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Are We Up to the Best Practises in Forage and Grassland Precision Harvest? A Review

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ABSTRACT

Grassland and forage crops are a domain where the application of precision agriculture techniques has been less intensive so far, compared to grain crops. This is especially evident in the case of variable yield assessment, the step that prompts the adoption of precision management techniques once farmers are faced by unexpectedly high yield spatial variation. Much work has been devoted to forage, grassland and pasture yield assessment since the early 2000's; evaluating the established achievements alongside the existing drawbacks and limitations is seen the best way to lay the foundation for future research work in this field. Self-propelled forage harvesters received most attention in the quest for on-the-go yield assessment. Both volumetric flow (feed-roll displacement sensing) and mass flow (impact force and torque sensing) assessments were tested prior to be developed into commercial applications. Nonetheless, their performances vary depending on harvested product characteristics (density, moisture, texture, etc.). Integrating multiple sensor technologies has emerged as the most effective solution to reduce this variability, despite the higher costs involved. Forage handling machines (mowers conditioners, waggon trailers and balers) were also largely addressed. Balers in the static weighing mode are one of the simplest and most reliable yield assessing platforms, although at the expenses of spatial discretization and positional lag of the yield data. Remote sensing based on spectral reflectance data from the standing crop is rapidly gaining interest, especially if performed from satellites. Multiple data sources (e.g., Landsat and MODIS images), sometimes processed through machine learning or neural network techniques, have demonstrated to provide more reliable yield assessments than single data sources. A cross cutting issue in all these techniques is the assessment of forage moisture. At the ground level, near infra-red sensors are gaining popularity over capacitance sensors, thanks to their ability to determine also quality parameters of the harvested biomass. Overall, the need for calibration and maintenance of all sensor types represents a critical point that requires to be carefully evaluated before selecting an appropriate system.

1 | Introduction

Grasslands and forage crops provide a wide range of ecosystem services by producing feed for livestock and conservation of the environment. The main purpose when dealing with forages and grassland communities is to maximise their utilisation and profit through advanced management practises on a sustainable basis. Sustainable livestock production involves meeting animal feed requirements with farm production obtained during the growing season. Planning feed production is the premise for balanced fresh grass intake per animal (Wilkinson et al. 2020), while assuring the most economical feed source for ruminant livestock production (Finneran et al. 2012). Furthermore, monitoring yield traits (quantity and quality) is the best premise to maximise utilisation and production in forage and grassland farming (Hanrahan et al. 2017; Beukes et al. 2019). This important agricultural sector could, therefore, benefit from accurate yield measurement systems for planning farm activity (Shalloo et al. 2018), owing to the circumstance that, mainly in grassland, the yields fluctuate very strongly (Köhler et al. 2017). In general, little information is available on the yields of forages and grasslands, as fodder is usually only used internally. Nonetheless, Köhler et al. (2017) evidenced a yield fluctuation by at least a factor of two for the different plots within a farm in Bavaria.

Therefore, the yield map definition is the starting point for the introduction of precision and digital agriculture in grassland management and represents the fundamental information to be used in decision making related to grassland and forage crop management.

To increase their widespread distribution, the yield estimation methods should not only be low cost but also easily implemented by growers (Sanderson et al. 2001; Matos et al. 2022). Unfortunately, there are a limited number of precision agriculture (PA) technologies commercially available in grass and crops, and the instruments to spatially manage inputs are scarcely used in forage and pasture-based farms (Rayburn et al. 2007; Shalloo et al. 2018). Many causes are at the basis of the low adoption of PA technologies, but certainly, the presence of high plant species diversity and their temporal variation, especially in grassland environments, play a decisive role (Schellberg et al. 2008). Traditional methods for grass yield determination are based on manual measurements of, for example, canopy height or crop sample weights in selected field positions, or the measurement of the mass of trucks and waggons filled in the field (Monteiro, Santos, and Gonçalves 2021). These systems do not allow actual yields to be accurately determined because of the heterogeneity typically found in permanent grasslands. Additionally, they require a lot of time and effort (Köhler et al. 2017).

Moreover, manual methods are not applicable in large areas because time and costs are strong limitation in biomass measurement (Villalobos and WingChing-Jones 2020; Matos et al. 2022). All this calls for the adoption of digital tools which allow measurements to be made economically and fast.

As with other crops in PA, two approaches for estimating grass yields and their field variability are available. The first approach involves determining the yield during the harvesting phase: in this case, the machines will be equipped with specific sensors for determining the mass or volumetric flow. The second approach is based on yield prediction during crop growth, generally using optical sensors for detecting crop spectral properties (Askari et al. 2019; Barnett and Shinners 1998; Gholizadeh et al. 2019; Grüner et al. 2020; Gholizadeh et al. 2019; Morais et al. 2021; Muro et al. 2022; Oliveira et al. 2020; Théau et al. 2021; Sibanda, Mutanga, and Rouget 2016; Wengert et al. 2022; Wijesingha et al. 2020).

Increasing the production and quality of fodder crops involves an adequate and well balanced nutrient supply. Nitrogen (N) is the most important nutrient as, beside supporting yields, determines increases in the crude protein (CP) content. Farm production systems that adopt variable rate N fertilisation can increase plant nitrogen use efficiency while maximising the utilisation of forage and grassland biomass (McCarthy et al. 2015; Dentler et al. 2020). The differentiated management of nitrogen would, therefore, combine increased farm profitability and more efficient nutrient exploitation with positive consequences from the environmental viewpoint. PA has a great potential to maximise the utilisation and accuracy in forage and grassland measurement systems. Within PA, spatio-temporal data allow farmers to monitor forage and grass variations, and consequently apply differentiated crop inputs in site-specific manner, for increasing profits and reducing environmental impacts (Schellberg et al. 2008). The diffusion of hay yield monitoring technologies is thought to determine a remarkable impact on forage cultivation: Beukes et al. (2019) reported a potential for a 15% increase in farm profitability through regular herbage measurements. Farmers who rely on pasture as primary feed source for their animals require accurate real-time measurement of pasture herbage mass and quality to optimise grazing and animal nutrition management. Each additional 1000 kg increase of pasture dry matter (DM) used per hectare was associated with a €173 greater profit per hectare in dairy farms (Hanrahan et al. 2018).

The continuous advancement of electronics applied on agricultural machinery is providing an important contribution to the ability to precisely map the quantity and quality of most crops, even those which, until now, have been less frequently focused among grassland and forage crops. The increase in the quantity and quality of information obtainable from the integration between electronic sensors and acquisition systems applicable to harvesting and handling machines provides a wealth of automatically acquired data to improve the management of these specific crops. The standardisation of the information transfer between agricultural tractors, implements, harvesters and on-board computers, thanks to the implementation of the ISO 11783 (ISOBUS) communication protocol, allows multiple automated acquisition data to be jointly used (Fountas et al. 2015) and will encourage greater diffusion of digitised survey technologies to improve the management of this crop group.

Based on the fragmented, sometimes inconsistent information available for this vast topic, the main aim of this review is to summarise the monitoring technologies in forage and grassland measurements, the available sensors, the potential role of remote sensing (RS) technologies in biomass yield and quality estimation, and the evaluation of field heterogeneity in the perspective of creating reliable decision support systems (DSS) for precision forage and grassland management.

2 | Mass Yield Measure Technologies Applied on Farm Machinery

The research has progressively been engaged in the study of technologies that could be applied directly on harvesting machines as self-propelled harvesters (SPFHs), mowers, windrowers, trailers transporting fodder and silage and balers through sensors and their combinations that allow the mass/volumetric flow of biomass to be directly measured/indirectly estimated (Lussem, Schellberg, and Bareth 2020).

The system used to determine the instant yield during harvest with SPFHs is a yield monitor that was initially designed for grain combine harvesters and was subsequently adopted in other harvesting machines (Queiroz et al. 2021).

The yield monitor system requires the integration of a series of technologies: (i) one or more sensors for yield measure; (ii) GNSS (Global Navigation Satellite System) receiver for georeferencing the yield data; (iii) control unit for data storage and processing; (iv) virtual terminal for displaying information and interacting with the operator. In addition, generally other sensors to measure the speed of the machine and crop moisture are adopted.

Within the yield monitoring technology, the most critical item is represented by the sensors for measuring the mass or volumetric flow during harvesting. The operating principle depends on the crop the sensor operates on; however, determining the accuracy and precision of the measurement often represents a critical issue. Different available sensors can be employed successfully on forage harvesters to measure biomass traits (Maughan et al. 2012; Cherney, Digman, and Cherney 2021). They include linear potentiometers (measuring feedroll displacement/volume flow), capacitance sensors (measuring moisture and mass flow rate), NIR spectrometers (measuring crop spectral properties and quality traits including DM content of hay and silage), torque sensors (determining torque and shaft speed), load cells (measuring weight of materials, crop flow and feedroll displacement), strain gauges (assessing crop weight and flow) and curved impact plates (measuring crop impact force).

Yield monitors can be used on SPFHs to measure yield and moisture data of lucerne (*Medicago sativa* L.; alfalfa), grass species and maize (*Zea mays* L.) silage (Long et al. 2016; Worek and Thurner 2021). But sensors for indirect mass estimation have also been applied on forage harvesting waggons, round and square balers and windrowers during swathing in the haymaking process. The sensors can determine a mass flow or a volumetric flow. While load cells applied to SPFHs are adopted to determine the mass flow of particles, the volumetric flow can be measured by installing transducers as a linear potentiometer (Shinners, Huenink, and Behringer 2003), a vertical displacement transducer (Savoie, Lemire, and Theriault 2002), and fixed load cells relying on springs (Forristal and Keppel 2001).

When transducers are used to provide a volumetric flow measurement, adjustment of yield data based on biomass density must be performed. To obtain the right dry biomass value and accurate sensor calibration, crop moisture must also be determined. The yield per hectare is obtained by considering the travelling speed of the harvester and its working width, and combining the mass flow value (or volumetric flow also assessing the density of the material) with the harvester's precise position detected through a GNSS with an adequate degree of signal correction.

Based on the design, operating principle, type of information and machine on which yield measurement systems are installed, an attempt to classify the mass flow measuring applications in forage crops according to the recent literature points is reported in Table 1, where a summary of the most relevant technologies to obtain mass or volumetric flow values for evaluating field yields in forage harvesters is shown.

2.1 | Flow Measure Systems on Harvest Machines

2.1.1 | Volumetric Flow Measure via Feedroll Sensing

The level of forage throughput is related to the volumetric flow of the biomass passing through the machine during harvesting. It represents a parameter that can be indirectly estimated in SPFHs or balers, by measuring the feedroll displacement that adjusts its position to accommodate different volumes of grass. Displacement can be measured in several ways: with linear transducers, vertical displacement sensors, linear potentiometers and load cells. Martel and Savoie (2000) evaluated different sensor types to assess mass-flow rate on a pull-type forage harvester during field and laboratory tests. Field tests conducted on chopped whole-plant maize harvest showed good correlations between the estimated mass flow rate and the feedroll displacement ($R^2 = 94\%$) measured using a vertical displacement transducer located at the feedroll.

However, in other studies, the relationship between the measurement of the feedroll displacement and the volumetric flow did not show such encouraging results. Forristal and Keppel (2001) used load cells connected to retaining springs to measure the effort recorded during feedroll movement. Based on their preliminary trial, the feedroll position did not significantly contribute to determine output. The authors attributed this result to the excessive oscillation of the feedroll due to the irregular flow of grass, which was transmitted to the measuring sensors. Savoie, Lemire, and Theriault (2002) highlighted results consistent with those of Forristal and Keppel (2001) when they instrumented a forage harvester with a transducer to measure feedroll displacement during harvesting of wilted grass with moisture between 45% and 78%. Feedroll displacement exhibited a good correlation with mass flow rate ($R^2 = 0.86$).

2.1.2 | Mass Flow Measure Based on Impact Force

The sensors used for measuring the mass flow by determining the impact force of the biomass are quite similar to those mounted in a combine harvester for grain yield monitoring. They consist of an impact plate hit by the flow of biomass during its passage. The grass is delivered from the forage harvester by the impelling force of the cylinder, which throws and blows the grass through the delivery chute to the trailer. The force exerted by the grass passing through the chute is proportional to the grass biomass. In the SPFHs generally, the load cell, connected to a strain gauge, is placed in the spout of the harvester, and the measured force is directly correlated with the forage mass flow (Maughan et al. 2012). In the tests conducted by Martel and Savoie (2000) in chopped whole-plant maize, the crop impact force against a hinged plate connected to a load cell inserted above the blower of a forage harvester showed a high correlation with the mass-flow rate ($R^2 = 0.95$). In any case, the efficiency

TABLE 1 | Summary of the most relevant flow/mass measurement systems applied on forage harvesters.

Machine	Crop	Target	Technology and sensors	Source
Self-propelled forage harvester	Whole maize and grass for silage	Mass flow measure	Radar sensor applied on the chopper spout to measure the speed of the grass material.	Auernhammer, Demmel, and Pirro 1995
Pull-type forage harvester	Wilted alfalfa and maize for silage	Mass flow measure	Multi sensor approach measuring feedroll spring force, feedroll displacement, crop impact force from the cutter-head and mass of crop in auger. Flow mass comparison with side forage dumping waggon equipped with continuously weighing load cells.	Barnett and Shinners 1998
Pull-type forage harvester	Wilted grass	Mass flow and moisture measure	Multi sensor approach: transducer to measure feedroll displacement; two sensors to measure torque at the power take-off (PTO) shaft and the cutter-head; load cell to measure impact force against a hinged plate in the spout; capacitance-controlled oscillator placed at the end of the spout. Flow mass comparison with dump waggons instrumented with sensors continuously determining the weight of accumulated mass.	Savoie, Lemire, and Theriault 2002
Pull-type forage harvester	Chopped maize whole-plant	Mass flow measure	Multi sensor approach: hinged plate connected to a load cell inserted above the blower to measure mass flow, and vertical displacement transducer to measure feedroll displacement.	Martel and Savoie 2000
Pull-type forage harvester	Grass, predominantly ryegrass and white clover	Mass flow measure	Multi sensor approach with impact sensor based on rectangular plate linked to a load cell in the delivery chute to determine mass flow; load cells connected to retaining springs measuring the effort recorded during feedroll movement; fixed load cells by springs to measure feedroll displacement; chopping cylinder speed sensors grass.	Forristal and Keppel 2001
Pull-type forage harvester	Wilted grass	Mass flow measure	Multi-sensor approach: hinged plate in the spout connected to a load cell to measure impact force; capacitance-controlled oscillator located at the end of the spout to measure mass flow rate; vertical displacement transducer to measure feedroll displacement; torque sensors to measure torque at the power take-off (PTO) shaft and the cutter-head. Dump waggon instrumented with sensors continuously determining the weight of accumulated mass.	Savoie, Lemire, and Theriault 2002
Self-propelled forage harvester	Wilted alfalfa and whole-plant maize for silage	Mass flow and yield measure	Multi-sensor approach: linear potentiometer to measure feedroll displacement; speed sensors to measure feedroll and blower speed; load cell to measure crop impact at the transition radius of the spout; ultrasonic sensor to measure the thickness of crop stream in the spout; radar to measure ground speed.	Shinners, Huenink, and Behringer 2003
Forage harvester	Different biomass materials	Mass flow measure	Radiometric sensor in laboratory and field tests (located in the spout of harvester) to measure the mass flow based on X-ray absorption.	Kormann 2004
Pull-type forage harvester prototype	Forage crops	Mass flow measure	Multi-sensor approach: hydraulic pressure sensors, inductive proximity sensors and potentiometer to correlate harvester power use and forage throughput.	Mohsenimanesh et al. 2015
Self-propelled forage harvester	Grass hay	Mass flow measure	Multi-sensor approach to estimate mass through plant height measure with Infrared and ultrasonic sensors.	Ramsey IV 2015

(Continues)

TABLE 1 | (Continued)

Machine	Crop	Target	Technology and sensors	Source
Self-propelled forage harvester	Alfalfa grass and maize for silage	Mass flow and moisture measure	Assessment of yield and moisture NIR sensing accuracy by comparison with actual yield and moisture measured in truck weights.	Long et al. 2016
Self-propelled forage harvester	Wilted forage and maize for silage	Mass flow and DM content measure	Comparison of online fresh mass yield and DM measurement in commercial systems installed on 4 self-propelled forage harvesters under field conditions.	Worek and Thurner 2021

of the yield measurement system depends on the type of sensor actually used (Bailey, Higgins, and Jordan 2000).

Similar results were obtained by Forristal and Keppel (2001). They adopted a rectangular plate placed in the path of the grass flow in the upper section of the harvester delivery chute fitted to an externally mounted shear-strain type load cell. The measurement system was tested during harvesting at three forward speeds. The plate sensor in the chute provided a very good relationship between sensed and measured throughput, with regression coefficients (R^2) between 0.88 and 0.96. Similar results were found by Savoie, Lemire, and Theriault (2002) who, with a curved impact plate connected with a load cell on a hinged plate in the harvester spout, measured the mass flow rate of the hay material with a 5% error, based on the moisture data through prediction modelling. Authors concluded that impact sensors are more reliable in measuring grass flow than feedroll displacement sensors, but not so durable (Savoie, Lemire, and Theriault 2002). The ability of impact sensors to represent actual mass flow varied from $R^2=0.84$ (Forristal and Keppel 2001) to $R^2=0.95$ (Savoie, Lemire, and Theriault 2002). Improvement of results can be obtained adding moisture values provided by a dedicated sensor in the prediction model (Savoie, Lemire, and Theriault 2002).

2.1.3 | Flow Measurement Based on Torque Sensors

An alternative approach proposed in some studies for the measurement of mass flow is based on the amount of torque needed to drive the machine as it is conditioned by the amount of crop flowing through the harvester (Wild, Ruhland, and Haedicke 2005; Maughan et al. 2012; Savoie, Lemire, and Theriault 2002). Torque sensors were applied on the power take-off (PTO) drive shaft, platform drive and cutter head (Maughan et al. 2012).

Savoie, Lemire, and Theriault (2002) instrumented a forage harvester with two sensors to measure torque at the PTO shaft and cutter head. The torque readings while operating on wilted grass with moisture between 45% and 78% showed a closer relationship for dry mass flow ($R^2=0.865$) than fresh mass flow ($R^2=0.705$). The authors underlined the need for moisture adjustments to improve the correlation between torque sensor reading and mass flow rate.

2.1.4 | Other Mass-Flow Sensors

Auernhammer, Demmel, and Pirro (1995) evaluated the mass flow measurement on 140 ha of chopped maize using a radar sensor applied on the chopper spout in SPFHs. The device measured the speed of the material while a second radar sensor determined SPFH speed. Based on these data and the working width, the actual yield (t/ha) was assessed every second, with a mean error of +3.06% (calibration offset).

Mechanical and electronic pasture sensors are available to measure standing pasture biomass before harvesting. Sanderson et al. (2001) used a non-destructive pasture meter to estimate standing biomass and compare the results with hand-clipped samples. According to this study. It was concluded that these methods to predict forage mass and bio-volume were quite inaccurate, with errors ranging from 26% to 33% (Sanderson et al. 2001).

Investigations with radiometric systems were conducted by Kormann (2004), measuring the mass flow based on X-ray absorption in the spout of choppers. Systems based on X-ray emission showed higher accuracies than other methods. However, due to concerns about a radioactive source on a harvesting machine, these systems have been dismissed.

Kviz, Kumhala, and Prosek (2007) evaluated mass-flow by passing the material between capacitor plates and subsequently measuring of sensor output voltage. The amount of material passing between plates was significantly correlated with the circuit output voltage, with a coefficient of determination ranging from $R^2=0.87$ to $R^2=0.98$, depending on the type and moisture of the material. A capacitive sensor was also employed by Kumhála et al. (2008); Kumhála, Prosek, and Kroulik (2010) for mass flow determination on forage crops and sugar beet (*Beta vulgaris* L.), to obtain yield maps. A parallel plate capacitive throughput sensor was used in laboratory tests where a conveying belt carried a known amount of material through the sensor, which was equipped with an electronic measurement device. The resulting coefficients of determination ranged around R^2 values of 0.96 for different forage crops, indicating a strong linear relationship between the feed rates of plant material passing through the sensor and the output signal of the measuring sensor circuit.

Ramsey IV (2015) measured the mass flow of grass hay based on the measurement of the standing plant height using two different sensor types, infrared and ultrasonic, applied on a SPFH. Despite a good level of accuracy obtained, the author concluded that the use of these sensors is impracticable (except for research purposes), due to the rapid wearing of the infrared sensor and the difficulty of adapting the ultrasonic sensor for commercial adoption.

2.1.5 | Multiple Sensor Fusion

Many forage crop species have different structural and morphological characteristics also depending on their harvest conditions (e.g., green, wilted grass, hay or straw, perennial ryegrass, etc.). To obtain useful information for evaluating field-scale heterogeneity, some researchers have developed mass flow measurement systems with a multi-sensor approach to obtain multiple information that can be used across a wide range of plant diversity.

A multi sensor approach was adopted by Savoie, Lemire, and Theriault (2002), who instrumented a forage harvester to measure mass flow rate during harvest of wilted grass at a moisture between 45% and 78%. A load cell was used to measure impact force against a hinged plate in the spout, in parallel to a capacitance-controlled oscillator placed at the end of the spout, whose changes in frequency depended on mass flow rate. The integration of load values with signals of frequency drop of the oscillator allowed the estimate of mass flow rate to be improved ($R^2=0.98$), based on single measurements related only to the impact force provided by a load cell.

Shinners, Huenink, and Behringer (2003) evaluated the combination of multiple sensors applied to forage harvesters to measure mass-flow of hay and forage of wilted alfalfa and whole plant maize for silage. The measurements included: feedroll displacement with linear potentiometer, feedroll and blower speed with speed sensors; impact force in the spout with a load cell and thickness of crop stream in the spout with ultrasonic sensors. Authors reported more accurate measurements in maize for silage than wilted alfalfa, mainly because the former forage was fed much more uniformly to the sensors. They concluded that multiple sensors need to be integrated into the estimation models because the values of feedroll displacement were highly correlated to mass-flow at high flow rates, but less correlated at low flow rates when feedroll displacement was quite small. Conversely, crop thickness measurements in the spout were well correlated at low throughputs when the crop stream was well defined, but poorly correlated at high throughputs when the spout became filled with material.

Kumhála, Kroulík, and Prošek (2007) combined the torque sensors and curved impact type yield sensors on a mowing machine for the measurements of forage yields. They found very good coefficients of determination (0.95) between the conditioner's power, impact force and material flow rate for assessing mass flow and delineating spatial yield maps.

Mohsenimanesh et al. (2015) proposed a mass flow measuring technology by instrumenting a pull prototype forage harvester with a multisensor system. A hydraulic pressure sensor measured the pressure at the input and output lines of the feedroll and at the header motors, while an inductive proximity sensor measured motor speed, and a potentiometer the crop mass flow. Two harvester forward speeds and two cut lengths were tested. The measurement of the hydraulic pressure and the calculated torque under various treatments on the header and feedroll motors highlighted a linear relationship between harvester power use and the rate of forage throughput.

2.2 | Sensors on Handling Machines for Flow Mass Determination

Much of the research on hay and silage mass flow measurements has been performed by instrumenting forage harvesters. However, some studies have focused on the use of sensors on the waggons for crop transport, mowers- conditioners and baling machines (Table 2).

2.2.1 | Waggons

Wheeler et al. (1997) first described the basic requirements for crop yield mapping systems based on continuous weighing of waggons. Subsequently, Godwin et al. (1999) continued research on this area using a trailer fitted with load cells which allowed mass flow rate and cumulated mass into the trailer to be measured. Lee, Schueller, and Burks (2005) proposed the definition of silage yield maps based on a continuous weighing of waggons equipped with load cells using Bluetooth technology for wireless transmission of harvester position and moisture sensor data to a host computer; the authors found a very high relationship ($R^2=0.99$) between silage mass measured by load cells versus a platform scale (Figure 1).

TABLE 2 | Summary of the most relevant yield measurement systems applied on handling machines.

Machine	Crop	Target	Technology and sensors	Source
Trailer	Hay crops	Forage yield maps	Trailer instrumented with load cells to estimate the cumulated mass within the trailer.	Godwin et al. 1999
Trailer waggons	Forage crops	Yield maps	Continuous weighing of trailer waggons equipped with load cells, Bluetooth data transmission of harvester position to obtain yield maps.	Lee, Schueller, and Burks 2005
Mowing machine	Forage	Mass flow measure	Continuous weighing of the conveying belt of a mower conditioner.	Demmel et al. 2002
Mower conditioner	Mixture of grass and alfalfa	Mass flow measure	Multi sensor approach: torque meter and strain gauge placed on conditioner shaft to measure the power input required; curved impact plate mounted at the output of the grass material to measure impact force.	Kumhála and Prosek 2003 and Kumhála, Kroulík, and Prošek 2007
Mower conditioner	Grass crops	Yield monitoring system	Laboratory and field test via multi-sensor approach: sensor for torque measure of the windrowing device, and sensor to measure the pressure of the hydraulic motor which drives the windrowing belt.	Wild, Ruhland, and Haedicke 2005

2.2.2 | Mowing Machines

Demmel et al. (2002) instrumented the belt in the windrowing device of a mower. The system involved measuring biomass in the mower through continuous weighing of the loaded windrower belt. The results obtained from the measurement showed that the sensors needed further improvement. Kumhála and Prosek (2003) adopted a multi sensor approach for the feed rate measurement of the cut fodder in a modern mowing machine equipped with a conditioner. The applied sensors consisted of a torque meter and a strain gauge placed on the conditioner shaft integrated with an RPM optical counter. The mowing machine was also equipped with a curved impact plate mounted at the forage output. The tests carried out in the laboratory on a mixture of grass and alfalfa showed a very high linear correlation between the conditioner's power input, output frequency of the impact force measuring apparatus, and feed rate through the mowing machine. Sensor fusion allowed a material feed rate difference of $0.5\,\mathrm{kg\,s^{-1}}$ to be highlighted. Shinners, Huenink, and Behringer (2003) instrumented a self-propelled haymaking machine performing the cutting, swathing and conditioning of grass for the measurement of mass flow and yield. The technology used a multi-sensor approach involving the use of a pressure sensor for the load of the platform driving motor, a sensor for the conditioning roll speed, an inclinometer for platform pitch, a load cell for crop impact on swath shaping shield, rotary potentiometers for crop volumetric flow past the swath shaping shield and, finally, a radar for ground speed. Grass biomass yield was measured by quantifying the torque and pressure on a windrowing device of a mower conditioner (Wild, Ruhland, and Haedicke 2005). The study involved the application of a torque sensor on the windrowing device and a pressure sensor at the hydraulic motor driving the windrowing device. Under laboratory conditions, a high accuracy was found between signal intensity and the amount of grass biomass, while in field trials the higher deviations from the actual grass biomass was observed.

2.2.3 | Balers and Other Applications

The implementation of yield monitoring systems has also concerned the fodder baling machines (Table 3). Load cells and strain gauges have been used both in round and square balers as methods to determine bale mass, and data were used to generate yield maps (Kayad et al. 2015). Wild and Auernhammer (1999) developed a system of mass measurement for round balers by equipping them with a load cell in the drawbar and strain gauges on each side of the baler axle (Figure 2). The accuracy of this system depended on whether a static or dynamic weight was focused. The weighing static method during vehicle stops produced errors lower than 1%, compared with 10% for continuous dynamic weighing (Wild and Auernhammer 1999). For measuring forage mass during baling, Shinners, Barnett, and Schlesser (2000) used a star wheel-driven rotary encoder measuring the bale forming time in a large square baler. Once the average mass of the square bales and the time of their formation were known, it was possible to calculate forage yield. The star wheel was located at the end of the bale chamber to reduce the effect of hay re-expansion. The results indicated that the displacement of the encoder was well correlated to the mass-flow of dry alfalfa (R^2 from 0.88 to 0.96). In subsequent studies, Shinners, Huenink, and Behringer (2003) measured the bale weight in dry alfalfa using a large square baler. The baler was instrumented with different sensors: star wheel-driven encoder to measure bale displacement rate; load cells in the bale chute to measure dynamic bale weight; radar to measure ground speed. The use of dynamic bale weight and speed of bale formation produced a very accurate estimate of the mass flow rate through the baler, demonstrating that the dynamic bale weighing method estimated the mass flow rate with high prediction accuracy (R^2=0.99). Huenink (2003) used a large square baler relying on feedroll displacement (flow speed) and bale weight assessment to measure mass flow rate. An alternative approach for measuring forage crop yields is that proposed by Masek et al. (2011), who placed a potentiometer to

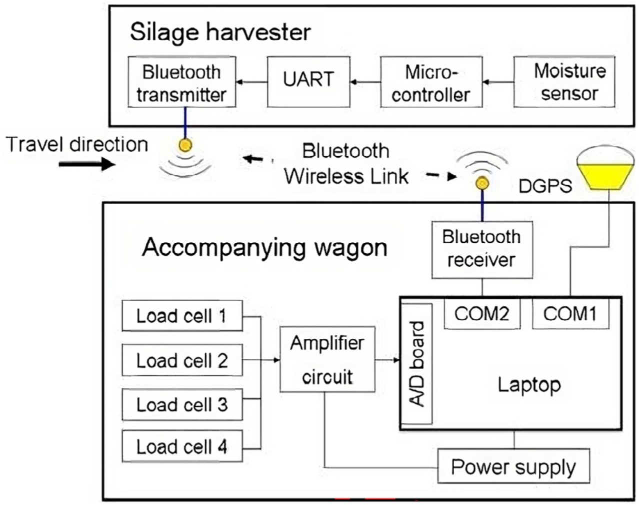

FIGURE 1 | Silage yield mapping system diagram proposed by Lee, Schueller, and Burks (2005).

sense the belt tension roller position in a round pick-up baler with a variable chamber. The system was used for hay and straw yield assessment. The potentiometer measured the position of the belt tension roller during chamber filling. The results showed a strong dependence of the tension roller position on the amount of the pressed hay or straw ($R^2 = 0.99$). Ramsey in his PhD thesis (2015) developed a measurement system based on two types of ultrasonic sensors installed on a John Deere 458 baler. The sensors allowed to estimate the windrow height and relate it to hay mass being fed to the baler, leading to a crop yield estimate showing errors of the order of 10%. An alternative weighing system for round hay balers equipped with a hydraulic kicker plate was also proposed by the same author (Ramsey IV 2015), involving the use of a pressure transducer installed in the hydraulic bale kicker circuit. The data provided by the transducer on two different round balers were correlated to bale weight to provide on-the-go bale weight estimates. Average absolute errors remained below 10%.

Finally, other studies have reported surveys involving standing biomass estimation directly in the field (Sanderson et al. 2001); mass flow measurement by applying sensors on forage windrowers (Shinners, Huenink, and Behringer 2003) and yield monitoring systems based on laboratory tests and data standardisation protocols (Table 4).

2.3 | Flow Mass Measure Accuracy From Harvesting and Handling Machines

2.3.1 | Moisture Sensors

Almost all the authors who have evaluated the mass through sensor impact force agree in considering it essential to include moisture values in the prediction model to improve the prediction quality. Therefore, for most applications an accurate on-harvester DM sensor has been deemed necessary (Forristal and Keppel 2001) (Table 5). This point is not only important for the calibration of mass flow measurements in SPFHs. In fact, Savoie, Lemire, and Theriault (2002) underlined how the moisture content can affect, for example, the accuracy of the torque meter in a forage harvester. As in combine harvesters equipped with moisture sensors, also in SPFHs capacitance sensors (located in the spout) are commonly adopted to determine crop moisture content, and much research has been conducted in this area (Barnett and Shinners 1998; Martel and Savoie 2000; Savoie, Lemire, and Theriault 2002). The use of near infrared (NIR) moisture sensing systems is the current alternative to resistivity sensors, compared with the added advantage of providing, beside moisture values, an assessment of crop composition in real-time (Digman and Shinners 2008; Akins, Dobberstain, and Shaver 2012; Long et al. 2016; Amiama, Bueno, and Pereira 2018; Kharel et al. 2019). Vomax (2012) reported that microwave sensing method (Figure 3) was more accurate in moisture measurement, compared to NIR sensing. However, NIR spectroscopy showed optimal results in monitoring DM contents under field conditions (Digman and Shinners 2008) as well as in laboratory tests (Welle et al. 2003; Akins, Dobberstain, and Shaver 2012).

2.3.2 | Calibration

Sensor adoption to assess crop mass always requires preliminary calibration, which often represents a critical point for yield estimation (Forristal and Keppel 2001; Matos et al. 2022). Calibration can be accomplished manually or with machinery operating over a small land area (Mannetje 2000; Sanderson et al. 2001). The actual weight of the collected biomass is used to evaluate the data quality of the automatic sensor systems and carry out their calibration (Rayburn et al. 2007; López-Guerrero, Fontenot, and García-Peniche 2011), through linear or multiple regressions (Rayburn et al. 2017; Cho et al. 2007). However, repeated calibration, by weighing trailer loads, is not readily available during the normal forage harvesting routine (Forristal and Keppel 2001). Furthermore, calibration should be implemented for a single, evenly distributed and consistently growing forage species (Auernhammer, Demmel, and Pirro 1995; Sanderson et al. 2001), which further complicates the process in the case of mixed, inconsistent forage stands. Furthermore, to improve signal quality from the acquisition sensors, calibration must be performed based on different field conditions and at least once a day in case of changes of forage density during harvesting operations (Rayburn et al. 2017). Therefore, a precise calibration for adaptive management during field operations should always be implemented (Anderson et al. 2011). The calibration procedure is slow and tedious. In practise, it is rarely carried out in full, resulting in poor application accuracy (Forristal and Keppel 2001).

2.3.3 | Data Cleaning

Raw yield data originating from sensors require a cleaning phase (Queiroz et al. 2021), as they may be subjected to systematic errors (Driemeier et al. 2016; Leroux et al. 2019; Kharel et al. 2019). The main error causes may depend on the delay in signal acquisition (lag error) versus the actual harvest point; incorrect setting of harvester working width; errors in GNSS receiver, in sensor accuracy and calibration (Chung et al. 2016; Sudduth and Drummond 2007). These errors can sum up to 10%–30% of the data, requiring much effort to limit their actual extent.

TABLE 3 | Summary of the most relevant yield measurement systems applied on balers.

Machine	Crop	Target	Technology and sensors	Source
Round baler	Hay	Measuring round bale mass	Baler instrumented with a load cell in the drawbar and strain gauges on each side of the baler axle. Comparison between static and dynamic weighing methods of measure.	Wild and Auernhammer 1999
Large square baler	Wilted alfalfa	Measuring forage mass during baling	Multisensor approach: star wheel driven optical rotary encoder mounted on the top of the bale chamber measuring the bale forming time; registration of signals of the plunger force via strain gauge sensors to correlate with the mass-flow rate; measure of bale weight via three load cells located in the bale chute.	Shinners, Barnett, and Schlesser 2000
Round baler with a variable chamber	Forage crop and straw	Measuring forage crop yield	Potentiometer to measure the belt tension roller position in a round pick-up baler with a variable chamber.	Masek et al. 2011
Large square baler	Alfalfa	Monitoring system for evaluation of hay mass flow	Evaluation of the performance of a commercial large square baler mass flow yield system (Claas 3200) at a different forward speeds and pressure settings.	Kayad et al. 2015
Round baler	Grass hay	Yield measure	On the go bale weight estimate based on the measure of the pressure in the cylinder actuating the baler kicker plate.	Ramsey IV 2015
Round baler	Grass hay	Yield measure	Ultrasonic sensors to estimate the windrow height and relate it to hay mass.	Ramsey IV 2015

2.4 | Manufacturers' Applications

Commercial implementation of mass flow sensors for yield measurement has been limited to forage harvesters and square balers; however, the square baler applications at present do not allow yield to be spatially determined. Some manufacturers, since 2005, have adopted mass flow and yield detection systems based on the measurement of the displacement of the feedroll (volume flow assessment system), as option for their self-propelled forage choppers (Schmidhalter et al. 2008). A subsequent step consisted in implementing the machines with GNSS systems to associate the mass values measured by the sensors with the field position, to obtain maps of yield data spatial variation.

2.4.1 | Forage Harvesters

The adoption of forage yield monitors on SPFHs has been slow, due to the cost of equipment and lack of confidence in both the performance of the equipment and the economic return on the investment (Digman and Shinners 2012). However, large manufacturers such as John Deere, Krone, New Holland have now integrated mass flow technology into their forage harvesters as a component of yield monitor systems. Most manufacturers adopt a multi-sensor approach, which allows for greater accuracy in measuring data. Mass-flow estimate based on feedroll displacement and impact force measured at the spout of choppers by means of curved or flat plates are the established solutions by manufacturers for mass-flow measurement.

The John Deere forage harvest equipment consists in a virtual terminal for yield data visualisation, mass-flow measures based on feedroll displacement, feedroll speed sensor, moisture sensor (HarvestLab, HL), GNSS and a computer that works out the information from sensors to be displayed (Deere & Company, 2002 John Deere, Moline, IL, USA). The HL sensor measures DM using NIR technology and is placed in the discharge chute of the machine. The mass flow sensor is placed in the cutter head and measures feedroll displacement with potentiometers. This displacement is correlated to the mass of crop flow, and this information is combined with the width and speed of the harvester, its flow rate (feedroll speed), moisture data and GNSS position. The information can then be stored and subsequently processed to obtain a DM yield map of the forage crop. Similarly, New Holland proposes, for its SPFH models, a yield monitoring and mapping system based on sensors located in the feedroll linkage continuously measuring the opening of the feedroll (Figure 4) and accounting for the width and speed of crop flow. In this case, the yield data are displayed on the Intellivoice IV display. The DM is measured by real-time moisture sensing based on a resistive type of sensor using three replaceable hardened contact pads to constantly measure the moisture in the feed flowing though the spout (New Holland, SPFHs). The harvester can be furnished with a NIR crop analyser NutriSense that monitors and records crop moisture and a variety of nutritional parameters in real time.

2.4.2 | Balers

Bale weighing systems are technologies integrated into large square balers by manufacturers such as New Holland, John

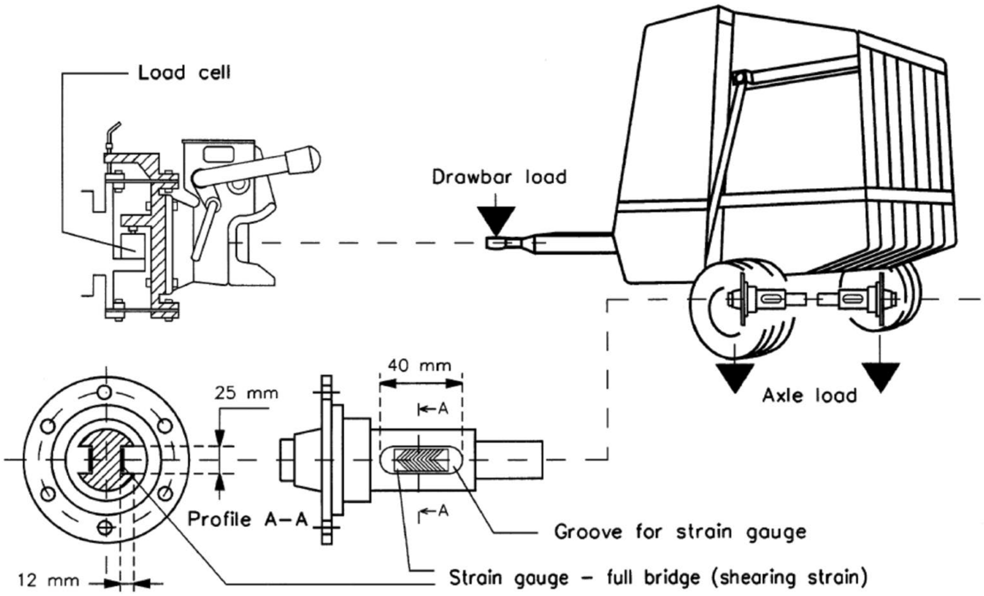

FIGURE 2 | Round baler instrumentation, from Wild and Auernhammer (1999).

TABLE 4 | Summary of other yield measurement systems.

Machine	Crop	Target	Technology and sensors	Source
Standing system	Forage yield	Predicting forage mass in the field	Non-destructive pasture meter to estimate standing biomass	Sanderson et al. 2001
Windrower	Alfalfa	Measuring mass-flow and yield data	Multi-sensor approach: pressure sensor for load of platform driving motor, sensor for conditioning roll speed, inclinometer for platform pitch, load cell for crop impact, rotary potentiometers for crop volumetric flow.	Shinners, Huenink, and Behringer 2003
—	Forage crops	Mass flow measure	Laboratory tests with capacitive sensors.	Kviz, Kumhala, and Prosek 2007
—	Forage crops, chopped maize and sugar beet	Mass flow determination	Laboratory tests with capacitive sensors to measure crop mass flow.	Kumhála et al. 2008 and Kumhála, Prosek, and Kroulik 2010
—	Maize for silage	Development of yield data cleaning protocol	Evaluation of yield monitoring data quality introducing a data cleaning standardisation protocol of raw data processing.	Kharel et al. 2019

Deere, Hesston and Challenger. Combined with a GNSS, bale weight data could be used to delineate a yield map that shows spatial differences in yield. Bale weighing is carried out at the chute of machines, and one of the key points is the system ability to systematically separate the determination of each individual bale.

Bale weighing systems of New Holland are integrated into the bale discharge chute of the BigBaler, and register bale weight at the point at which the bale is set free from the chute, just before it drops to the ground (New Holland, Large Square Balers). The Active Weigh system allows each bale to be weighed without slowing working speed, as the bale weight is collected 'on-the-go' and is independent of the bale length. Data of single bale weights and tons per hour are displayed on the IntelliView display (Figure 5).

The John Deere bale weighing system adopts sensors mounted at the pre-compression chamber floor that provide bale weights throughout the baling process, allowing the operator to continuously monitor bale density. Both New Holland and John Deere allow large square balers to be equipped with sensors to provide bale moisture levels throughout the baling process.

TABLE 5 | Summary of the most relevant moisture measurement systems.

Machine	Crop	Target	Technology and sensors	Source
Portable device	Maize and alfalfa for silage	Moisture measurement	Portable NIR analyser to monitoring DM	Akins, Dobberstain, and Shaver 2012
Baler	Hay	Hay moisture assessment in large square balers	Microwave reflectance sensors to measure bale moisture content	Vomax 2012
Forage chopper	Maize forage	NIR sensor calibration to apply on a harvesting machine	Diode array spectrometer mounted on a forage chopper	Welle et al. 2003
Pull-type forage harvester	Wilted alfalfa and maize for silage	Moisture measurement	Two-plate capacitance sensor located in the spout and in the auger trough	Barnett and Shinners 1998
Self-propelled forage harvester		Moisture measurement	Mobile, diode-array NIR spectrometer placed in the spout of forage harvester	Digman and Shinners 2008

FIGURE 3 | Hay moisture meter for large square balers based on transmission of high frequency electromagnetic waves (https://vomax.com.au).

FIGURE 4 | Yield monitoring system based on continuously measuring of the opening of the feedrolls proposed by New Holland in his FR series forage harvesters. (New Holland 2024a, 2024b)

3 | Optical Sensing Technologies for Yield and Quality Measurements

In recent years, sensor systems have been developed for biomass measurements in limited time and with reduced labour (Ali et al. 2016; Aquilani et al. 2021; Thapa, Lovell, and Wilson 2023). Satellite and proximal sensing technologies, operating at more than two meters from the earth surface (Rossel et al. 2011), can provide useful information on soil and crop conditions, and potential yields (Table 6).

Development of homogeneous field zones based on remote data plays an imperative role in precision forage and grassland

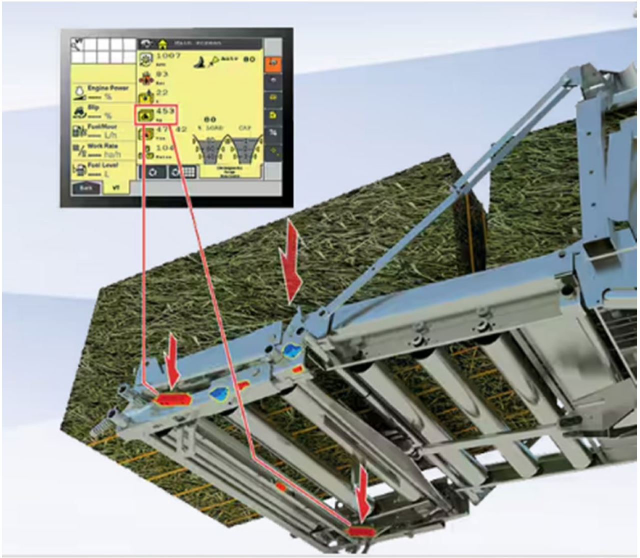

FIGURE 5 | New Holland baler Active Weigh™ System integrated with the roller bale chute.

farming (Cicore et al. 2016; Jin et al. 2017; Breunig et al. 2020; Raab et al. 2021; Badreldin, Prieto, and Fisher 2021). However, field zones under mixed grassland do not allow users to differentiate among plant species. Therefore, methods of delineating such zones should be plant specific and reflect topological characteristics (Atkinson et al. 2005; Andrieu, Josien, and Duru 2007). In this framework, high resolution maps of forage yields were produced based on aerial and satellite sensing data for precision grassland management (Liu et al. 2021). Raab et al. (2020) combined the Sentinel-1 and Sentinel-2 images into successful prediction of forage quantity and quality for the management of semi-natural grasslands. Hill (2004) used soil data at low resolution with vegetation indices at high resolution for grassland management. Slaughter et al. (2008) used the high-resolution data from airborne imageries for precision grassland management. Spectral techniques have also been successfully used for mapping grassland plant diversity based on spectral and functional data (Zhao et al. 2021).

Multi-spectral data can be used in forage and grassland assessments. However, a knowledge gap affects multi-spectral sensing techniques, as they are provided with an insufficient number of bands for determining plant biochemical or physiological traits (Carlson et al. 2007). Moreover, occurrence of mixed species in grasslands increases the difficulty in assessing the grassland biodiversity by means of high-resolution data (Gholizadeh et al. 2019). Consequently, spatial information from a reduced number of bands reduces the quality of the image and the ensuing information (Øvergaard et al. 2010; Øvergaard, Isaksson, and Korsaeth 2013). One main advantage of multi-spectral sensors is that they are quite cheaper than hyperspectral sensors.

The issues among spatial, temporal and spectral resolution can be epitomised by hyperspectral imaging (Asner et al. 2005). Rahman et al. (2003) demonstrated that 6 m resolution might be enough for monitoring spatial biomass, chlorophyll and water contents of shrubs and grass species.

Hyperspectral RS through Un-manned Aerial Vehicles (UAVs) has been employed efficiently in yield monitoring systems (Wachendorf, Fricke, and Möckel 2018). Oliveira et al. (2020) stated that an integration of hyperspectral sensing and 3D imagery can be used to obtain reliable multi-spectral information of Finish swards. This sensing system, equipped with high resolution camera can be used to monitor grassland biodiversity (Gholizadeh et al. 2019). Fresh biomass and DM content of grassland species can be measured through UAV-borne hyperspectral imagery (Wengert et al. 2022). Wijesingha et al. (2020) analysed the forage quality through UAV-hyperspectral sensing. Capolupo et al. (2015) performed the multivariate analysis on hyperspectral imagery to determine the canopy structure and quality traits of grass species. They stated that adding spectral resolution in hyperspectral data, through high signal to noise ratio (SNR) imaging technique, has potential in measuring quantitative traits of grass and pasture species. Furthermore, integration of hyperspectral thermal sensors and low-noise sensors improves soil moisture measurement in view of site-specific irrigation. Beside these studies, a push-broom instrument mounted on a manned aerial vehicle was shown successful in monitoring yield and quality traits (Cho et al. 2007; Pullanagari, Kereszturi, and Yule 2018).

Light detecting and ranging (LiDAR) technique in combination with RS data can be used for the measurement of biomass in grassland farming. Obanawa et al. (2020) used the LiDAR data for the prediction of Italian ryegrass biomass.

Small-sat technology is another option for assessing biomass data. For example, Compact High Resolution Imaging Spectrometer (CHRIS) could be applied for determining the structural components of plant species (Chopping, Laliberte, and Rango 2004). However, latest hyperspectral missions such as The Environmental Mapping and Analysis Program (EnMAP) (Kaufmann et al. 2015) and the Italian PRISMA (Pignatti et al. 2013) are more rapid, cost-effective and accurate in monitoring grassland ecosystem properties as physical and chemical variables under different CO_2 concentrations and weather conditions (Obermeier et al. 2019).

Satellite-based high resolution remote data have been efficiently used to measure biomass, yield and quality traits of grass species (Sibanda, Mutanga, and Rouget 2016; Askari et al. 2019). A synthetic aperture radar (SAR) is an advanced technology that can overcome cloud effects in measuring biomass height of grass species (Barnett and Shinners 1998).

4 | Discussion and Conclusions

Precision management technologies are rapidly advancing in many agricultural sectors worldwide. The greater the economic return and the wider the application field, the bigger the efforts in implementing new ideas, methods, approaches. It results that PA development proceeds at a variable speed, and sectors possessing to a lesser degree the above characteristics risk to receive less attention than needed.

This may be the case of forage crops and pastures with respect to arable crops as cereals, pulses and oilseeds. These latter crops share the same equipment especially in the harvest phase: their

TABLE 6 | Potential applications of optical sensing technologies in precision forage and grassland agriculture.

Target applications	Methods and results
Grassland cut detection, mowing events, start of season	• Dujakovic et al. (2024) used the Sentinel-2 time series through integration of Sentinel-1 SAR and weather data for precision grassland cut detection in view of modelling grassland yield and quality traits. • Sentinels-2 time series data were used for in-season harvesting decisions (Watzig et al. 2023). • Combination of Sentinel-2 and Landsat time series for the survey of grassland cut intensity at national scale (Griffiths et al. 2020). • Mowing events were detected using Sentinel-1 and Sentinel-2 time series (De Vroey et al. 2022). • Lobert et al. (2021) integrated the Sentinel-1, Sentinel-2, and Landsat 8 time series data for detecting mowing events in permanent grasslands. • Integration of remote sensing (MODIS NDVI at 250 m) with weather data to evaluate the actual time of grassland cuts for hay and silage production (Dujakovic et al. 2024).
Monitoring grassland biodiversity	• Hyperspectral remote sensing for identifying grassland vegetation species (Lucas and Carter 2008) and attributes, such as leaf physiological traits for functional biodiversity (Zhao et al. 2021). • Airborne remote sensing potential use for spectral biodiversity (Jackson et al. 2022). • UAV-based hyperspectral imagery used for assessing plant functional traits in alpine meadows (Zhang et al. 2022). • Multiscale remotely sensed hyperspectral data for monitoring diversity of grassland species (Gholizadeh et al. 2022). • Fusion of various satellite sensors data effectively used to improve the monitoring of grassland biodiversity (Kong et al. 2023).
Biomass measurement	• Fresh and DM yield of grassland using machine learning to process UAV-borne hyperspectral data (Wengert et al. 2022). • Alfalfa yield estimation for precision management based on hyperspectral images of UAV through machine learning method (Feng et al. 2020). • Yield variability in alfalfa was determined by Landsat-8 images and hay yield monitor data, where yield monitors were mounted on a rectangular baler to measure ground truth actual yield. Highest correlations between actual and predicted yield were found with the soil adjusted vegetation index (SAVI) (Kayad et al. 2016). • Machine learning methods were used for the prediction of alfalfa yield based on weather, satellite and drone data. The research concluded that the most prominent results were shown by random forest algorithm (Sadenova et al. 2022). • Liu et al. (2021) combined the Landsat and MODIS images into fused NDVI index, and the FAPAR index was developed through the APSIM model. Finally, forage yield was estimated in terms of spatial variability of absorbed photosynthetically active radiation (APAR). • High resolution digital camera was used to measure the biomass of short grassland (Vanamburg et al. 2006).
Dry matter yield estimation	• Integrated structural and spectral datasets from UAV-based sensors were used to estimate dry matter yield in paddock pasture (Karunaratne et al. 2020), and perennial ryegrass herbage yield in breeding trials (Pranga et al. 2021). • Fusion of satellite-sensing, ground measurements and the BASGRA model were employed in dry matter yield assessment in grassland plants (Persson et al. 2024). • Dusseux et al. (2022) estimated the grass height and density using Sentinel-2 data in terms of accurate estimation of dry matter yield in agricultural plots.

(Continues)

TABLE 6 | (Continued)

Target applications	Methods and results
Prediction of vegetation parameters	• Integration between RS (LiDAR, hyperspectral-based indexes) and weather data to predict sorghum biomass using a recurrent neural network (RNN) model (Masjedi et al. 2019). • Remotely sensed and field data with the APSIM model were used to predict sorghum biomass based on phenology and yield-related traits (Yang et al. 2021). • Leaf area index was determined using Landsat-2 data for permanent grassland grown under irrigated conditions (Abubakar et al. 2022); fusion of Sentinel-2 data with radiative transfer modelling (RTM) was used for the estimation of leaf area index (Klingler et al. 2020). • Grassland mowing events were established by integrating Sentinel-1 and Sentinel-2 images, using RGB camera, and enhanced vegetation index (EVI) developed by threshold-based algorithm (Reinermann et al. 2022). • Above-ground biomass of grassland species estimated through SAVI vegetation index (Ren et al. 2018); and NDVI index (Clementini et al. 2020). • Liu et al. (2021) used the NDVI data to determine productivity levels in mixed grassland, while Zhang et al. (2019) addressed fractional vegetation cover of typical grassland species, and Karimi et al. (2018) determined the grassland leaf area index using satellite based NDVI index. • Pamploni and Sarabandi (2004) stated that canopy biomass measured by SAR imaging technique is affected by various attributes as soil properties, plant moisture and varied degree of spectral wavelength, so these factors must be considered in canopy biomass detection.
Plant height and canopy parameters	• Canopy height, cumulative growing degree units and nutrient contents of alfalfa were measured using RS and air temperature data through LiDAR and covariate modelling based approach (Noland et al. 2018). • Landsat thematic maps and SAR images were merged for canopy structure assessment based on greenery, thickness and uniformity (Hill et al. 2005). • Advanced very high-resolution radiometer (AVHRR)-based NDVI and thematic maps were used for land cover classification based on canopy structure (Hill and Aspinall, 2000). • Chopping et al. (2004) measured the height and canopy width of shrubs through multi-angle remote imageries for precision farming applications. • Automated plant height was measured through visible light spectrum (Bendig et al. 2013; Borra Serrano et al. 2017). • Gross primary product was developed using Moderate Resolution Imaging Spectroradiometer (MODIS) data (Zhu et al. 2018). • Vegetation height was measured by UAV images through linear model and multivariate linear regression method (Lussem et al. 2019). • Obanawa et al. (2020) successfully used the Light Detection and Ranging (LiDAR) technique for the prediction of Italian ryegrass height.
Mixed species (i.e., grasses/ legumes)	• Cherney et al. (2021) used the handheld NIR sensors in monitoring biomass and nutrient contents of mixed hay and maize silage. • Remotely sensing data from Sentinel-1, 2 and MODIS technology was used to develop spatial maps of mixed grassland, for precision farming in grassland agriculture (Badreldin et al. 2021). • Xie et al. (2008) determined the vegetation types and relationships among species by processing spectral properties of remotely sensed images • Hyperspectral imageries were utilized in developing grass floristic gradients (Schmidtlein and Sassin 2004).

(Continues)

TABLE 6 | (Continued)

Target applications	Methods and results
Soil moisture contents	• Soil moisture contents were determined using SAR imaging (Wagner and Scipal 2000) and advanced microwave scanning radiometer (Moran et al. 2004). • Optical and microwave technology were widely applied in soil moisture measurements (Njoku et al. 2002; Chauhan 2003). • Soil moisture was measured by optical indices such as soil adjusted vegetation index (SAVI) and normalized difference moisture index (NDMI) (Cahyono et al. 2022).
Fertilizer management zones	• Nitrogen management zones were developed based on chlorophyll indices (Gitelson et al. 2006); they could be useful in precision grassland management. • Combination of remotely sensed and ground level data was used to supply precision fertilizers for bee forages (Adgaba et al. 2017). • Coupling of AVIRIS and Spectro-radiometric data in nutrient management for floristic measurements including grassland species (Asner et al. 2005).
Determination of homogeneous management areas	• Hyperspectral images were used to determine the stressed areas in halophyte vegetation (Day et al. 2006). • Nutrient management (phosphorus, potassium, calcium and magnesium contents) for rangeland species using band depth analysis (Mutanga et al. 2005). • Spectral and topographic pattern of grassland vegetation intensity were developed based on stepwise clustering, and classes for the management of meadows and pasture species were defined (Stumpf et al. 2020). • Vegetation indices were developed through airborne videography for precision crop and pasture management (Metternicht 2003).
Precision fodder biomass, soil carbon and organic matter contents	• Spectro-radiometers were used for on-farm measurements of grassland yield and quality contents (Schut et al. 2006). • Landsat thematic imageries were used to measure biomass and growth rate of fodder species (Edirisinghe et al. 2002). • Application of AVHRR for net primary productivity (NPP) (Wang et al. 2005).
Plant growth efficiency	• AVHRR and MODIS were used to determine pasture growing rate (Hill 2004; Pineiro et al. 2006). • MODIS imageries were used for vegetation growth (Reeves et al. 2006).
Determining plant water content	• Based on short wave infrared (SWIR) bands, the SWIR water stress index was developed using MODIS near- and shortwave infrared data (Fensholt and Sandholt 2003) • Bhoutika et al. (2022) used the evapotranspiration index to determine the crop water efficiency through developing actual evapotranspiration (AET) model. • Hyperspectral imageries and SAR water cloud models were used for water contents at canopy level (Roberts et al. 2004).
Identification of Invasive species	• Hyperspectral imaging of perennial herbaceous plants (Williams and Hunt 2002). • Papp et al. (2021) used hyperspectral data produced by UAV platform, based on algorithm developed by Support Vector Machine (SVM) and deep learning method for the detection of common milkweed, using field reference data as a target; higher accuracy was achieved by Artificial Neural Network (ANN) method (99.6% prediction accuracy) than SVM (92.9%).
Detection of Contaminants	• Ferwerda (2005) used the airborne hyperspectral images for the prediction of Sideroxylonal, a secondary metabolite of Eucalyptus, in rangeland foliage (Dury et al. 2001).

dry grains/seeds require to be separated from the residual plant portion using combine harvesters as the sole kind of machinery suited for the task. Despite a certain variation amid types of combine harvesters and yield sensors, the task of assessing instant yield is facilitated by a reduced number of combinations in commercial applications. Not surprisingly, there is unequivocal consensus that reliable yield assessment can be achieved in grain crops, provided that suitable operational conditions are ensured.

Hopefully, some systems devised for grain crops can also be applied to biomass crops including forages. This is especially true in the case of mass flow sensors which are in principle the same as those mounted on combine harvesters. However, their application in forage harvesters is less standardised and their reliability more critical owing to a quite higher amount of fresh biomass impacting the sensors, compared to the amount of almost dry product in the case of grain crops.

One of the main difficulties in obtaining reliable yield data through machine sensing is the occurrence of several factors that contribute to reducing measurement accuracy. Firstly, the machines are designed to operate on multiple crop types (maize for silage, immature cereals, fresh or wilted grass, straw, etc.), so the sensors must be able to detect such variability. Secondly, the same crop may be harvested at a different growth stage corresponding to differences in DM content, fibre structure and strength. These factors reflect on the amount of power required to obtain data related to mass flow. Finally, the species, density and growth heterogeneity that characterises mixed grasslands.

Implementing moisture sensors in parallel to mass flow sensors is also more critical in forage harvest, owing to the wider range of moisture in forages that may be harvested freshly cut (~80% moisture), wilted (~50% moisture) or under different conditions. The NIRS technologies make it necessary to perform accurate and repeated calibrations, which are specific for each crop plant also depending on the type of sensor installed and the technical configuration of the harvesting machine (Schellberg et al. 2008). This routine represents the main limitation for the practical use of these sensors.

Forage texture (stem size, with/without reproductive organs, simply cut, cut and conditioned, chopped, etc.) is another source of uncertainty in reliably assessing forage yield, in comparison with grain yield.

However, difficulties of a higher order arise in the case of yield monitoring systems specifically devised for forages. Among them, volumetric flow sensors based on feedroll sensing represent a large category of experimental and commercial applications. The inconsistent reliability of these sensors among literary sources not only depends on the different ways to assess feedroll displacement; the kind of forage and its moisture can also be responsible, owing to the fact that more uniform forage conditions as those found in chopped maize for silage (Martel and Savoie 2000) and wilted grass (Savoie, Lemire, and Theriault 2002) compared to fresh grass (Forristal and Keppel 2001) are conducive to more reliable results. According to the last authors, operating in grassland farms intrinsically poses more difficulties than operating in arable farms where maize and other seasonal forages are grown. It is perceived that the rougher soil surface often found in grassland farms contributes to the excessive feedroll oscillations, which are blamed for the unsatisfactory performance in yield assessment.

Torque sensors as proxy method to assess mass flow have shown some promising results (Savoie, Lemire, and Theriault 2002), although also in this case the concurrent assessment of moisture is considered a fundamental step to improve yield data reliability. The use of torque sensors to measure the power absorbed by the engine or the hydraulic motors driving the forage harvester's equipment is generally associated with a multi-sensor approach, as these sensors' reliability is linked to crop maturity, moisture content, cut length and the degree of sharpness of the knives.

It may not pass unnoticed that in both volumetric flow sensors and torque sensors, the principal literary sources date back to 15–20 years ago, indicating that perhaps the weak points evidenced in those works are difficult to overcome, and interest in further research has declined. Typically, measuring yields using a volumetric approach is not as reliable as using a mass flow approach. This is because determining mass from volume always requires assessing the density of the material, a parameter prone to fluctuate under several influences (e.g., in field wilting of cut grass). As a result, frequent determination of the biomass density is necessary. It is therefore felt that a more dependable assessment of forage yield could be based on multiple sensor fusion, an approach where the reciprocal advantages and disadvantages of different systems could be compensated, leading to response models accounting for differences in harvest conditions (Shinners, Huenink, and Behringer 2003). This echoes the fusion of multiple plant and soil sensors which is frequently practised during crop growth. However, it may not pass unnoticed that more sensors based on different principles involve higher costs and the need for calibration, maintenance, etc.

Another step towards easier yield assessment is equipping with mass flow sensors the handling machines instead of harvesting machines. In mowers, which also perform the conditioning and/or windrowing, the same sensor types were tested as in forage harvesters, obtaining also in this case a certain inconsistency between sensed and actual grass biomass (Kumhála and Prosek 2003; Wild, Ruhland, and Haedicke 2005). To overcome single sensor limitations, the multi-sensor approach is seen a winning strategy also for mowing machines (Shinners, Huenink, and Behringer 2003), although the same disadvantages apply as in forage harvesters.

If the objective is simply to obtain a measurement of crop yield, this can be achieved by equipping waggon trailers and balers with load cells that allow the harvested biomass to be continuous weighed. This can be associated with trailer or baler positioning through GNSS-receiver systems directly applied on them. Reported errors with respect to actual yield are generally lower than 2% (Wild and Auernhammer 1999; Godwin et al. 1999).

Balers are a category that has been extensively focused in view of equipping them with yield sensors. Both direct (load cells and strain gauges) as well as indirect methods (bale forming time and average mass) were tested, with yield prediction performances from satisfactory to very good. It is perceived that the consistently low moisture at which hay or, alternatively, straw is baled helps in obtaining reliable yield estimates. However, also in balers combined sensors provide the most accurate predictions (Shinners, Huenink, and Behringer 2003), at the expenses of a higher degree of complexity and costs. Additionally, the yield data obtained by balers may refer to a field position different from that the record is attributed to; this is due to rakes and windrowers dragging the forage during machine displacement, so the measurement of baled mass may not correspond to the position where that mass was produced.

Yield sensing based on proximal and remote assessments without any contact with forage crops, grasslands and pastures represents the other big family of sensing technologies. The physical drawbacks that have been quite often reported in direct assessment methods are avoided, in exchange for different challenges and constraints.

Among the principal platforms available for the task (Table 1), the satellites and other far-reaching instruments (e.g., the LiDAR) play a prominent role with respect to imaging systems operating closer to the surveyed scene as optical sensors mounted on UAVs. UAVs equipped with multispectral/hyperspectral cameras provide data on crop canopy reflectance which can be processed into spectral vegetation indices and, potentially, yield prediction models.

Depending on the optical apparatus they are equipped with, UAVs can also provide 3D images of the plant community structure helping to understand crop growth pattern. This sort of information retains a non-negligible interest in tree crops as fruit orchards and vineyards, where the shape and thickness of tree crowns during the growing season can be an important clue to the final yield performance. Conversely, this information is soon lost during the growing season of forages, grasslands and pastures, as their biomass becomes so dense that single plants can no longer be distinguished. This makes any image from low distance and low angles on the horizon modestly useful in the case of thick plant stands that are commonly found in these crop types.

Compared to remote/aerial imaging systems, ground-based systems (e.g., tractor mounted sensors) have generally been tested at experimental level but have not been extensively employed so far.

Whether they are obtained from satellites or aerial vehicles, canopy reflectance data are primarily used to assess crop growth status and provide valuable information about forage yield and quality. More accurate yield predictions quite often rely on multiple data sources as Landsat and MODIS images (Liu et al. 2021), as in the case of multiple sensor fusion in yield measuring systems mounted on forage harvesting and handling machines. However, in the case of RS this does not involve the burden associated with multiple systems applied to a single machine. This, in turn, prompts the attempts to combine various RS data sources, which have quite often proved successful (Masjedi et al. 2019; Clementini et al. 2020; Liu et al. 2021; Sadenova et al. 2022). In several cases, data originating from single/multiple image acquisition systems are processed through machine learning or neural network techniques that have proved their ability in turning raw data into reliable yield assessments (Masjedi et al. 2019; Feng et al. 2020; Sadenova et al. 2022; Wengert et al. 2022).

However, proximal and RS methods can hardly discriminate plant species in mixed stands, although some combinations as satellite and SAR images have proved useful in canopy structure assessment (Hill et al. 2005). Therefore, attempts have been made to run a compositional analysis of mixed stands from remote (Xie, Sha, and Yu 2008; Badreldin, Prieto, and Fisher 2021). This would be a useful means to better assess the nutritional potential of grasslands and pastures.

In conclusion, the analysis of the scientific literature addressing the topic of yield and quality mapping in forage crops and grasslands, from a precision farming perspective has shown that the most critical points are the response of the sensors to the variation of crop species and related properties. This also depends on the type of forage focused (fresh, hay, silage …), and harvesting stage. Furthermore, the need to assess forage moisture using NIRS sensors as the instrument of choice, introduces the need for correct calibration, which is a limitation for the practical use of the system, especially under variable field conditions such as in the case of mixed grasslands. The last difficulty, when monitoring systems are applied to handling machines as waggon trailers and balers, is to precisely associate product mass with the field position where that mass was obtained.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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