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Review

Precision Livestock Farming Applications (PLF) for Grazing Animals

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Abstract: Over the past four decades the dietary needs of the global population have been elevated, with increased consumption of animal products predominately due to the advancing economies of South America and Asia. As a result, livestock production systems have expanded in size, with considerable changes to the animals' management. As grazing animals are commonly grown in herds, economic and labour constraints limit the ability of the producer to individually assess every animal. Precision Livestock Farming refers to the real-time continuous monitoring and control systems using sensors and computer algorithms for early problem detection, while simultaneously increasing producer awareness concerning individual animal needs. These technologies include automatic weighing systems, Radio Frequency Identification (RFID) sensors for individual animal detection and behaviour monitoring, body temperature monitoring, geographic information systems (GIS) for pasture evaluation and optimization, unmanned aerial vehicles (UAVs) for herd management, and virtual fencing for herd and grazing management. Although some commercial products are available, mainly for cattle, the adoption of these systems is limited due to economic and cultural constraints and poor technological infrastructure. This review presents and discusses PLF applications and systems for grazing animals and proposes future research and strategies to improve PLF adoption and utilization in today's extensive livestock systems.

1. Introduction

The need for the improved quantity and higher quality of animal products, especially in developing countries [1], has led to the increase in size of animal herds, whereas the number of farmers has declined [2–4] and the availability of grasslands has been reduced because of cropping [1]. As a result, farmers have less time to assess individual animal needs and the grazing animal's feed resources are shrinking, resulting in welfare impairment [5,6] and health-related and performance concerns [7]. Precision Livestock Farming (PLF) techniques have shown great potential in solving such problems, since they represent a unique opportunity to convert herd management from manual to automated or semi-automated systems. They can potentially contribute to an amelioration of health and welfare status, minimize of on-farm labour and veterinary costs, improve farm waste management, and increase environmental and economical sustainability [8–14].

Grazing land represents 60% of the world's agricultural land, and is used by nearly 360 million cattle and over 600 million sheep and goats [15]. Grazing animals represent 10% of beef and about 30% of sheep and goat meat consumption globally [15]. Furthermore, it is estimated that grazing animals are the only source of livestock for over 200 million people [15]. A major advantage of grazing animals is that they utilize by-products that

otherwise would be wasted, improve the diversity of grasses by dispersing seeds with their hooves, and ensure soil health with their manure. In addition, as the animals trample the soil, they break up the crust and increase the stimulation of grass growth and soil regeneration [15]. However, many of the world's grazing areas are threatened, as policies are contributing to the conversion of pasture into cropland. When the land is exhausted and returned to fallow, it does not revert to good pasture and, therefore, it is deserted. Thus, optimal utilization of the lands through improved grazing techniques where the animals continuously change allocated areas can lead to more sustainable farming and grazing systems [1,16].

PLF systems focus on managing any variable that interferes with the production process and trigger a series of alarm signals whenever a problem is detected [4]. The animals will express their discomfort due to lack of feed or undesirable environmental conditions, using bio-responses (i.e., changes in behaviour) that the system detects. Therefore, the first step in creating a PLF model is behavioural analysis through animal-based observations [17]. The development and analysis of large behavioural datasets produce models and algorithms that will be used as the "golden rule"—code for the automatic classification and identification process [9,18]. Detected behavioural changes will be automatically classified by the controller as normal or non-normal according to the behavioural pattern of best fit. After the classification process, the system's output will either assess the problem automatically or produce a series of alarm signals and provide possible suggestions, assisting the farmer in the decision-making process [19]. The bio-responses analysis may include both steady-state and dynamic component modelling methods [20]. Therefore, the resulting model should include at least one relationship between the variable of interest and the behaviour, and it should be able to predict future behaviour from previously recorded data. The comparison between the predicted and the actual measured behaviour (i.e., prediction error) will indicate if the animals' status has changed [4]. This information is used as an input for the controller in making the necessary adjustments to return the animals to their "normal state". In other words, the animals' bio-responses are used as indicators for the system and, in a sense, they represent the feedback sensor in a closed-loop control system [7].

Various PLF applications have been developed over the past two decades, including precision grazing technologies and management software support tools [21–23], image analysis methods for grazing measurements [24], electronic identification systems such as RFID tags [25,26], movement detection systems including accelerometers [27,28] and GPS [29], audio analysis systems [30], flock management systems such as virtual fencing [31], and drones [32] and health detection and welfare assessment systems with the use of implanted sensors [33]. This paper illustrates a variety of PLF applications for grazing livestock, pointing out potential improvements and providing ideas for further research in the area. All studies presented were retrieved through Google Scholar, ScienceDirect, MDPI, ResearchGate and Web of Science. For better understanding, the term grazing livestock refers to herbivores, such as cattle, sheep and goats, and omnivores such as poultry and pigs, both domesticated and wild, that are fed mainly or partially through forage. Some keywords that were used for the research were: "Precision Livestock Farming or PLF", "technology", "camera-based", "audio analysis", "RFID", "GPS", "GIS", "collars", "data loggers", "environmental conditions", "virtual fence or VF", "robots", "electronic drinker or feeder", "IoT", "convolutional neural network or CNN", "applications", "advancements", "grazing", "free ranging", "cattle or cow", "sheep or lamp or ewes", "goat", "ruminant", "poultry", "chicken or chic", "pigs" and "duck". General research was conducted, and in each case that a positive technological application or study was retrieved, specific research was performed separately. The research period we used was 1991–2022 as we wanted to include as many publications as possible. As a result, a total of 173 articles were included in our database presenting applications and related research in PLF for grazing animals.

2. PLF in Grazing Cattle

The average milk and dairy consumption has been constantly increasing over the past four decades, and it is expected that by 2050 it will increase by 50% compared with that of 2010 [34]. The increase in animal numbers per herd and the introduction of the high milk yield breeds of cows in the production process during the past century improved yield, while the farmers' ability to assess individual animal needs decreased [7,35,36]. Therefore, the relationship between animals and humans, animal health and welfare status along with the consumers' increasing need for food safety in quality products and the units' sustainability are production elements that have been affected [36]. PLF technologies have demonstrated great potential in assessing or even solving these problems. The farmer can monitor the animals' everyday lives noninvasively, no matter the size of the herd, and assess farming practices from their computer [36,37]. Therefore, PLF systems can potentially improve the animals' well-being, enhance soil health, pasture utilization and management, while simultaneously improving animal performance (i.e., quality and quantity of the end-product) and enhance farmers' annual income.

Various PLF technologies have been developed for grazing cattle, including RFID tags, boluses, collars, and noseband sensors for grazing behaviour measurement [38], in addition to monitoring cardiovascular and respiratory patterns (i.e., heart and breathing rates and oxygen saturation) for health and welfare assessment [39]. Ear tags and injectable glass tags are used for individual identification [40–42], individual data documentation (e.g., maternal pedigree), and disease trajectory monitoring [43]. Other PLF systems are walk-over-weight platforms and electronic scales, thermal analysis systems for body temperature assessment, camera analysis models for position detection and methane emissions estimation [44], sound analysis systems for rumination classification and analysis [45], video analysis for early disease detection, behavioural patterns classification and mating behaviour [46], GPS, GIS and accelerometers for individual animal location detection, theft prevention, feeding and ruminating behaviour detection [47], feed intake and reproduction monitoring [48]. It should be noted that PLF applications as such collect large amounts of data depending on the sensor type used and therefore large storage devices are mandatory. However, Bhargava et al. [49] presented a useful method to overcome this issue by using Wireless Sensor Networks combined with Edge Mining for data compression, memory usage optimization, and assessing future real-time PLF application models. However, internet access in most farms in the Mediterranean is limited; therefore, a LAN-based system could be more useful.

2.1. RFID Technologies

Radio Frequency Identification (RFID) technology has been widely applied in grazing cattle, as it offers an affordable solution for remote, non-contact, continuous identification, and monitoring of animals with high credibility [48,50]. RFID tags store large amounts of valuable information, such as age, sex, breed, weight, and health status [40]. RFID technologies can be divided into two categories with respect to operating frequency [40]: low-frequency, primarily used for animal identification, and high-frequency, primarily used to track populations and not individuals [41]. RFID tags can be further classified as active or passive tags that emit (or not) radio waves, respectively. Active tags emit high frequencies varying between 455 MHz, 2.45 GHz, and 5.8 GHz, with a reading range between 20–100 m, whereas passive tags offer a reading range of no more than 3 m [40]. Managerial software has been developed based on data collected from the ear tags, where individual characteristics such as medical treatments, growth performance, pedigree, and reproductive traits are automatically recorded and stored [25,50].

As shown in Table 1, various applications can be found in the literature, including individual identification [51], detecting and monitoring watering behaviour under different environmental conditions [52], monitoring drinking behaviour and water intake [53,54], licking behaviour [55,56], individual supplement intake [57], feed intake and grazing activity [58], individual mineral intake, feeding behaviour and growth performance [59],

movement tracking [60], estrus detection [61], heat stress detection and automatic artificial shading [62]. It is evident that RFID technologies have shown great potential towards the automation of the production process due to their ease of use, highly accurate measurements, and precise sensor readings [25]. It should be noted that their main disadvantages are the increased labour effort for configuration and installation and their high operational costs [40,63].

2.2. GPS and GIS Systems

Most of the literature regarding the activity of grazing animals and grazing strategies adopted by farmers is primarily focused on economically oriented pasture systems [64–66]. This lack of information on more holistic approaches in grazing systems is attributed to the difficulty of data collection and storage [67]. Animals often graze under harsh conditions in rangelands, making the conventional animal tracking methods challenging and labour intensive [68]. It should be noted that a considerable portion of foraging and grazing activity takes place at night, making data collection even more difficult [69,70]. GPS and GIS technologies could potentially help overcome this problem. This kind of technology is a low-cost tool used for monitoring grazing animals during long periods [67]. Additionally, as grazelands become more intensified and biodiversity is under threat of extinction [71], these technologies could help farmers manage the herd's grazing behaviour in a more environmentally friendly manner. Furthermore, they can be easily combined with other low-cost methods such as RFID technology for welfare assessment and health-related problem detection [68].

Turner et al. [72] developed a combined GPS-GIS system for cattle behaviour monitoring and pasture use. Lightweight GPS collar receivers were used to map the area mostly used by the animals. Additional information regarding the system's development is provided by Turner et al. [73]. Within approximately 8 m, the system showed an accuracy of 95% for location detection and a classification of 94.8% for active grazing activity. As indicated, a combination of GPS collars and accelerometers can potentially track the animals during grazing and drinking [68]. Hassan-Vásquez et al. [74] used GPS technology to monitor animals' field distribution and behaviour. They reported that their method can potentially improve grazing management, grazeland utilization and reduce the environmental footprint of the production process. Riaboff et al. [75] combined GPS and accelerometers to monitor cattle grazing, walking, ruminating, resting, lying behaviours, and preferred pasture site characteristics. Two different pastures of 1.6 and 2.3 ha were available for grazing. The preferred area for lying and ruminating was under the trees. The preferred grazing areas of pasture for the first paddock (i.e., permanent grassland) were directly related to the pasture characteristics. However, for the second paddock, the cows showed more socializing behaviours rather than pasture characteristics-oriented behaviour, probably due to the presence of heifers in the nearby fields. It should be noted that no information concerning the PLF evaluation parameters was reported. Brosh et al. [70] used a combined GPS and motion sensors system to monitor standing, locomotion, grazing and lying behaviours. They reported that cows' intake preferences and plot biomass variations could affect the quality and quantity of the end-product and the reproductive status of the animals ($p < 0.001$). This was the first study in which the animals' behaviour and incremental energy expenditure were measured simultaneously throughout the day. Therefore, some findings, such as the late-night grazing frequency, cannot be compared with previous studies. It should be noted that the total activity costs accounted for 5.8 to 11.4% of the daily energy affected only by herbage quality (i.e., the proportion increased when the quality dropped). However, no information was provided concerning the system's PLF evaluation parameters. Spedener et al. [76] used a similar combination of GPS collars and activity sensors and successfully monitored the activity of 16 cows during grazing, resting and pasture preference with a precision of 94.1%. Larson-Praplan et al. [77] used GPS collars embedded with temperature and movement sensors and successfully ($R^2 = 0.81$) monitored grazing activity during seasonal changes for four years. They found that during

the warmer months grazing activity was mainly concentrated around the trees and shade, while in winter and early spring, grazing activity was widely distributed. Resting sites act as beginnings and endings of grazing bouts; thus, shade distribution could potentially be used as an additional grazing management technique. The system was able to detect individual grazing behaviour only and failed to detect group or herd behaviours due to limited pasture size and the lack of analysis of the spatial distribution of the herds. Furthermore, a thorough economic analysis of the system's estimation costs and profits could be drawn towards convincing farmers to adopt such technologies.

The studies suggest that GPS-GIS technology could potentially aid in identifying animal-environment interactions, monitoring the animals' activity, detecting behavioural changes associated with diseases and welfare impairment, and pasture design according to the animals' preferences and needs. Furthermore, they could potentially improve both pasture management and pasture design. However, commercial applications are still under development and lack economically viable solutions for the farmers.

2.3. Other Multi-Sensors PLF Applications

PLF consists of various combinations of sensors and mathematical models for welfare assessment and management improvement techniques. Complex systems are comprised of multiple sensors used in conjunction for data collection under a single dedicated analysis system. For example, automatic milking robots are utilized as a data collection source for multiple variables including daily milk production, milk temperature, quantity, and quality (i.e., somatic cell count, milk fat and protein percentage), body weight, and concentrate intake.

Osei-Amponsah et al. [62] used infrared and thermal cameras to monitor body temperature, and successfully identified cows under heat stress. The automatic milking machine recorded and documented individual traits using the RFID ear tags. The stage of lactation significantly affected ($p \leq 0.05$) the average daily milk yield, fat %, protein % and concentrate feed intake, while the reverse relationship was documented between Temperature-Humidity Index (THI) and milk yield, feed intake and rumination time. McCarthy et al. [59] used electronic feeders and successfully monitored individual mineral intake, feeding behaviour, and performance in terms of growth in 28 grazing Angus cow-calf pairs. PLF technology could be used as a management decision making tool for welfare assessment, but no information concerning the systems' economic viability (i.e., economic analysis) and evaluation parameters, such as accuracy, precision, specificity, or sensitivity was provided [56,59]. Simanungkalit et al. [56] used tri-axial accelerometers embedded in ear tags, RFID sensors, automatic weight scales and automatic supplement blocks, and successfully identified the licking behaviour of Angus and Brahman cattle. Williams et al. [53] used RFID ear tag readers, motion sensing accelerometer collars, and two cameras installed at the water point for model evaluation. The drinking behaviour and water intake of Brahman and Droughtmaster grazing beef heifers was successfully monitored for approximately two consecutive months. The water flow meter demonstrated an accuracy of 99%, but no information was provided concerning the overall accuracy of the system. Simanungkalit et al. [78] developed a model to evaluate a walk-over weighing (WoW) system for individual body weight estimation and supplement intake. WoW systems could potentially provide useful information on the body weight of grazing cows with sufficient accuracy. The system overpredicted the body weight of calves and cows by 3.2% and 3.4%, respectively. However, the model needs further long-term validation under various environmental conditions and herd sizes, whereas an economic analysis for the total costs is essential for the development of a commercial application. Durst et al. [57] used a portable, self-contained individual feeding unit and cameras, and successfully monitored cow presence and feed intake ($p<0.01$, $r^2 = 0.95$). The system demonstrated a high sensitivity of 97% for true positive results (i.e., feeder attendance and usage) and 99% for true negative results (i.e., feeder attendance only). Further research is needed to examine the individual animal feeding behaviour and preferences under different environmental conditions, breeds, stocking rates, herd sizes, and field topography. Chelotti et al. [79]

developed an online dynamic model for grazing behaviour, foraging activity recognition, and rumination estimation using audio analysis. Although the system showed improved efficiency compared with other commercial systems, further research is needed with regard to improving the recognition performance and total system cost. It should be noted that no information concerning the evaluation parameters (i.e., precision, specificity, accuracy and sensitivity) of the system was provided. Finally, a model consisting of an accelerometer, a magnetometer and a gyroscope was used for monitoring cattle's lying activity and ruminating behaviour in different environments (i.e., outdoors, or indoors) [80]. The system was validated using camera recordings in both environments, showing an average of 95.6%, 80.5% and 87.4% for sensitivity, specificity, and accuracy, respectively. Furthermore, the system accuracy for outdoors and indoors was 93.2 and 81.4%, respectively. However, further research is needed to improve the prediction model for in-barn usage and commercial application development.

Other systems include Internet of Things (IoT) sensors that have shown promising data collection and transfer for farmers. Park and Park [81] used an existing system that was primarily used in tracking wildlife activity (i.e., ZebraNet). This system consists of a Wireless Sensor Network (WSN), a Cloud platform which processes the collected data, and a digital user interface. The WSN refers to the GPS sensors attached to the collars and transfers position data using 3G/4G cellular communication transmission. To avoid data losses due to loss of connection, the animals' collars were equipped with 3G communication modules. The data was stored on an online database to minimize the system's costs and a Graphical User Interface (GUI) screen displayed all the information collected in a digital format utilizing the Google Maps software. It should be noted that this system is under development towards a commercial application that estimates and predicts the health status of the animals. Martinez-Rau et al. [82] developed a processor that analyzes real time data collected from a wearable acoustic sensor to identify jaw movement in grazing cattle for noiseless and noisy conditions with a recognition rate of 91.4% and 90.2%, respectively. Although the system is still under development, it could potentially identify the efficiency of rumination and, thus, the total feed efficiency. However, further research is needed under different managerial techniques, genotypes, and environmental conditions, along with an economic analysis index for the development of a commercial application. Wang et al. [83] developed an IoT-based behavioural classification system using data collected from water-proofed leg tags with embedded tri-axial accelerometers. The model exceeded 90% accuracy for all behavioural categories, and specificity was 96.98% for normal walking behaviour. However, further research is needed to improve the classification algorithm parameters to effectively identify behavioural patterns. Natori et al. [84] developed a system for cattle activity monitoring and position detection using a combination of a GPS module and an acceleration sensor consisting of a tri-axial accelerometer, a tri-axial gyroscope, and an electromagnetic compass in a single package. The data was transferred and stored wirelessly. Furthermore, the system used an environmentally friendly monocrystalline silicon solar panel as a power source for the IoT module. The system could potentially be used in behavioural analysis, welfare assessment, and health-related problems detection, but further research and validation is needed for the development of a commercial application. Barbedo et al. [85] developed a convolutional neural network (CNN) and deep learning model for animal detection from aerial images for non-ideal environmental conditions such as low illumination, excessive brightness, blur presence and low visibility. The model is described as a "remarkably robust system" since it could achieve accuracy rates close to 100%. However, this system is under development, as new breeds, other than Canchim, and new image datasets from different landscapes should be included. Li et al. [86] developed a neural-network-based monitoring model to emulate different rotating states of an accelerometer implanted on the collar. Their method was able to verify behaviours such as feeding, walking, drinking, rumination and resting, with an average accuracy of over 98%. Moreover, this system could potentially be used for early detection of disease or estrus. An interesting concept regarding powering energy sensors was presented by Blažević et al. [87],

in which IoT technologies and energy wearable harvesters convert the kinetic energy of the animals (i.e., the motion of the ear or general locomotion of the animals) into electrical energy. However, this technology needs further research under various environmental conditions and with different breeds, as well as full economic analysis for the development of a commercialized product.

Virtual fencing (VF) is another commercial application introduced as an alternative grazing management method over the past two decades. A VF system consists of a collar equipped with audio signal reproduction mounted on every animal and a GPS-based virtual fence created in various locations within the limits of the grazing area [88–90]. When the animal approaches the boundaries of the virtual fence that may be stationary or moving, either an electrical stimulus, audio signal, or both are delivered by the collar. The stimuli stops when the animal stops walking or turns back [91,92]. This system replaces the traditional methods of herd management such as temporary fences and electric fences at considerably lower costs as the construction materials and labour installation costs are minimized [90,91,93,94]. Furthermore, it does not affect the animals' health and performance [90,92], while at the same time it may be used to protect biotopes and maintain biodiversity [95]. Various studies that demonstrate the potential of this technology as a commercial application can be found in the literature [89,90,92,96–109]. However, Boyd et al. [96] developed a Virtual Fencing (VF) system for burned land grazing protection based on GPS collars with a success rate of 96% ($p < 0.0001$). The system successfully prevented the cows from grazing in the burned land, compared with a normal fence. It should be noted that in the case of a conventional fence, the cows spent more than 40% of their time within the burned area and foraging was nearly 70%. The main problem of the VF system was the topographic barriers that limited the radio and cellular communications between the collars and the base station, and the base station and the data storage. This resulted in data loss concerning the animal locations and limited the user's ability to change input parameters such as frequency of animal data location storage and electrical/auditory stimulus parameters. The system total costs for a single fence solar-powered base were approximately $12,500 and the number of stations needed depended on the topography of the fenced area. In addition, every collar used was leased at an annual cost of $40. Therefore, the VF demonstrates considerably higher purchase and installation costs compared with a barbed wire fence with an annual cost of approximately $8,000 (USD/km). Aaser et al. [109] reported that personality and herd structure should be considered when selecting individuals for the VF grazing management method. In the 139-day period, the system successfully kept the cattle herd within the specified area and only four breakouts were reported due to poor fence placement. However, no evaluation parameters such as accuracy, efficiency, specificity or precision, and no economic analysis concerning the installation, the operational and the total costs of the system were provided. Furthermore, this technology is still under investigation regarding its impact on animal behaviour and welfare, which may be an important factor resulting in its limited adoption by farmers.

Table 1. Application of precision livestock farming advancements and their evaluation in grazing cattle.

	Applied Technology	Parameter of Interest	PLF Evaluation Parameters	Reference
RFID	MooMonitor+ RumiWatch	Grazing behaviour and rumination	Accuracy: 94 and 97%, respectively Accuracy: 96 and 98%, respectively	[38]
	Handheld Walk through device	Movement tracking	Efficiency: >98.1% Efficiency: 89.5–98.5%	[60]
	RFID and Accelerometer	Licking behaviour monitoring	Efficiency: 98% Efficiency: 89%	[55]

Table 1. *Cont.*

Applied Technology	Parameter of Interest	PLF Evaluation Parameters	Reference
RFID	Welfare assessment	Accuracy: 93.12%	[39]
	Individual identification	Not provided	[41,42]
	Individual data documentation Disease detection		[43]
	Detecting and monitoring watering behaviour and water intake	Efficiency: 100%	[52]
	Feed intake monitoring Grazing activity monitoring	Not provided	[58]
	Individual mineral intake monitoring Feeding behaviour monitoring Growth performance monitoring		[59]
	Oestrus detection	Sensitivity: 65% and Specificity: 60%	[61]
	Individual identification	Not provided	[62]
RFID and Cameras	Individual identification	Precision: 89%	[51]
Cameras	Position detection	Precision: 84.6–99.9% (depending on the distance between the cameras and the observation)	[44]
	Methane emissions estimation	Accuracy: 97%	
	Disease detection Behavioural patterns classification Mating behaviour detection	Not provided	[46]
	Behaviour monitoring	Efficiency: 91%	[92]
Thermal cameras and infrared sensors	Body temperature monitoring Heat stress detection	Not provided	[62]
Sound analysis systems	Rumination detection	Precision (R2): 87% (n = 51)	[45]
GPS and GIS	Behaviour monitoring	Classification Accuracy: 91.7%	[72]
	Pasture usage monitoring	Classification Accuracy: 94.8%	[73]
GPS and accelerometers	Grazing behaviour monitoring Movement tracking Ruminating behaviour monitoring Resting detection Lying behaviour detection Feeding behaviour monitoring	Accuracy: 98%	[75]
GPS	Location detection Field distribution behaviour monitoring	Precision: 82.8%	[74]
GPS and motion sensors	Standing detection Locomotion monitoring Grazing behaviour monitoring Lying behaviour detection	Not provided	[70]
	Grazing behaviour monitoring Resting behaviour monitoring Pasture preference classification	Precision: 94.1%	[76]
IoT system (GPS, WSN, Cloud platform)	Health status prediction	Not provided	[81]
GPS, temperature and movement sensors	Grazing activity monitoring	Accurate classification (R2): 81%	[77]

Table 1. *Cont.*

Applied Technology	Parameter of Interest	PLF Evaluation Parameters	Reference
GPS, GIS and accelerometers	Individual animal location detection Theft prevention Feeding behaviour detection Ruminating behaviour detection	Accuracy > 90%	[47]
RFID, accelerometers, automatic weight scales, automatic supplement blocks	Licking behaviour monitoring	Licking and non-licking detection accuracy: 81 and 94%, respectively	[56]
RFID, motion sensors, flow meter, cameras	Drinking behaviour monitoring Water intake monitoring	Flow meters accuracy: 99%	[53]
Walk-over-weighing (WoW) system	Individual weight estimation Supplement intake monitoring	Prediction error for calves and cows: 3.2 and 3.4%, respectively	[78]
Electronic feeder, cameras	Feed intake monitoring Feeding behaviour monitoring	True positive and true negative sensitivity: 97 and 99%, respectively	[57]
Sound analysis systems	Grazing behaviour detection Foraging activity recognition Rumination estimation	Not provided	[79]
	Rumination efficiency monitoring Total feed efficiency monitoring	Grazing detection accuracy in noiseless and noisy conditions: 91.4 and 90.2%, respectively	[82]
Accelerometer, gyroscope, magnometer	Lying activity monitoring Rumination detection	Sensitivity: 95.6% Specificity: 80.5% and accuracy: 87.4%	[80]
IoT system, gyroscope, accelerometer, electromagnetic compass, solar panel power source	Activity monitoring Position detection	Not provided	[84]
IoT system, accelerometers	Behavioural patterns classification	Accuracy: >90% and specificity (walking behaviour): 96.98%	[83]
CNN, image analysis	Animal detection	Accuracy ~ 100%	[85]
CNN, accelerometers	Feeding behaviour detection Walking behaviour detection Drinking behaviour detection Rumination detection	Accuracy >98%	[86]
IoT system, energy wearable harvesters	Kinetic into electrical energy conversion	Not provided	[87]
Virtual fencing	Prevent access to certain VF protected area	Efficiency: 99.8%	[108]
	Biotopes protection	Not provided	[99]
	Grazing activity control	Efficiency: 95–96%	[89,90,96,98]
		Not provided	[99,102,107,109]
		Reliability: 100%	[105]
		Efficiency: 100%	[106]
	Activity control	Efficiency: 97%	[101]
		Efficiency: 100%	[100,103,106]

3. PLF in Small Ruminants

Extensive grazing-based systems are of particular interest for small ruminants, since they require low input costs and offer improved resilience against market fluctuations.

Sheep and/or goat farms are often of small scale and their owners are generally conservative, and reserved towards new technologies, parameters that hinder the adoption of PLF on a regular basis within the production process [110], although variations exist around the world (e.g., Mediterranean dairy farms versus meat production systems in Australia or New Zealand). Moreover, poor technological infrastructure (e.g., electricity, telephone, and internet networks) and other financial barriers also limit PLF's regular use [111].

Various PLF technologies have been developed over the previous decades in pasture-based farming systems of small ruminants (Figure 1). Electronic identification (EID) systems, such as ear tags, ruminal boluses, and subcutaneous transponders are the applications that are more frequently used, since they are mandatory in the European Union (EU). Innovative technologies that simplify flock management based on on-animal sensors are also employed and include global positioning systems (GPS), accelerometers, gyroscopes and social activity loggers that can provide data regarding several behavioural parameters, health, and welfare status. Furthermore, robots that identify wildlife and classify it as dangerous (i.e., predators) or harmless for added herd protection are under development. Finally, there are also other commercially available management systems that assist farmers, namely virtual fencing, flock monitoring using drones, and image analysis techniques, automatic weight monitoring using walk-over-weighing, or weighting crates and other milking parlour-related technologies [48,111].
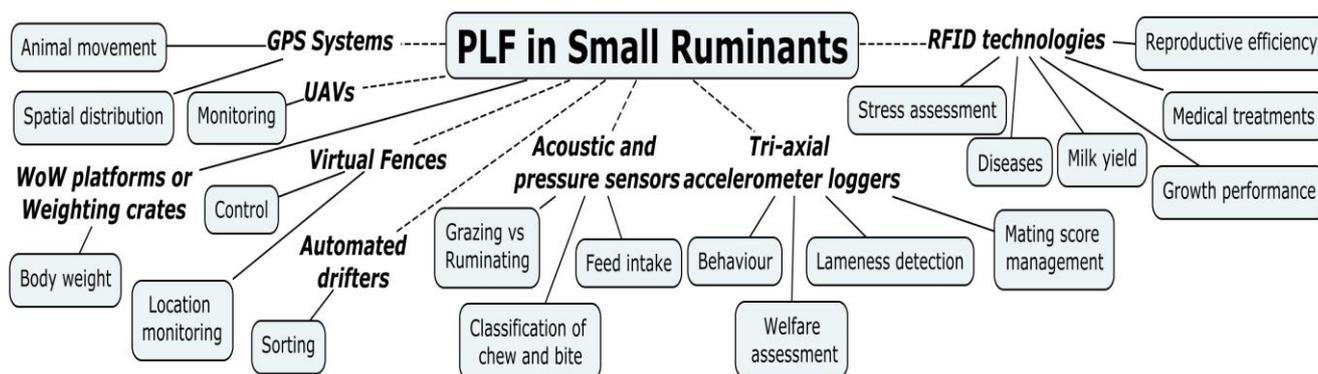

Figure 1. PLF applications in grazing sheep and goats.

3.1. Electronic Identification (EID) Systems

Electronic identification is mandatory in the EU and is generally ensured through radio frequency identification (RFID) tags that transmit information on different radio frequency levels (low, high, or ultra-high) to the tag reader. RFID is a cost-effective way to track and monitor individual animals and in combination with other PLF applications could automatically provide records for growth performance, milk yield, reproductive efficiency, and medical treatments [25,26]. Ear tags are the cheapest EID method, but its application to the ear increases the possibility of its loss, especially in outdoor paddocks. On the other hand, ceramic boluses ensure permanence after their insertion in the rumen of small ruminants [112]. Finally, subcutaneous temperature transponders inserted under the skin can potentially be used [113], but their migration and difficulty of removal in meat-producing sheep and goats should be considered [40,114].

3.2. On-Animal Sensors

Wearable sensors such as tri-axial accelerometer loggers, GPS systems, microphones, and acoustic and pressure sensors are applied on each animal and collect data referring to body position, locomotion, temperature, estrus detection, etc., which are then correlated with specific grazing or locomotion patterns [115] or physiological conditions, such as estrus or lameness [2].

The accelerometers record movement in a three-dimensional pattern and provide information for several animal behaviors such as resting, grazing, ruminating, or moving [27,28,116,117].

They can also contribute to welfare assessment [118], lameness detection [119], or mating score measurement [120].

The GPS systems provide data related to animal movement and spatial distribution in pasture [29], but the relatively high cost of application hinders its regular use in small ruminants [121]. Moreover, a GPS system coupled with a thermistor below the vulva could also provide information regarding urination frequency and consequently liquid and nitrogen emissions and their spatial distribution patterns by recording urination events as ambient temperature changes [122]. However, concerns are frequently raised regarding energy supply—battery lifespan in the field, lack of wireless data transmission and the accuracy, interpretation, and contribution of these measurements to the decision-making process [123].

Acoustic signals collected by a microphone mounted on the foreheads of sheep resulted in an accurate estimation of feed intake [30], while acoustic and pressure sensors placed on the head of the animal make possible the discrimination between grazing and ruminating, since jaw movements can be classified into chew, bite, or chew-bite events [124,125]. An Alpha-D detector (AD) is also an example of a system aiming at electronic estrus detection in sheep. In detail, rams are equipped with a harness where a custom RFID reader is fixed and triggered at the time of mounting to read the caudal transponder tagged in ewes [126,127].

Finally, subcutaneously implanted sensors could provide reliable measurements for heart rate and body temperature, two indicators that can be used for the early detection of diseases and stress [33]. Caudal data-loggers programmed to record temperature could also be applied for lambing time identification in sheep [128].

3.3. Virtual Fencing and Flock Monitoring Using Drones, Robots and Image Analysis Techniques

VF can be used to alter the animal distribution within large, fenced areas, although they cannot replace conventional fences for absolute control of small ruminants [129]. Animals understand the limits of their area through the receiving of an electric shock if they ignore the acoustic cue [31,130]. However, there are several parameters that limit VF application on a commercial basis, such as its high cost, the lack of technological infrastructure in farms, the difficulty in developing a sufficient learning protocol and welfare concerns due to the electric shocks [131–134]. At the same time, flock size could influence the success of training, namely the reaction of each animal because of the acoustic cue, and may not be economically feasible for large flocks [135,136].

Low-cost time-lapse cameras, machine learning, and image registration could be combined to monitor the location of goats with great precision and sensitivity. It should be noted that for such a system to work, no objects, other than animals, are present inside the pasture, there is no background with a colour that could be confused with the colour of an animal, and the camera does not face the sun, among others [137].

Unmanned aerial vehicles (UAVs) also offer a feasible solution for the monitoring of small ruminants in pasture-based systems [32,138]. Whether sheep are frightened by drones flying above them requires further research, but a small, quiet drone that maintained a minimum altitude might not even be detected by the animal [139].

Del Castillo et al. [140] introduced a camera-based system that automatically detects dangerous animals such as the Iberian wolf, and distinguishes them from prey such as dogs in real time. They reported that the YOLOv5m archives proved to be the most accurate for the requirements of pasture-based systems, with a processing power of 64 FPS and achieving a mean average precision of 99.49%. This system could be an additional tool for farmers for the protection of the herd.

3.4. Walk-Over-Weighting or Weighting Crates and Automatic Drafter

Accurate body weight measurement is crucial in pasture-based systems since it determines stocking density per paddock and the necessary supplementary feeding. The traditional use of a scale may provide reliable measurements but is time-consuming and

induces stress to the animals. However, walk-over-weight (WoW) platforms and weighting crates (WC) can be used as alternatives. For accurate results the WoW platforms require the isolation and the immobilization of the animal in a passage corridor that is closed by the operator when each animal enters. They are coupled with solar-powered batteries and data transmission systems that enable automatic weight data collection and storage in pasture-based systems [141,142]. They communicate with the EID tags of animals and are placed in a one-way corridor that leads to the waterer or trough and as a result animals are forced to pass through. Data regarding each animal is stored and compared daily, resulting in more accurate management. In general, 3 weeks are required to obtain consistent weight records [141], since problems related with data reliability may occur if more than one animal stands on the platform at once, or if the animal is running or standing with only two legs on the platform [143].

Drafting systems are based on automated drafters (AD) which rely on the combined use of other PLF, such as WoW and/or RFID, and assist in sorting the animals and allocating them into different groups according to the parameter of interest such as body weight [144], pregnancy level, medical treatment [145], or milk yield [146]. As a result, manual labour is reduced, and supplementary feeding control is more effective [139].

3.5. Other Milking Parlour-Related Technologies

The longest interaction of the farmers with their animals occurs during the milking period, which lasts from 140 to 240 days a year [111]. It is therefore the most critical aspect of dairy systems, even of pasture-based production, and could contribute significantly to proper herd management.

Criteria such as time limitation (2–3 min activity) and milk flow measurement (a level between 100 and 250 g/min) can be used for the automatic vacuum shut off, thus allowing the farmer to manage a greater number of clusters and avoid the risk of overmilking [147]. One of the most important milk parameters is somatic cell counts, which correlate with udder health and mastitis incidence, and can be assessed by electric conductivity [148] or light scattering [149]. The latter technology in combination with mid-infrared spectroscopy can also be applied for the measurement of milk coagulation properties and acidity [150].

4. PLF in Other Species

4.1. Pigs

Extensively housed (i.e., semi-free and free-range) pigs provide meat products of high quality that generally enjoy increased prices in the market [151,152]. Due to the nature of the managerial techniques and the limited number of extensive pig farms, there has been little commercial demand for implementation of PLF in this sector [152]. However, PLF technologies could be proved beneficial, as they provide security against theft, wildlife [153] and records concerning animals' health status and overall performance [7]. Furthermore, PLF could positively affect breeding, fattening performance and health status through monitoring and control, and strengthen consumer confidence by collecting data that refer to the characteristics of both the animal and farm [2]. Some PLF applications for free-ranging pigs are presented in the next paragraph.

Alexy and Horváth [152] presented results from the development of a continuous monitoring PLF tool for sows of the Mangalica breed that were extensively housed on a total area of 2.5 ha. RFID ear tags were attached to each sow and a monitoring area was designated. The extensive breeding site consisted of a tank drinker, a wooden feeder, the wallowing area (mostly created by the sows themselves), a wooden building used by the sows for resting, and five individual farrowing cottages. Four reading units were installed on a fence close to the wallowing area. A weather station recorded the climate data on an hourly basis. The system successfully recorded the hourly activity of the sows. They reported that the environment and the weather affected the activity of the wallowing site, as the sows tended to use it most in a temperature range between 0 to 4°C. Furthermore, it was stated that this particular activity was strongly connected with the animals' welfare status.

With regard to social behaviour, the sows tended to create small groups that visited and left the wallowing site simultaneously. However, the system's evaluation parameters such as accuracy, precision, specificity, or efficiency were not provided. The researchers stated that additional reading units need to be installed in the pasture area and that additional sows will be marked with RFID ear tags. Aubé et al. [154] used hand-controlled video cameras and recorded and analysed sows' posture (i.e., standing, sitting, kneeling or lying) and activity (i.e., grazing, rooting or any other behaviour). Furthermore, a GPS receiver was fixed between each sow's shoulders and an accelerometer was installed on the lower part of one back leg for general activity assessment. An open-source geographic information system was used for GPS data processing, and they managed to successfully record frequency, duration, and the location of the foraging and resting behaviors of the sows, time spent on the pasture, and distance travelled. The authors reported that the applied method in their study was firstly used by Ringgenberg et al. [155], implying that simple systems used for indoor housing can potentially be used for free ranging animals. Van Damme et al. [156] used GPS receivers and successfully ($p = 0.014$) monitored the foraging and exploratory behaviours of free roaming pigs in Zambia. It should be noted that in both studies the authors only addressed the animal behaviour point of view and no PLF evaluation parameters for the systems were provided.

4.2. Poultry

In January 2012, the European Union issued the Council Directive 1999/74/EC banning battery cages for egg production in the poultry sector. By 2019, hens housed in alternative systems including floor, aviary, free-range and organic reached 50% of their total population in Europe, as indicated by the European Commission Eggs Market Situation Dashboard. Such systems provide additional behavioural freedom for the everyday activities of poultry, resulting in improved welfare status [157,158]. Furthermore, it has been reported that free-range laying hens demonstrate improved plumage condition, final body weight and egg weight compared with their counterparts that are housed indoors [157–161]. It should be noted that even after switching to non-cage systems, welfare challenges such as keel bone damage [162] and damaging behaviours such as feather, toe and vent/cloacal pecking and cannibalism still persist [158,163–165]. Furthermore, in free range systems, the higher exposure to parasites, pathogens and predation contribute to poultry welfare impairment [161,166]. Wild animals can cause severe damage in free ranging systems. For example, red foxes, which are a common predator of chickens, can eliminate the whole flock within a single night, resulting in severe losses [167]. PLF technologies could potentially minimize these negative effects and improve welfare and performance status.

As reported by Rowe et al. [168], more than 42% of the PLF systems use image analysis to assess welfare in poultry. This phenomenon is mainly attributed to the fact that image and video analysis and processing are inexpensive ways to record and analyse the behaviour of the birds without disturbing them [158]. Similarly, Campbell et al. [169] used a series of cameras to capture the indoor rearing pens and range area of each pen, and successfully classified the dust bathing and foraging behaviours, as well as the time the birds spent interacting with enrichment materials and the time the chicks spent expressing play behaviours with each other. Unfortunately, no information concerning the precision, efficiency, accuracy, or specificity of the system was provided. Montalcini et al. [170] developed a combined camera-based and RFID tracking system that automatically monitors individual bird movement over long periods of time for free-ranging commercial farms with an accuracy of 99%. The system overestimated the number of transitions carried out by the birds per zone (i.e., three stacked tiers of a commercial aviary, a littered floor and the winter garden), explaining only 23% of the actual variation, hence further research is needed to improve the performance of this application. Various camera-based methods can be found in the literature including wildlife interactions with free-ranging ducks [171] and chickens [172,173], activity [174,175] and ranging behaviour [176–178] monitoring, counting, or detecting of dead chickens [179], weight estimation [180], shelter preference

behaviour monitoring [181], enrichment utilization monitoring [182], and meat colour and quality classification [183,184]. All of the methods are still under development and therefore further research is needed for the development of a commercial application.

Another widely spread PLF application in poultry is RFID systems. A variety of different sizes and settings have been developed, and they are available for commercial use, focusing on individual behaviour recording [185–187], feed intake monitoring [188], individual range use [186,189–193], range behaviour tracking [160,169,194–196], response to stressors monitoring [197], welfare assessment [198], range behaviour and health status evaluation [199], individual identification [200], individual movement parameters monitoring such as speed, ability to snatch feed and resting behaviour for disease detection [201], body weight, feed intake, egg production and quality evaluation [202], behavioural preferences, and indoor and outdoor resource utilization monitoring [192,203]. It should be noted that an alternative system to RFID technology consisting of a small, light-based monitoring system was developed by Buijs et al. [204]. The system demonstrated 89% or better accuracy for hens' position detection. Hedman et al. [205] developed a GPS-based system for individual chickens' position and movement monitoring but did not provide any PLF evaluation parameters. Finally, Stadig et al. [206] developed an automated Ultra-Wideband positioning system for location monitoring with an accuracy of 68%. Further research is needed for the improvement of the system's internal characteristics and accuracy.

More complex systems have been introduced during the previous decade, including automatic egg collection robots [207,208], behaviour monitoring [209], dead chicken removal robots [210], and guardian dog monitoring using a combination of GPS and camera equipment for auto-guidance for the repulsion of wildlife such as red foxes [167]. Gilsdorf et al. [153] also reviewed a variety of different technologies concerning the use of frightening devices for wildlife repulsion and therefore wildlife damage management. They reported that today's ultrasonic devices are ineffective at repelling birds and mammals. However, the potential of a combination of frightening devices could provide a cost-effective integrated system that considerably reduces wildlife damage. However, only a few commercial applications have been released due to their complexity and limited field testing. Furthermore, a thorough economic analysis for the systems' total costs is essential for the development of commercial products [4].

5. Conclusions

The constantly increasing global need for higher quality food and improved animal welfare status based on sustainable farming systems highlights the necessity of high-quality livestock management. PLF technologies have shown great potential in addressing this issue in an animal-friendly manner, while simultaneously providing the farmers with information that further assists them in decision making. The application of such technologies is directed towards the automatization of simple procedures, the minimization of labour and environmental impact, and the improvement of animal welfare. PLF applications can only serve as decision making support tools for farmers, since automatic decisions for efficient handling and critical health and welfare issues are not feasible at present. Furthermore, although various PLF applications for grazing animals are available commercially, their use is limited and can be found mainly in cattle production rather than in small ruminants or other species. This is likely attributed to individual animal value and producers' reluctance due to financial constraints, unresolved welfare concerns, lack of specialized nearby service, and complexity in using the technologies. The limited testing and the lack of cost-benefit evaluation make these technologies undesirable for farmers. Future PLF research should focus on improving the systems' evaluation parameters and should be based on realistic and thorough economic analysis, emphasizing their beneficial impact. In parallel, "friendly" software and effective marketing techniques should be applied to persuade more farmers to adopt the technologies.

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