials and economic studies suggest that a higher error of prediction may cause economic losses [9,22,64,65]. Around a 10% to 15% error is considered acceptable in most of the RPM studies to generate profits for a farming system [9,10,64]. Generally, RPMs are used for day-to-day decision-making; however, they have some limitations, including potential for high variability with different assessors/operators, and inaccuracy of measurements as a result of rapid pasture growth changes in spring and herbage accumulation on ungrazed areas [13,60].

The error rate can be substantially reduced through appropriate techniques and an approach including an adequate number of readings, selecting a representative area to walk (walking pattern), and correct use of the RPM. Previous studies showed that increasing the number of readings per area reduced the error of average HM estimation. Around 50 to 80 readings are required for maximum accuracy [13,43,60,66]. Previous research conducted in Australia by Gargiulo, Clark, Lyons, de Veyrac, Beale, and Garcia [43] revealed no effect of the walking pattern on the accuracy of RPM. However, ensuring representative sampling is essential to increase accuracy because variations in pasture height and density vary widely across paddocks due to topography, soil characteristics, pasture composition, and grazing patterns [67]. Generally, to avoid operator bias and maximise measurement precision, the sampling points should be randomly selected and spatially balanced throughout a paddock. This can be challenging to implement in practice, so a 'W'-shaped walking pattern is commonly recommended [13]. Because the operator needs to walk across paddocks to take multiple readings, this is often perceived to be laborious and time-consuming. However, the RPM, despite its issues, potentially has the greatest potential as an on-farm tool to estimate HM at scale, e.g., at the whole farm level, as it is generally a sufficiently accurate, quick, user-friendly, and cost-effective method.

2.2. Remote Sensing and More Recent Technologies for Measuring Herbage Mass

Smart farming integrates technologies and traditional farming approaches to improve the quality and quantity of agricultural production, whilst significantly lowering inputs through the utilisation of different techniques [68,69]. The advancement of the Internet of Things, sensing technologies, machine learning, and unmanned/unoccupied aerial vehicles (UAVs) has supported the vision of sustainable smart farming [68,70,71].

Proximal sensing technologies, such as handheld sensors or sensors mounted on UAVs flying at low altitudes, can potentially collect large amounts of data with reduced time and labour investment [13,70,72]. Remote sensing from satellite data has provided a precise estimation of the productivity of large areas [29,43,73], along with growth characteristics [17]. Commonly, broad-waveband sensors carried by Earth Observation Satellites are used in grassland remote sensing [9,43]. However, the high cost of this new technology, including actual equipment costs and licensing, may be prohibitive.

(a) Non-satellite pasture measurements

The most common measurements used in proximal-sensing pasture assessments are digital photographs, Light Detection and Ranging (LiDAR), ultrasonic measurements [39,74], handheld grassland vegetation monitoring systems [75,76], and decision support models [34,77]. Pasture height photographic estimation can be achieved with a simple red–green–blue camera mounted onto a UAV or other vehicle [78]. The pictures are rapidly taken by a UAV, flown over pastures at low altitudes, and loaded into a structure from a motion (SfM) photogrammetry program. Structure from motion uses the ground control point (high-visibility objects used to provide a frame of reference for determining the position of the UAV in the pasture being photographed) to restructure the path of the UAV and generate a point cloud, from which a digital surface model (DSM) and digital elevation model (DEM) are derived [72]. The canopy height for a given point can be calculated by subtracting the DEM height from the DSM height [72]. Lincoln University Dairy Farms, NZ, reported that there is a stronger linear relationship between photogrammetry-derived plant height and actual HM when compared to the normalised difference vegetation index (NDVI). The coefficient of determination was higher for photogrammetry methods (R^2 = 0.92_{May} and R^2 = 0.78_{June}) than the NDVI (R^2 = 0.65_{May} and 0.66_{June}) [79].

The LiDAR generates point clouds similar to SfM techniques but via a different mechanism [72]. Light Detection and Ranging systems measure distance using the time a laser beam takes to reflect off an object and return [38,72]. The combination of the position of the UAV and LiDAR data can provide thousands of pasture height measurements with a single flight, which then provides predicted HM data to the farmers [72]. Optical proximal sensors and aerial vehicle remote sensing can analyse light reflectance correlated with pasture parameters. They do this by extracting reflectance out from wavelengths through remote sensing, which enables the analysis of vegetation indices, including NDVI and leaf area index [70,80,81]. This then provides average HM data to the operators.

The C-Dax (New Zealand) rapid pasture meter (PM) is an example of LiDAR, developed in NZ, which has the potential to provide fast and accurate estimates of pasture HM [82]. This tool is driven around a paddock to obtain many measurement points. The PM comprises a set of light and optical sensors placed at 20 mm intervals. The accompanying software includes an equation to compute the amount of HM per hectare (ha), which can be calibrated using grass height [36,82]. The use of a PM can reduce the time required to estimate the HM at the paddock level [36,83] and has low inter-operator variation due to minimal operator input [36]. The PM has been calibrated for temperate dairy pastures [36,82], and kikuyu [*Cenchrus clandestinus* (Hochst. ex Chiov.) Morrone]-based pastures [36]. However, its suitability for more diverse pastures, or subtropical/tropical pastures, is unclear.

Handheld grassland vegetation monitoring systems, utilising multispectral imaging, are an emerging tool for monitoring HM [75,84]. Generally, multispectral image collection relies on spaceborne, airborne, or UAV platforms. However, due to the advanced development of remote sensing techniques, handheld and ground-based tools such as agricultural field robots [85] or a Specium IQ [84] have been developed [75]. Unfortunately, these tools are expensive and require expert operation skills. More recently, smartphones with high-resolution cameras, wireless connectivity, and Global Positioning System (GPS) technologies have been developed, which are relatively inexpensive compared to previous methods used to capture images [75]. The handheld GreenSeeker, Crop Cirlce™, and CROPSCAN™ are sensor-based NDVIs, which are relatively affordable, user-friendly tools for measurement of plant growth and plant nutrient status [86–89]. GreenSeeker can be effectively used to determine the impact of irrigation and nitrogen (N) fertiliser application on crop plants, particularly in semi-arid regions [76].

Ultrasonic sensors work similarly to LiDAR by emitting a signal and calculating sward height based on the time it takes the signal to return to the sensor [72]. However, ultrasonic sensors use ultrasound and light together, and the height of the sensors relative to the ground needs to be constant for accuracy [39,72].

Decision support models, including Farmax Dairy Pro, DairyNZ pasture growth model, GRAZPLAN, GrazeGro, Overseer, and LINGRA-CC, predict pasture growth rates and help to monitor the HM by utilising sward details and meteorological inputs, including photosynthetically active radiation, mean air temperature and rainfall, and fertiliser (especially N) applications [34,77,90]. These mathematical models are complex and require careful specification and statistical rigour. In some instances, even highly mechanistic models are generally poorly suited to predict pasture growth, reflecting inadequate error handling and data scarcity [33].

Digital assistants or Artificial Intelligence (AI) are anticipated to facilitate and drive significant improvements and advancements across multiple sectors, including pastoral farming [91]. Increased focus on the development and use of AI-based technologies/models in pasture monitoring and decision-making has provided estimations of pasture growth and quality based on a variety of resources, including satellite imagery, weather data, digital photographs, GPS locations, and farm management records [92]. Recent AI-based applications, including AIMER™ (Hamilton, New Zealand), Halter Pasture Pro™ (Halter USA Inc., Boulder, CO, USA), and Proveye™ (Dublin, Ireland), provide HM estimation, pasture cover forecasts, cow position/animal behaviour, animal health data, and virtual fencing capabilities [92–95]. However, while these applications represent a significant advancement in pastoral management, we suggest that their full potential and integration with other 'technology' is yet to be achieved in NZ farming systems and therefore warrants further study.

(b) Satellite pasture measurements

Satellites provide global data acquisition coverage when compared to other technologies [81]. Using satellites to monitor pastures can help monitor large areas with lower labour requirements [70]. The satellite pasture measurement method is a potentially practical and reliable technology for monitoring pastoral lands, because of recent developments in spatial and temporal resolution, image processing and data analysis, and image cost [16,24,43], and provides global data acquisition coverage compared to other technologies [81].

Currently, increasing availability of free or relatively affordable satellite data from both public entities [National Aeronautics and Space Administration (NASA), and the European Space Agency (ESA)] and private companies, including AgroInsider (Évora, Portugal), Data Farming (Toowoomba City, Australia), LIC SPACE™ (LIC, Hamilton, New Zealand), Pasture.io (Pasture.io Pty Ltd., Sandy Bay, Australia), and Pasture Watch (Australia), encourages the use of satellite pasture monitoring methods [18].

The Pasture from Space™ (PFS) technology estimates green feed on offer (above-ground green HM) and pasture growth rate [96–98]. The Moderate Resolution Imaging Spectroradiometer collects the information from PFS, which can rapidly calculate the NDVI [96,97]. However, the NDVI calculated using satellite images varies among observed and predicted feed on offer because it depends on cloud and atmospheric conditions, geometric characters, pasture composition, and seasonal changes [97]. The principle behind this technology is similar to multispectral imaging. The reflectance from plant solar radiation differs in the red and the near-infrared parts of the electromagnetic spectrum. This difference is used to create an index of plant greenness or the NDVI. By using systematic relationship models such as regression models, the NDVI can be used to estimate herbage mass [96]. The tools or online platforms developed using these models deliver information in real time, at low cost, and are user-friendly [99].

In 2017, Livestock Improvement Corporation (LIC) launched LIC SPACE™ as an innovative method of monitoring NZ pasture HM using satellite technologies [100]. The LIC SPACE™ algorithm was used to transform the reflectance values into HM estimates [100]. Research conducted in the Canterbury region of NZ reported that LIC SPACE™ enabled quick pasture management decisions without investing additional time, with 329 kg dry matter (DM)/ha of standard deviation of error in the model predictions [101]. However, a review was undertaken of the LIC SPACE^{TM} service in May 2025 by the LIC team, and subsequently, a decision was made to close the LIC SPACE^{TM} service, which was attributed to a lack of alignment with the company's future goals [100].

Pasture.io is a similar satellite pasture monitoring platform, which was founded in 2005 and officially launched as a commercial service in 2014 [102]. The main difference between LIC SPACE^{TM} and Pasture.io is that Pasture.io utilises a machine-learning environment with three primary sources of information, including satellite imagery, weather parameters, and farm records. This platform, accounting for approximately 30 indices, is purported to produce tailored insights and adapt to seasonal variability and farm-specific conditions [102]. However, this has not been subject to scientific studies, highlighting the need for research to provide a more comprehensive understanding of its implications.

A range of issues can arise from these new technologies and techniques regarding accessibility, availability, accuracy, and inadequate scientific evidence. In addition, there is a need for robust protocols, refinement of methods, and ground truthing for the collection and interpretation of data, and this is compounded by current difficulties in considering spatial and temporal variations in different pasture species [13,16,43,70,103]. Furthermore, challenges associated with these new technologies include: (i) scarcity and equipment limitations (for example in plant phenotyping); (ii) inadequate networking communication in rural areas which may result in the inability to perform and/or unreliable data transfer; (iii) difficulty in selecting an optimal model for the particular crop due to lack of available data for a particular pasture mixture; (iv) lack of knowledge and/or skilled professionals for data interpretation and appropriate application; (v) concern surrounding data ownership and security; and (vi) influences of environmental conditions like atmospheric, cloud, and sun conditions [96,99,104–106]. However, cloud cover is not regarded as a major challenge for long-term use of satellite data [107], as multiple images can be averaged, which expands the possibilities for more data, which in turn supports accurate calibration [70]. Integration of cloud detection systems and use of cloud filtering systems in the satellite data post-processing steps can also lessen challenges associated with image quality [43,108–110].

The methods and protocols for conducting pasture assessments with new technologies are still being developed, and equipment and software vary considerably, resulting in compatibility and proprietary issues between different data streams, which potentially reduces the accuracy and utility of these assessment methods [72]. It is critical to develop a simple and more reliable workflow for the real-time application of data from these new technologies. For example, the complexity of image processing, time requirements, cost of equipment, and the amount of technical knowledge and expertise needed to generate and interpret usable data may, at least in the beginning, be prohibitive to its adoption and utilisation [70,111].

Machine-learning approaches have demonstrated a greater potential for yield estimation from vegetation index data. Accurate yield estimations have been achieved throughout the year over multiple years and include management changes/activity [112,113]. The development of a model using machine learning, satellite imagery, and other data can be an effective tool for grassland monitoring and management [112–115]. However, further studies are required to determine the potential and the implementation of this approach. Morais [113] reported that a model derived by machine learning can be used to estimate the productivity of sown biodiverse pastures with an estimation error of ~882 kg/ha. This model demonstrated good generalisation performance (predictive accuracy) as it did not overfit the training data, indicating that it had learned general patterns in the data rather than just memorising the training examples.

3. Next Steps to Improve Accuracy and Uptake of Remote Tools

The underpinning key to successful pasture HM estimation includes ease and timeliness of relevant data collection and simplicity of data conversion into useful and applicable information, so that the best decisions can be made with all relevant information available [116]. Figure 2 illustrates the trade-offs between the various measurement techniques and tools based on time taken to obtain results, relative cost, and accuracy. The data presented in Figure 2 are from a 9-point hedonic scale, where '9' represents very high and '1' represents very low. These values are not absolute, solid numbers, but rather represent an ordinal scale, which is ranked by using the existing literature and is subject to variation based on context and methodology. Where the scientific literature is scant or does not exist, 'accuracy' could not be determined.

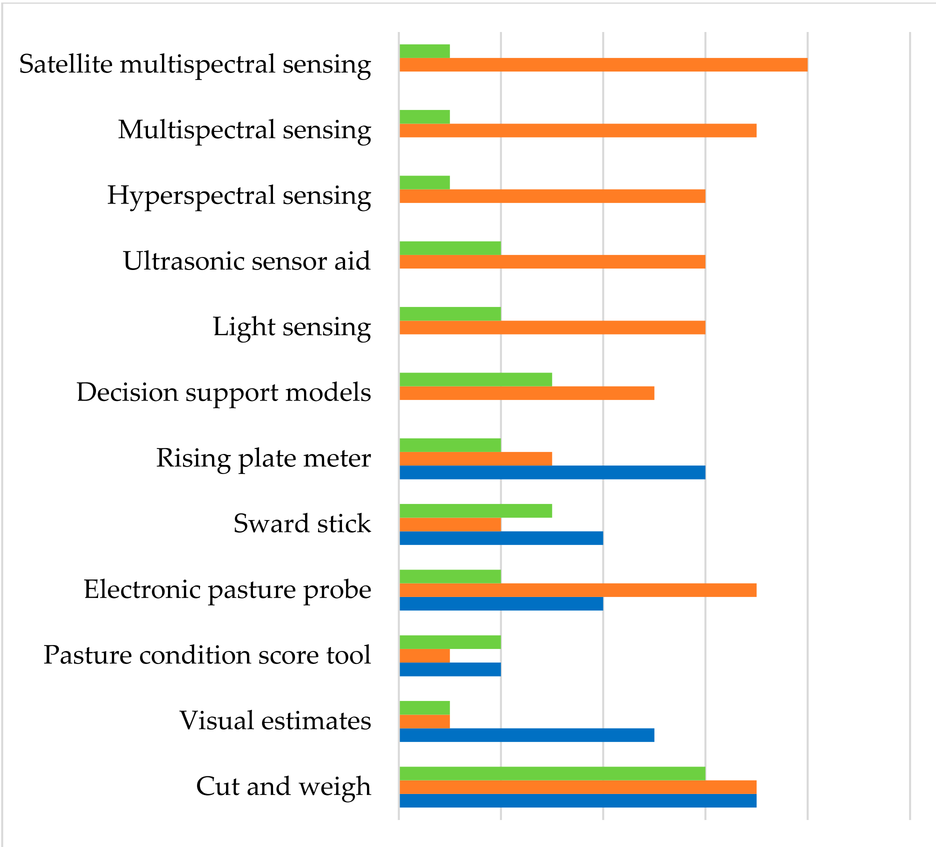

Figure 2. Relative comparison of herbage mass measurement techniques and tools based on time to results (green), relative cost (orange), and accuracy (blue).

The advanced technologies offer a relatively faster response than traditional methods. However, when applying advanced techniques at the farm level, the primary limiting factor for successful adoption encompasses data interpretation and integration (different technologies and/or providers) and cost. Additionally, data calibration and validation/ground truthing are needed, as the data generated are an approximation of an actual value, and each data point has varying levels of quality and uncertainty [72,103,117].

Furthermore, applying advanced technologies remains difficult on more diverse swards because of the variance in the actual species contribution, plant spacing, morphology, distinct canopy characteristics, and colour when compared to a single crop genotype [116]. There is still uncertainty about the extent to which we can sense/collect and attribute individual vegetative properties, along with difficulty in applying program/machine learning. For example, constraints associated with satellite pasture measurements, including pixel size (spatial resolution), frequency of data collection (temporal resolution), errors from cloud cover, geometric corrections, and weather conditions, have prevented the widespread application of this technology [16,18,43]. It is apparent from the methods and research outlined here that for many terrestrial, proximal, and aerial sensing techniques, more extended, detailed studies over numerous seasons and pasture/crop types need to be conducted before these technologies can become established within pasture-based agriculture. On the other hand, the sward stick and the RPM offer a good balance between quick results and cost with moderate accuracy. However, time and workload are scalable and may increase with the size of the land being monitored.

Alternatively, combining different methods could provide a more accurate estimation and help to overcome some of the aforementioned limitations [100,112,114,117]. A study conducted in the Waikato and Canterbury regions of NZ by Anderson, Rawlings, and Ogle [100] revealed that improved accuracy (R^2 and root mean square error (RMSE) improved from 0.672 to 0.703, and from 334 to 309 kg DM/ha, respectively) was observed when the statistical pasture growth model was combined with satellite pasture measurements to help overcome saturation. A comparison study conducted by Ali, Cawkwell, Green, and Dwyer [112] reported that a satellite imagery and machine learning combined model (R^2 = 0.86, RMSE = 11.07 kg DM/ha) outperformed a traditional model (multiple linear regression, R^2 =0.31, RMSE = 25.05 kg DM/ha) [112].

4. Current Challenges Related to Precision Herbage Mass Measurements and the Future of Pasture Monitoring

Effective pasture management and monitoring require the selection of appropriate tools or techniques and the proper application of the selected method, which can reduce errors and increase the accuracy of HM estimation. This review provides an overview of commonly used HM assessment techniques and describes their limitations, synergies, and trade-offs (Table 1). Some of the challenges which limit the use of HM tools and techniques have been highlighted in the review, including sward characteristics, environmental factors, and financial and labour requirements.

Moreover, because of conflict in priorities among farm activities, measuring HM may be difficult, especially in the spring [118,119]. A recent technology survey reported that in NZ, over half of the surveyed dairy farmers were practicing visual estimation (54%) for pasture monitoring in spring, while 22% of respondents used RPM, 5% used satellite-based systems, and 9% of respondents used a tow-behind device [120]. A survey conducted by Eastwood, Dela Rue, and Kerslake [121] revealed that ~68% and ~70% of dairy farmers were practicing some form of objective assessments to rank paddocks and/or determine grazing rotation length in spring and summer, respectively. For example, more than 43% of respondents use RPM, and 19% use a PM in summer. On the other hand, around 27% of respondents in spring and 24% of respondents in summer relied on visual assessment of pasture for decision-making [121]. However, ~10% of farmers did not measure at all over the spring [120].

Within the literature outlined in this review, it is evident that there is a considerable need for optimisation or improvement of HM measuring techniques to increase accuracy and labour efficiency. Additionally, adequate training needs to be provided to the operator to ensure appropriate use of techniques and interpretation of data [13,117]. Hall, Turner, Irvine, and Kilpatrick [122] suggested that operators who are well trained in the HM measuring techniques/methods are more confident in their pasture management ability and are more likely to use these skills in their day-to-day pasture management.

5. Pasture Data Integration: Opportunities and Challenges

Advances in remote sensing, proximal sensing, animal monitoring, and farm management software have expanded the range of measurements available to farmers to support pasture management [117,123]. These data streams, if integrated effectively, hold considerable opportunities for improving on-farm grazing decision-making by linking biophysical (soil, plant, and animal) processes with real-time management. However, translation of remote sensing outputs into actionable grazing plans is challenging. For example, satellite-derived metrics such as the NDVI and related spectral products provide broad spatial coverage and repeatable measurements of pasture conditions [16,124]. Yet, these indices often lack a direct calibration to pasture DM yield, quality, and/or regrowth potential that farmers require for informed decision-making [125], while reflectance from dense/thick pasture canopy may result in underestimation of pasture availability during peak growth periods, and/or under situations of environmental or production stresses [126,127]. This in turn may be compounded by the frequency of remote data collection events, reflecting costs and climatic variability (i.e., cloud cover), which may constrain temporal resolution in fast-growing temperate pasture systems, where optimal defoliation rates are nuanced and context-dependent [128].

We suggest that data integration challenges may also extend beyond sensor limitations. Data 'harmonisation' across platforms/resources/providers may be limited by inconsistencies in measurement scales, formats, and frequency [129,130]. Furthermore, current farm management software is frequently designed for financial or compliance reporting rather than for on-farm grazing decision-making, which we feel may result in 'weak' interoperability with remote sensing platforms and available data streams. The lack of 'standardised' data schemes means that current satellite-derived pasture metrics often cannot be easily incorporated into grazing management tools without substantial preprocessing or model-based translation, which may restrict the ability of farmers and rural professionals to access the data and limit 'useful' interpretation (e.g., paddock rotation schedules, stocking adjustments, or feed budgeting). Current limitations in how these new digital/technological tools present information in an intuitive and actionable format, where data streams are integrated and translated into scalable grazing metrics, along with associated costs, will result in underutilisation, despite their technological potential. We suggest that the development of integrated decision support systems will require co-design with farmers and rural professionals, thereby ensuring that pasture data integration across remote sensing systems/platforms, in-situ sensors, and farm management software packages align with the 'realities' of grazing management.

Advances in machine learning, a 'refocus' on edge computing (i.e., where data processing, analysis, and storage are moved closer to where data are generated, rather than sending it to a centralised cloud or data centre), coupled with proximal sensors and animal-borne devices, offer strategic pathways to overcome latency, with faster response times, reduced network costs (by minimising data transmission), and improved efficiency and reliability, enabling real-time, localised on-farm decision-making [131,132]. Machine learning approaches could be 'trained' to translate raw spectral indices into pasture DM and nutritive metrics under diverse seasonal and regional conditions, and this, coupled with edge-based processing, would allow data integration and decision support to occur in near real time [133,134]. We feel the development of open, standardised data frameworks and participatory innovation models that embed farmer knowledge into system design, will be key drivers of new technologies for pasture data integration. We suggest that these advances could shift satellite-derived information from 'descriptive monitoring' to effective, prescriptive, context-dependent, system-integrated grazing management tools.

6. Linking Measurement Quality to Economic and Environmental Outcomes

Accuracy and reliability of pasture measurements are key drivers of economic efficiency, environmental sustainability, and system resilience [69,135,136]. Inaccurate or low-resolution data on pasture DM, quality, and/or regrowth dynamics may result in misaligned stocking rates, inefficient pasture allocation, and suboptimal rotation timing, which may translate into tangible costs. For example, overestimation of available pasture may result in overgrazing, leading to pasture degradation and reduced animal performance, while underestimation of pasture availability may result in unnecessary supplementary feeding, thereby elevating input costs and reducing profitability. We suggest that both scenarios will likely negatively affect farm profit and may also compromise long-term sustainability and resilience, in which relatively small per-ha inefficiencies can accumulate into significant annual losses.

Environmental implications of measurement quality are equally critical to pasture management. Inaccurate assessment of pasture availability can intensify the risk of overgrazing, soil compaction, and nutrient imbalances. Furthermore, overgrazing reduces biomass and soil organic matter accumulation, diminishing long-term carbon sequestration potential [137,138]. In addition, misjudged pasture allocation may also increase reliance on purchased feed, indirectly raising greenhouse gas (GHG) emissions through imported concentrates and silage, and through associated fertiliser application, harvesting, handling, and transportation. Poor temporal resolution in monitoring may also delay adjustments to grazing pressure, exacerbating N leaching and phosphorus runoff during precipitation events [138–140].

Quality measurements, by contrast, enable finer control of grazing intensity and rotation frequency. When pasture growth rates and herbage quality are measured with greater precision, animal demand with pasture supply can be better aligned, thereby optimising pasture utilisation while maintaining sufficient residual biomass for regrowth and soil protection. We suggest that this 'balance' not only supports consistent animal production but also reduces input dependency and associated GHG emissions. Emerging evidence suggests that farms employing integrated measurement systems, for example, combining remote sensing, ground-based sensors, and predictive modelling, can achieve simultaneous gains in profitability and environmental outcomes through improved feed efficiency and reduced nutrient losses (as reviewed by Papadopoulos, Arduini, Uyar, Psiroukis, Kasimati, and Fountas [141]).

We argue that ultimately, the data in pasture-based systems are not valuable in terms of quantity but rather in quality or 'decision relevance'. Measurement systems that minimise error, improve temporal and spatial resolution, and integrate pasture quality metrics have the potential to transform grazing management from reactive to predictive, which would support greater economic resilience of grazing systems and enhance capacity to meet current and future environmental compliance and sustainability targets [142]. Integration of pasture measurements methods with technological data streams should be viewed as both a 'technical' agronomics challenge, but also as an economic strategy, where enhanced precision and integration of pasture data drives profitability, by fully exploiting potential cost advantages of pasture-based production, while buffering against financial risks associated with pasture shortages and/or mismanagement.

7. Practical Implications

As discussed in this review, appropriate pasture management has the potential to improve farm profitability. We suggest that the integration of pasture management information into decision-making processes has the potential to make a significant positive impact on farm pasture and livestock performance. However, the interface between technologies and practice is still in need of refinement, and while new technologies have been developed to make the laborious, repetitive tasks involved in pasture measuring easier, there still appears to be some way to go. Furthermore, new and promising remote-sensing technologies for HM measurement require additional ground truthing for validation and appropriate incorporation into the pasture management decision-making process.

Author Contributions: Conceptualisation, V.S., D.J.D., A.D.C., P.R.K. and N.W.S.; data curation and writing—original draft preparation, V.S.; writing—review and editing, D.J.D., A.D.C., P.R.K. and N.W.S.; supervision, D.J.D., A.D.C., P.R.K. and N.W.S.; funding acquisition, D.J.D. and A.D.C. All authors have read and agreed to the published version of the manuscript.

Funding: This study is an output from the Whenua Haumanu programme, funded by the Ministry for Primary Industry (MPI). Whenua Haumanu is a partnership between Massey University and the MPI through the Sustainable Food and Fibre Futures fund. Programme research delivery partners include Lincoln University, Bioeconomy Science Institute (AgResearch and Manaaki Whenua – Landcare Research) and the Riddet Institute. The authors acknowledge the publication funding support from the School of Agriculture and Environment, College of Sciences, Massey University.

Data Availability Statement: No new data were generated for this review. All information used in this review are derived from published sources.

Acknowledgments: We gratefully thank the Whenua Haumanu Program and Sinclair Cummings Veterinary and Animal Sciences Scholarship for financial support of Varthani Susruthan and the T.R. Ellett Agricultural Research Trust for financial support of Andrew D. Cartmill.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
CSH	Compressed sward height
CV	Coefficient of variation
DEM	Digital elevation model
DM	Dry matter
DSM	Digital surface model
ESA	European Space Agency
GHG	Greenhouse gas
GPS	Global Positioning System
HM	Herbage mass
LIC	Livestock Improvement Corporation
LiDAR	Light Detection and Ranging
N	Nitrogen
NASA	National Aeronautics and Space Administration
NDVI	Normalised difference vegetation index
NZ	New Zealand
PFS	Pasture from Space™
PM	Pasture meter
R^2	Coefficient of determination
RMSE	Root mean square error
RPE	Relative prediction error
RPM	Rising plate meter
S.D.	Standard deviation
S.E.	Standard error
SfM	Structure from a motion

SSH	Sward surface height
UAV	Unmanned/unoccupied aerial vehicle

References

1. García, S.C.; Clark, C.E.F.; Kerrisk, K.L.; Islam, M.R.; Farina, S.R.; Evans, J. Gaps and variability in pasture utilisation in Australian pasture based dairy systems. In *Proceedings of the 22nd International Grassland Congress, Sydney, Australia, 15–19 September 2013*; Michalk, D.L., Millar, G.D., Badgery, W.B., Broadfoot, K.M., Eds.; Department of Primary Industries: Sydney, Australia, 2013; pp. 1709–1716.
2. Ferris, C.P.; Watson, S.; Gordon, A.W.; Barley, J. Physical and economic performance of dairy cows managed within contrasting grassland-based milk production systems over 3 successive lactations. *J. Dairy Sci.* **2022**, *105*, 3153–3175. [CrossRef]
3. Liu, T.; Bruins, R.J.F.; Heberling, M.T. Factors Influencing Farmers' Adoption of Best Management Practices: A Review and Synthesis. *Sustainability* **2018**, *10*, 432. [CrossRef]
4. Hennessy, D.; Delaby, L.; van den Pol-van Dasselaar, A.; Shalloo, L. Increasing grazing in dairy cow milk production systems in Europe. *Sustainability* **2020**, *12*, 2443. [CrossRef]
5. Thomas, D.T.; Flohr, B.M.; Monjardino, M.; Loi, A.; Llewellyn, R.S.; Lawes, R.A.; Norman, H.C. Selecting higher nutritive value annual pasture legumes increases the profitability of sheep production. *Agric. Syst.* **2021**, *194*, 103272. [CrossRef]
6. Edvan, R.; Bezerra, L.; Marques, C.; Carneiro, M.S.; Oliveira, R.; Ferreira, R. Methods for estimating forage mass in pastures in a tropical climate. *Rev. Ciências Agrárias* **2016**, *39*, 36–45. [CrossRef]
7. 't Mannetje, L. Measuring biomass of grassland vegetation. In *Field and Laboratory Methods for Grassland and Animal Production Research*; 't Mannetje, L., Jones, R., Eds.; CABI Publishing: Wallingford, UK, 2000; pp. 151–177.
8. Frame, J. Herbage mass. In *Sward Measurement Handbook*, 2nd ed.; Davies, A., Baker, R.D., Grant, S.A., Laidlaw, A.S., Eds.; The British Grassland Society: Berkshire, UK, 1993; pp. 39–68.
9. López-Díaz, J.E.; Roca-Fernández, A.I.; González-Rodríguez, A. Measuring Herbage Mass by Non- destructive Methods: A Review. *J. Agric. Sci. Technol.* **2011**, *1*, 303–314.
10. Sanderson, M.A.; Rotz, C.A.; Fultz, S.W.; Rayburn, E.B. Estimating forage mass with a commercial Capacitance meter, Rising plate meter, and Pasture ruler. *Agron. J.* **2001**, *93*, 1281–1286. [CrossRef]
11. Paczkowski, A.; Isselstein, J.; Hartmann, S. Prediction of herbage mass in pure stands of lucerne and red clover using a plate meter. In *28th General Meeting of the European Grassland Federation, Helsinki, Finland, 19–22 October 2020*; Virkajärvi, P., Hakala, K., Hakojärvi, M., Helin, J., Herzon, I., Jokela, V., Peltonen, S., Rinne, M., Seppänen, M., Uusi-Kämppä, J., Eds.; The Organising Committee of the 28th General Meeting of the European Grassland Federation, Natural Resources Institute Finland: Helsinki, Finland, 2020; Volume 25, pp. 37–39.
12. Bucci, G.; Bentivoglio, D.; Belletti, M.; Finco, A. Measuring a farm's profitability after adopting precision agriculture technologies: A case study from Italy. *Acta IMEKO* **2020**, *9*, 65–74. [CrossRef]
13. Murphy, D.J.; Murphy, M.D.; O'Brien, B.; O'Donovan, M. A Review of precision technologies for optimising pasture measurement on Irish grassland. *Agriculture* **2021**, *11*, 600. [CrossRef]
14. Shalloo, L.; Byrne, T.; Leso, L.; Ruelle, E.; Starsmore, K.; Geoghegan, A.; Werner, J.; O'Leary, N. A review of precision technologies in pasture-based dairying systems. *Ir. J. Agric. Food Res.* **2021**, *59*, 279–291. [CrossRef]
15. Aquilani, C.; Confessore, A.; Bozzi, R.; Sirtori, F.; Pugliese, C. Review: Precision Livestock Farming technologies in pasture-based livestock systems. *Animal* **2022**, *16*, 100429. [CrossRef] [PubMed]
16. Ogungbuyi, M.G.; Mohammed, C.; Ara, I.; Fischer, A.M.; Harrison, M.T. Advancing skyborne technologies and high-resolution satellites for pasture monitoring and improved management: A review. *Remote Sens.* **2023**, *15*, 4866. [CrossRef]
17. Persson, T.; Murguzur, F.J.A.; Davids, C.; Höglind, M.; Jørgensen, M. Combining satellite-sensed and ground data and the BASGRA model to predict grass yield in high-latitude regions. *Field Crops Res.* **2024**, *318*, 109610. [CrossRef]
18. Pinna, D.; Pezzuolo, A.; Cogato, A.; Pornaro, C.; Macolino, S.; Marinello, F. Applications of satellite platforms and machine learning for mapping and monitoring grasslands and pastures: A systematic and comprehensive review. *Smart Agric. Technol.* **2024**, *9*, 100571. [CrossRef]
19. Vermeire, L.T.; Gillen, R.L. Estimating herbage standing crop with visual obstruction in tallgrass prairie. *J. Range Manag.* **2001**, *54*, 57–60. [CrossRef]
20. Somasiri, S.C.; Kenyon, P.; Morel, P.; Kemp, P.; Morris, S. *Alternative Method to Measure Herbage Dry Matter Mass in Plantain and Chicory Mixed Swards Grazed by Lambs*; New Zealand Society of Animal Production: Napier, New Zealand, 2014; Volume 74, pp. 115–120.
21. Catchpole, W.R.; Wheeler, C.J. Estimating plant biomass: A review of techniques. *Aust. J. Ecol.* **1992**, *17*, 121–131. [CrossRef]
22. Murphy, W.M.; Silman, J.P.; Barreto, A.D.M. A comparison of quadrat, capacitance meter, HFRO sward stick, and rising plate for estimating herbage mass in a smooth-stalked, meadowgrass-dominant white clover sward. *Grass Forage Sci.* **1995**, *50*, 452–455. [CrossRef]

23. Stockdale, C.R.; Kelly, K.B. A comparison of a rising-plate meter and an electronic capacitance meter for estimating the yield of pastures grazed by dairy cows. *Grass Forage Sci.* **1984**, *39*, 391–394. [CrossRef]
24. Reddersen, B.; Fricke, T.; Wachendorf, M. A multi-sensor approach for predicting biomass of extensively managed grassland. *Comput. Electron. Agric.* **2014**, *109*, 247–260. [CrossRef]
25. Campbell, N.A.; Arnold, G.W. The visual assessment of pasture yield. *Aust. J. Exp. Agric. Anim. Husb.* **1973**, *13*, 263–267. [CrossRef]
26. Cayley, J.W.D.; Bird, P.R. *Techniques for Measuring Pastures*; Victoria Dept of Agriculture, Energy and Minerals: Victoria, Australia, 1996.
27. Cropper, J.B.; Cosgrove, D. Pasture Condition Scoring. In Proceedings of the 37th North American Alfalfa Improvement Conference, Madison, WI, USA, 16–19 July 2000; Phillips, M., Terrill, T., Belesky, D., Berdahl, J., Eds.; American Forage and Grassland Council: Berea, KY, USA, 2000; pp. 141–145.
28. Sanderson, M.A.; Goslee, S.C.; Gonet, J.; Stout, R. Pasture monitoring at a farm scale with the USDA NRCS pasture condition score system. *J. Soil Water Conserv.* **2009**, *64*, 423–433. [CrossRef]
29. Tucker, C.J.; Vanpraet, C.L.; Sharman, M.J.; Ittersum, G.V. Satellite remote sensing of total herbaceous biomass production in the Senegalese Sahel: 1980–1984. *Remote Sens. Environ.* **1985**, *17*, 233–249. [CrossRef]
30. Stewart, K.E.J.; Bourn, N.A.D.; Thomas, J.A. An evaluation of three quick methods commonly used to assess sward height in ecology. *J. Appl. Ecol.* **2002**, *38*, 1148–1154. [CrossRef]
31. Haultain, J.; Wigley, K.; Lee, J.M. *Rising Plate Meters and a Capacitance Probe Estimate the Biomass of Chicory and Plantain Monocultures with Similar Accuracy as for Ryegrass-Based Pasture*; New Zealand Grassland Association: Alexandra, New Zealand, 2014; Volume 76, pp. 67–74. [CrossRef]
32. Rayburn, E. Plate meter calibrations for forage mass follow a continuum of sward basal density. *Crop Forage Turfgrass Manag.* **2020**, *6*, 6–11. [CrossRef]
33. Woodward, S.; Rollo, M. *Why Pasture Growth Prediction is Difficult*; Agronomy Society of New Zealand: Palmerston North, New Zealand, 2002; Volume 32, pp. 17–26.
34. Bryant, J.R.; Ogle, G.; Marshall, P.R.; Glassey, C.B.; Lancaster, J.A.S.; García, S.C.; Holmes, C.W. Description and evaluation of the Farmax Dairy Pro decision support model. *N. Z. J. Agric. Res.* **2010**, *53*, 13–28. [CrossRef]
35. Eastwood, C.; Dela Rue, B. Developing decision-support systems for pasture and rangeland management. In *Improving Data Management and Decision Support Systems in Agriculture*; Burleigh Dodds Series in Agricultural Science; Burleigh Dodds Science Publishing: Sawston, UK, 2020; pp. 279–310.
36. Rennie, G.M.; King, W.M.; Puha, M.R.; Dalley, D.E.; Dynes, R.A.; Upsdell, M.P. Calibration of the C-DAX Rapid Pasturemeter and the rising plate meter for kikuyu-based Northland dairy pastures. *Proc. N. Z. Grassl. Assoc.* **2009**, *71*, 49–55. [CrossRef]
37. McCarthy, A.C.; Raedts, P.; Foley, J.; Hills, J. Improving pasture growth assessment using machine vision. In *Australasian Dairy Science Symposium*; Australasian Dairy Science: Queensland, Australia, 2022; pp. 103–106.
38. Obanawa, H.; Yoshitoshi, R.; Watanabe, N.; Sakanoue, S. Portable LiDAR-based method for improvement of grass height measurement accuracy: Comparison with SfM methods. *Sensors* **2020**, *20*, 4809. [CrossRef] [PubMed]
39. Legg, M.; Bradley, S. Ultrasonic arrays for remote sensing of pasture biomass. *Remote Sens.* **2019**, *12*, 111. [CrossRef]
40. Askari, M.S.; McCarthy, T.; Magee, A.; Murphy, D.J. Evaluation of Grass Quality under Different Soil Management Scenarios Using Remote Sensing Techniques. *Remote Sens.* **2019**, *11*, 1835. [CrossRef]
41. Numata, I.; Roberts, D.; Chadwick, O.; Schimel, J.; Galvao, L.; Soares, J. Evaluation of hyperspectral data for pasture estimate in the Brazilian Amazon using field and imaging spectrometers. *Remote Sens. Environ.* **2008**, *112*, 1569–1583. [CrossRef]
42. Edirisinghe, A.; Clark, D.; Waugh, D. Spatio-temporal modelling of biomass of intensively grazed perennial dairy pastures using multispectral remote sensing. *Int. J. Appl. Earth Obs. Geoinf.* **2012**, *16*, 5–16. [CrossRef]
43. Gargiulo, J.; Clark, C.; Lyons, N.; de Veyrac, G.; Beale, P.; Garcia, S. Spatial and Temporal Pasture Biomass Estimation Integrating Electronic Plate Meter, Planet CubeSats and Sentinel-2 Satellite Data. *Remote Sens.* **2020**, *12*, 3222. [CrossRef]
44. Sanderson, M.A.; Goslee, S.C.; Cropper, J.B. Pasture assessment in the Northeast United States. *Forage Grazinglands* **2005**, *3*, 1–9. [CrossRef]
45. Hutchings, N.J. Factors affecting sonic sward stick measurements: The effect of different leaf characteristics and the area of sward sampled. *Grass Forage Sci.* **1992**, *47*, 153–160. [CrossRef]
46. Fricke, T.; Richter, F.; Wachendorf, M. Assessment of forage mass from grassland swards by height measurement using an ultrasonic sensor. *Comput. Electron. Agric.* **2011**, *79*, 142–152. [CrossRef]
47. Fricke, T.; Wachendorf, M. Combining ultrasonic sward height and spectral signatures to assess the biomass of legume–grass swards. *Comput. Electron. Agric.* **2013**, *99*, 236–247. [CrossRef]
48. Beef + Lamb New Zealand. *Measuring Pasture Covers Using the Sward Stick—Fact Sheet 2013*; Beef + Lamb New Zealand: Wellington, New Zealand, 2013; p. 92.

49. Ogura, S.; Nagatomo, Y.; Hirata, M. Estimation of herbage mass in a bahia grass (*Paspalum notatum*) and a centipede grass (*Eremochloa ophiuroides*) pasture using a capacitance probe, a sward stick and a rising plate. *Trop. Grassl.* **2005**, *39*, 22–30.
50. Martin, R.C.; Astatkie, T.; Cooper, J.M.; Fredeen, A.H. A Comparison of Methods Used to Determine Biomass on Naturalized Swards. *J. Agron. Crop Sci.* **2005**, *191*, 152–160. [CrossRef]
51. Earle, D.F.; McGowan, A.A. Evaluation and calibration of an automated rising plate meter for estimating dry matter yield of pasture. *Aust. J. Exp. Agric. Anim. Husb.* **1979**, *19*, 337–343. [CrossRef]
52. Thomson, N.A.; Upsdell, M.P.; Hooper, R.; Henderson, H.V.; Blackwell, M.B.; McCallum, D.A.; Hainsworth, R.J.; MacDonald, K.A.; Wildermoth, D.D.; Bishop-Hurley, G.J.; et al. Development and evaluation of a standardised means for estimating herbage mass of dairy pastures using the rising plate meter. *Hamilton* **2001**, *63*, 149–157. [CrossRef]
53. Murphy, D.J.; O' Brien, B.; Hennessy, D.; Hurley, M.; Murphy, M.D. Evaluation of the precision of the rising plate meter for measuring compressed sward height on heterogeneous grassland swards. *Precis. Agric.* **2020**, *22*, 922–946. [CrossRef]
54. McSweeney, D.; Coughlan, N.E.; Cuthbert, R.N.; Halton, P.; Ivanov, S. Micro-sonic sensor technology enables enhanced grass height measurement by a Rising Plate Meter. *Inf. Process. Agric.* **2019**, *6*, 279–284. [CrossRef]
55. Griggs, T.C.; Stringer, W.C. Prediction of Alfalfa Herbage Mass Using Sward Height, Ground Cover, and Disk Technique. *Agron. J.* **1988**, *80*, 204–208. [CrossRef]
56. L'Huillier, P.J.; Thomson, N.A. *Estimation of Herbage Mass in Ryegrass/White Clover Dairy Pastures*; New Zealand Grassland Association: Matamata, New Zealand, 1988; Volume 49, pp. 117–122. [CrossRef]
57. McSweeney, D.; Delaby, L.; O'Brien, B.; Ferard, A.; Byrne, N.; McDonagh, J.; Ivanov, S.; Coughlan, N.E. Dynamic algorithmic conversion of compressed sward height to dry matter yield by a rising plate meter. *Comput. Electron. Agric.* **2022**, *196*, 106919. [CrossRef]
58. Pontes, L.d.S.; Carpinelli, S.; Stafin, G.; Porfírio-da-Silva, V.; Santos, B.R.C.d. Relationship between sward height and herbage mass for integrated crop-livestock systems with trees. *Grassl. Sci.* **2017**, *63*, 29–35. [CrossRef]
59. Serrano, J.M.; Peça, J.O.; Marques da Silva, J.; Shahidian, S. Calibration of a capacitance probe for measurement and mapping of dry matter yield in Mediterranean pastures. *Precis. Agric.* **2011**, *12*, 860–875. [CrossRef]
60. Lile, J.A.; Blackwell, M.B.; Thomson, N.A.; Penno, J.W.; Macdonald, K.A.; Nicholas, P.K.; Lancaster, J.A.S.; Coulter, M. Practical use of the rising plate meter (RPM) on New Zealand dairy farms. *Proc. N. Z. Grassl. Assoc.* **2001**, *63*, 159–164. [CrossRef]
61. Nobilly, F.; Bryant, R.H.; McKenzie, B.A.; Edwards, G.R. *Productivity of Rotationally Grazed Simple and Diverse Pasture Mixtures Under Irrigation in Canterbury*; New Zealand Grassland Association: Tauranga, New Zealand, 2013; Volume 75, pp. 165–171.
62. Cárdenas, J.; Balocchi, O.; Calvache, I. Calibration of the rising plate meter for mixed pastures of ryegrass (*Lolium perenne* L.) and Kikuyu (*Cenchrus clandestinus*). *Chil. J. Agric. Anim. Sci.* **2020**, *36*, 216–223. [CrossRef]
63. Wilson, R.L.; Bionaz, M.; MacAdam, J.W.; Beauchemin, K.A.; Naumann, H.D.; Ates, S. Milk production, nitrogen utilization, and methane emissions of dairy cows grazing grass, forb, and legume-based pastures. *J. Anim. Sci.* **2020**, *98*, skaa220. [CrossRef]
64. Chapa, J.M.; Pichlbauer, B.; Bobal, M.; Guse, C.; Drillich, M.; Iwersen, M. Field evaluation of a rising plate meter to estimate herbage mass in Austrian pastures. *Sensors* **2023**, *23*, 7477. [CrossRef]
65. Rayburn, E.B.; Rayburn, S.B. A standardized plate meter for estimating pasture mass in on-farm research trials. *Agron. J.* **1998**, *90*, 238–241. [CrossRef]
66. Thomson, N.A.; McCallum, D.A.; Howse, S.; Holmes, C.W.; Matthews, P.N.P.; Matthew, C. Estimation of dairy pastures—The need for standardisation. *Proc. N. Z. Grassl. Assoc.* **1997**, *59*, 221–225. [CrossRef]
67. Aarons, S.R.; Gourley, C.J.P.; Hannah, M.C. Between and within paddock soil chemical variability and forage production gradients in grazed dairy pastures. *Nutr. Cycl. Agroecosyst.* **2015**, *102*, 411–430. [CrossRef]
68. Islam, N.; Rashid, M.M.; Pasandideh, F.; Ray, B.; Moore, S.; Kadel, R. A review of applications and communication technologies for Internet of things (IoT) and Unmanned aerial vehicle (UAV) based sustainable smart farming. *Sustainability* **2021**, *13*, 1821. [CrossRef]
69. French, P.; O'Brien, B.; Shalloo, L. Development and adoption of new technologies to increase the efficiency and sustainability of pasture-based systems. *Anim. Prod. Sci.* **2015**, *55*, 931–935. [CrossRef]
70. Gargiulo, J.I.; Lyons, N.A.; Masia, F.; Beale, P.; Insua, J.R.; Correa-Luna, M.; Garcia, S.C. Comparison of ground-based, unmanned aerial vehicles and satellite remote sensing technologies for monitoring pasture biomass on dairy farms. *Remote Sens.* **2023**, *15*, 2752. [CrossRef]
71. Chen, A.; Xu, C.; Zhang, M.; Guo, J.; Xing, X.; Yang, D.; Xu, B.; Yang, X. Cross-scale mapping of above-ground biomass and shrub dominance by integrating UAV and satellite data in temperate grassland. *Remote Sens. Environ.* **2024**, *304*, 114024. [CrossRef]
72. Ghajar, S.; Tracy, B. Proximal Sensing in Grasslands and Pastures. *Agriculture* **2021**, *11*, 740. [CrossRef]
73. Ogungbuyi, M.G.; Guerschman, J.; Fischer, A.M.; Crabbe, R.A.; Ara, I.; Mohammed, C.; Scarth, P.; Tickle, P.; Whitehead, J.; Harrison, M.T. Improvement of pasture biomass modelling using high-resolution satellite imagery and machine learning. *J. Environ. Manag.* **2024**, *356*, 120564. [CrossRef]

74. Moeckel, T.; Safari, H.; Reddersen, B.; Fricke, T.; Wachendorf, M. Fusion of ultrasonic and spectral sensor data for improving the estimation of biomass in grasslands with heterogeneous sward structure. *Remote Sens.* **2017**, *9*, 98. [CrossRef]
75. Zhang, A.; Hu, S.; Zhang, X.; Zhang, T.; Li, M.; Tao, H.; Hou, Y. A Handheld Grassland Vegetation Monitoring System Based on Multispectral Imaging. *Agriculture* **2021**, *11*, 1262. [CrossRef]
76. Hammad, H.M.; Ahmad, A.; Abbas, F.; Farooque, A.A.; Willkerson, C.; Ahmad, S.; Hoogenboom, G. Handheld Sensor-Based NDVI Measurement as an Alternative to Destructive Sampling for Growth and Yield Assessment in Maize. *Int. J. Plant Prod.* **2025**, *19*, 363–376. [CrossRef]
77. Barrett, P.D.; Laidlaw, A.S.; Mayne, C.S. GrazeGro: A European herbage growth model to predict pasture production in perennial ryegrass swards for decision support. *Eur. J. Agron.* **2005**, *23*, 37–56. [CrossRef]
78. Cunliffe, A.M.; Brazier, R.E.; Anderson, K. Ultra-fine grain landscape-scale quantification of dryland vegetation structure with drone-acquired structure-from-motion photogrammetry. *Remote Sens. Environ.* **2016**, *183*, 129–143. [CrossRef]
79. Wigley, K.; Owens, J.L.; Westerschulte, M.; Riding, P.; Fourie, J.; Werner, A. Photogrammetry for assessment of pasture biomass. *J. N. Z. Grassl.* **2019**, *81*, 33–40. [CrossRef]
80. Edirisinghe, A.; Hill, M.J.; Donald, G.E.; Hyder, M. Quantitative mapping of pasture biomass using satellite imagery. *Int. J. Remote Sens.* **2011**, *32*, 2699–2724. [CrossRef]
81. Defalque, G.; Santos, R.; Bungenstab, D.; Echeverria, D.; Dias, A.; Defalque, C. Machine learning models for dry matter and biomass estimates on cattle grazing systems. *Comput. Electron. Agric.* **2024**, *216*, 108520. [CrossRef]
82. Oudshoorn, F.W.; Hansson, S.L.; Hansen, H. Calibration of the C-Dax pasture meter in a Danish grazing system. In Proceedings of the 16th Symposium of the European Grassland Federation, Gumpenstein, Austria, 29–31 August 2011; Pötsch, E.M., Krautzer, B., Hopkins, A., Eds.; Agricultural Research and Education Center: Irdning, Austria, 2011; pp. 166–168.
83. Schori, F. Sward surface height estimation with a rising plate meter and the C-Dax Pasturemeter. In *Grassland Science in Europe*; Dasselaar, A.v.d.P.-v., Aarts, H.F.M., Vliegher, A.D., Elgersma, A., Reheul, D., Reijneveld, J.A., Verloop, J., Hopkins, A., Eds.; European Grassland Federation: Wageningen, The Netherlands, 2015; Volume 20, pp. 310–312.
84. Behmann, J.; Acebron, K.; Emin, D.; Bennertz, S.; Matsubara, S.; Thomas, S.; Bohnenkamp, D.; Kuska, M.T.; Jussila, J.; Salo, H.; et al. Specim IQ: Evaluation of a New, Miniaturized Handheld Hyperspectral Camera and Its Application for Plant Phenotyping and Disease Detection. *Sensors* **2018**, *18*, 441. [CrossRef]
85. Chebrolu, N.; Lottes, P.; Schaefer, A.; Winterhalter, W.; Burgard, W.; Stachniss, C. Agricultural robot dataset for plant classification, localization and mapping on sugar beet fields. *Int. J. Robot. Res.* **2017**, *36*, 1045–1052. [CrossRef]
86. Trotter, T.F.; Frazier, P.S. Objective biomass assessment using an active plant sensor (Crop Circle TM)—Preliminary experiences on a varity of agricultural landscapes. In Proceedings of the 9th International Conference on Precision Agriculture, Denver, CO, USA, 20–23 July 2008; pp. 20–23.
87. Pullanagari, R.R.; Yule, I.; King, W.; Dalley, D.; Dynes, R. The use of optical sensors to estimate pasture quality. *Int. J. Smart Sens. Intell. Syst.* **2011**, *4*, 125–137. [CrossRef]
88. Lapidus, D.; Salem, M.E.; Beach, R.H.; Zayed, S.; Ortiz-Monasterio, I. Greenhouse gas mitigation benefits and profitability of the GreenSeeker Handheld NDVI sensor: Evidence from Mexico. *Precis. Agric.* **2022**, *23*, 2388–2406. [CrossRef]
89. Kimaro, O.D.; Gebre, S.L.; Hieronimo, P.; Kihupi, N.; Feger, K.-H.; Kimaro, D.N. Handheld NDVI sensor-based rice productivity assessment under combinations of fertilizer soil amendment and irrigation water management in lower Moshi irrigation scheme, North Tanzania. *Environ. Earth Sci.* **2023**, *82*, 78. [CrossRef]
90. Rodriguez, D.; Van Oijen, M.; Schapendonk, A.H.M.C. LINGRA-CC: A sink–source model to simulate the impact of climate change and management on grassland productivity. *New Phytol.* **2002**, *144*, 359–368. [CrossRef]
91. Efremova, N.; Foley, J.C.; Unagaev, A.; Karimi, R. AI for Sustainable Agriculture and Rangeland Monitoring. *Ethics Artifcial Intell. Sustain. Dev. Goals* **2023**, *152*, 399–422. [CrossRef]
92. Gard, S.; Neal, M.; Minnee, E. Pasture performance tools: Current and future state. *J. N. Z. Grassl.* **2024**, *86*, 273–279. [CrossRef]
93. Halter. How It Works. 2023. Available online: https://www.halterhq.com/dairy-overview (accessed on 8 July 2025).
94. Proveye. Revolutionising Precision Insights Through Advanced Image Analysis. 2024. Available online: https://www.proveye.io/#platform (accessed on 8 July 2025).
95. Aimer_Farming. Aimer Features. 2025. Available online: https://www.aimer-farming.com/features (accessed on 8 July 2025).
96. Mata, G.; Clark, D.A.; Edirisinghe, A.; Waugh, D.; Minneé, E.; Gherardi, S.G. *Predicting Accurate Paddock-Average Pasture Cover in Waikato Dairy Farms Using Satellite Images*; New Zealand Grassland Association: Wairakei, New Zealand, 2007; Volume 69, pp. 23–28. [CrossRef]
97. Dolling, P.; Curnow, M. Understanding Pastures from Space™ for South West Western Australia | Agriculture and Food. Department of Primary Industries and Regional Development's Agriculture and Food Division. 2022. Available online: https://www.agric.wa.gov.au/sheep/understanding-pastures-space%E2%84%A2-south-west-western-australia (accessed on 6 March 2024).

98. Roberts, D.; Dolling, P. Pastures from Space™—FOO and PGR for Agricultural Properties in WA. Department of Primary Industries and Regional Development's Agriculture and Food Division. 2023. Available online: https://www.agric.wa.gov.au/pastures-from-space-wa (accessed on 6 March 2024).
99. Anderson, G.; Rawlings, M.; Ogle, G. Mitigation of saturation in satellite pasture measurement via incorporation of a statistical pasture growth model. *J. N. Z. Grassl.* **2020**, *82*, 191–198. [CrossRef]
100. LIC. Space. 2025. Available online: https://www.lic.co.nz/products-and-services/space/ (accessed on 10 July 2025).
101. Anderson, G.; McNaughton, L. Validation of a satellite pasture measurement system. In Proceedings of the 8th Australasian Dairy Science Symposium, Palmerston North, New Zealand, 21–23 November 2018; pp. 191–195.
102. Pasture.io. *The Best LIC Space Alternative*; Pasture.io: Sandy Bay, Australia, 2019; Volume 2025.
103. Stevens, D.R.; Thompson, B.R.; Johnson, P.; Welten, B.; Meenken, E.; Bryant, J. Integrating digital technologies to aid grassland productivity and sustainability. *Front. Sustain. Food Syst.* **2021**, *5*, 602350. [CrossRef]
104. Clark, D.; Litherland, A.; Mata, G.; Burling-Claridge, R. Pasture Monitoring from Space. In Proceedings of the SouthIsland Dairy Event, Invercargill, New Zealand, 26–28 June 2006; pp. 108–123.
105. Smith, R.C.G.; Adams, M.; Gittins, S.; Gherardi, S.; Wood, D.; Maier, S.; Stovold, R.; Donald, G.; Khohkar, S.; Allen, A. Near real-time Feed On Offer (FOO) from MODIS for early season grazing management of Mediterranean annual pastures. *Int. J. Remote Sens.* **2011**, *32*, 4445–4460. [CrossRef]
106. Sharma, V.; Tripathi, A.K.; Mittal, H. Technological revolutions in smart farming: Current trends, challenges & future directions. *Comput. Electron. Agric.* **2022**, *201*, 107217. [CrossRef]
107. Christopher, S.A.; Gupta, P. Satellite remote sensing of particulate matter air quality: The cloud-cover problem. *J. Air Waste Manag. Assoc.* **2010**, *60*, 596–602. [CrossRef]
108. Hollstein, A.; Segl, K.; Guanter, L.; Brell, M.; Enesco, M. Ready-to-Use Methods for the Detection of Clouds, Cirrus, Snow, Shadow, Water and Clear Sky Pixels in Sentinel-2 MSI Images. *Remote Sens.* **2016**, *8*, 666. [CrossRef]
109. Jeppesen, J.H.; Jacobsen, R.H.; Inceoglu, F.; Toftegaard, T.S. A cloud detection algorithm for satellite imagery based on deep learning. *Remote Sens. Environ.* **2019**, *229*, 247–259. [CrossRef]
110. Nazarova, T.; Martin, P.; Giuliani, G. Monitoring Vegetation Change in the Presence of High Cloud Cover with Sentinel-2 in a Lowland Tropical Forest Region in Brazil. *Remote Sens.* **2020**, *12*, 1829. [CrossRef]
111. Sishodia, R.P.; Ray, R.L.; Singh, S.K. Applications of Remote Sensing in Precision Agriculture: A Review. *Remote Sens.* **2020**, *12*, 3136. [CrossRef]
112. Ali, I.; Cawkwell, F.; Green, S.; Dwyer, N. Application of statistical and machine learning models for grassland yield estimation based on a hypertemporal satellite remote sensing time series. In Proceedings of the 2014 IEEE Geoscience and Remote Sensing Symposium, Quebec City, QC, Canada, 13–18 July 2014; pp. 5060–5063. [CrossRef]
113. Morais, T.G.; Jongen, M.; Tufik, C.; Rodrigues, N.R.; Gama, I.; Serrano, J.; Domingos, T.; Teixeira, R.F.M. Estimation of Annual Productivity of Sown Rainfed Grasslands Using Machine Learning. *Grass Forage Sci.* **2025**, *80*, 12707. [CrossRef]
114. De Rosa, D.; Basso, B.; Fasiolo, M.; Friedl, J.; Fulkerson, B.; Grace, P.R.; Rowlings, D.W. Predicting pasture biomass using a statistical model and machine learning algorithm implemented with remotely sensed imagery. *Comput. Electron. Agric.* **2021**, *180*, 105880. [CrossRef]
115. Correa-Luna, M.; Gargiulo, J.; Beale, P.; Deane, D.; Leonard, J.; Hack, J.; Geldof, Z.; Wilson, C.; Garcia, S. Accounting for minimum data required to train a machine learning model to accurately monitor Australian dairy pastures using remote sensing. *Sci. Rep.* **2024**, *14*, 16927. [CrossRef] [PubMed]
116. Schellberg, J.; Hill, M.J.; Gerhards, R.; Rothmund, M.; Braun, M. Precision agriculture on grassland: Applications, perspectives and constraints. *Eur. J. Agron.* **2008**, *29*, 59–71. [CrossRef]
117. Bretas, I.L.; Dubeux, J.C.B.; Cruz, P.J.R.; Oduor, K.T.; Queiroz, L.D.; Valente, D.S.M.; Chizzotti, F.H.M. Precision livestock farming applied to grazingland monitoring and management—A review. *Agron. J.* **2023**, *116*, 1164–1186. [CrossRef]
118. Eastwood, C.; Dela Rue, B. Identification of operational performance attributes for pasture measuring devices. *J. N. Z. Grassl.* **2017**, *79*, 211–216. [CrossRef]
119. Dalley, D.; Clark, D.; Pairman, D.; Dynes, R.; Yule, I.; King, W.; Mata, G. Technologies for measuring grass/crops. In Proceedings of the South Island Dairy Event, Invercargill, New Zealand, 28–30 January 2009; pp. 134–151.
120. Dela Rue, B.; Eastwood, C. *Technology and Workplace Practices Survey Report 2023*; DairyNZ: Hamilton, New Zealand, 2023.
121. Eastwood, C.; Dela Rue, B.; Kerslake, J. Developing an approach to assess farmer perceptions of the value of pasture assessment technologies. *Grass Forage Sci.* **2020**, *75*, 474–485. [CrossRef]
122. Hall, A.; Turner, L.; Irvine, L.; Kilpatrick, S. Pasture management and extension on Tasmanian dairy farms –who measures up? *Rural Ext. Innov. Syst. J.* **2017**, *13*, 32–40. Available online: https://search.informit.org/doi/10.3316/informit.187067789467790 (accessed on 10 January 2025).

123. Edwards, J.P.; Qasim, M.; Bryant, R.H.; Thomas, C.; Wright-Watson, C.; Zobel, G.; Neal, M.B.; Eastwood, C.R. On-animal sensors may predict paddock level pasture mass in rotationally grazed dairy systems. *Comput. Electron. Agric.* **2024**, *219*, 108779. [CrossRef]
124. Wang, Z.; Ma, Y.; Zhang, Y.; Shang, J. Review of Remote Sensing Applications in Grassland Monitoring. *Remote Sens.* **2022**, *14*, 2903. [CrossRef]
125. Ali, I.; Cawkwell, F.; Dwyer, E.; Barrett, B.; Green, S. Satellite remote sensing of grasslands: From observation to management. *J. Plant Ecol.* **2016**, *9*, 649–671. [CrossRef]
126. Green, J.K.; Zhang, Y.; Luo, X.; Keenan, T.F. Systematic Underestimation of Canopy Conductance Sensitivity to Drought by Earth System Models. *AGU Adv.* **2024**, *5*, e2023AV001026. [CrossRef]
127. Huemmrich, K.F.; Vargas Zesati, S.; Campbell, P.; Tweedie, C. Canopy reflectance models illustrate varying NDVI responses to change in high latitude ecosystems. *Ecol. Appl.* **2021**, *31*, e02435. [CrossRef]
128. Reinermann, S.; Asam, S.; Kuenzer, C. Remote Sensing of Grassland Production and Management—A Review. *Remote Sens.* **2020**, *12*, 1949. [CrossRef]
129. Jones, J.W.; Antle, J.M.; Basso, B.; Boote, K.J.; Conant, R.T.; Foster, I.; Godfray, H.C.J.; Herrero, M.; Howitt, R.E.; Janssen, S.; et al. Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agric. Syst.* **2017**, *155*, 269–288. [CrossRef]
130. Abiri, R.; Rizan, N.; Balasundram, S.K.; Shahbazi, A.B.; Abdul-Hamid, H. Application of digital technologies for ensuring agricultural productivity. *Heliyon* **2023**, *9*, e22601. [CrossRef]
131. O'Grady, M.J.; Langton, D.; O'Hare, G.M.P. Edge computing: A tractable model for smart agriculture? *Artif. Intell. Agric.* **2019**, *3*, 42–51. [CrossRef]
132. Javaid, M.; Haleem, A.; Khan, I.H.; Suman, R. Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Adv. Agrochem* **2023**, *2*, 15–30. [CrossRef]
133. Candido, B.; Mindala, U.; Ebrahimy, H.; Zhang, Z.; Kallenbach, R. Integrating Proximal and Remote Sensing with Machine Learning for Pasture Biomass Estimation. *Sensors* **2025**, *25*, 1987. [CrossRef]
134. Smith, C.; Karunaratne, S.; Badenhorst, P.; Cogan, N.; Spangenberg, G.; Smith, K. Machine Learning Algorithms to Predict Forage Nutritive Value of In Situ Perennial Ryegrass Plants Using Hyperspectral Canopy Reflectance Data. *Remote Sens.* **2020**, *12*, 928. [CrossRef]
135. Kaine, G.W.; Tozer, P.R. Stability, resilience and sustainability in pasture-based grazing systems. *Agric. Syst.* **2005**, *83*, 27–48. [CrossRef]
136. Shalloo, L.; O'Donovan, M.; Leso, L.; Werner, J.; Ruelle, E.; Geoghegan, A.; Delaby, L.; O'Leary, N. Review: Grass-based dairy systems, data and precision technologies. *Animal* **2018**, *12*, s262–s271. [CrossRef]
137. Liu, M.; Ouyang, S.; Tian, Y.; Wen, S.; Zhao, Y.; Li, X.; Baoyin, T.-T.; Kuzyakov, Y.; Xu, X. Effects of rotational and continuous overgrazing on newly assimilated C allocation. *Biol. Fertil. Soils* **2020**, *57*, 193–202. [CrossRef]
138. Piñeiro, G.; Paruelo, J.M.; Oesterheld, M.; Jobbágy, E.G. Pathways of grazing effects on soil organic carbon and nitrogen. *Rangel. Ecol. Manag.* **2010**, *63*, 109–119. [CrossRef]
139. Lai, L.; Kumar, S. A global meta-analysis of livestock grazing impacts on soil properties. *PLoS ONE* **2020**, *15*, e0236638. [CrossRef]
140. Wang, Y.; Ren, Z.; Ma, P.; Wang, Z.; Niu, D.; Fu, H.; Elser, J.J. Effects of grassland degradation on ecological stoichiometry of soil ecosystems on the Qinghai-Tibet Plateau. *Sci. Total Environ.* **2020**, *722*, 137910. [CrossRef]
141. Papadopoulos, G.; Arduini, S.; Uyar, H.; Psiroukis, V.; Kasimati, A.; Fountas, S. Economic and environmental benefits of digital agricultural technologies in crop production: A review. *Smart Agric. Technol.* **2024**, *8*, 100441. [CrossRef]
142. Leddin, C.; Morse-McNabb, E.; Smith, K.; Ho, C.; Jacobs, J. How can improved farmer decisions and farm system impacts resulting from the use of digital forage measurement technologies on dairy farms be valued? *Agricultural Systems* **2023**, *212*, 103755. [CrossRef]