Italian Journal of Animal Science

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tjas20

Precision livestock farming: an overview on the application in extensive systems

Gloria Bernabucci, Chiara Evangelista, Pedro Girotti, Paolo Viola, Raffaello Spina, Bruno Ronchi, Umberto Bernabucci, Loredana Basiricò, Luca Turini, Alberto Mantino, Marcello Mele & Riccardo Primi

To cite this article: Gloria Bernabucci, Chiara Evangelista, Pedro Girotti, Paolo Viola, Raffaello Spina, Bruno Ronchi, Umberto Bernabucci, Loredana Basiricò, Luca Turini, Alberto Mantino, Marcello Mele & Riccardo Primi (2025) Precision livestock farming: an overview on the application in extensive systems, Italian Journal of Animal Science, 24:1, 859-884, DOI: 10.1080/1828051X.2025.2480821

To link to this article: https://doi.org/10.1080/1828051X.2025.2480821

Published online: 24 Mar 2025.

ITALIAN JOURNAL OF ANIMAL SCIENCE
2025, VOL. 24, NO. 1, 859–884
https://doi.org/10.1080/1828051X.2025.2480821

Taylor & Francis
Taylor & Francis Group

REVIEW ARTICLE

OPEN ACCESS Check for updates

Precision livestock farming: an overview on the application in extensive systems

Gloria Bernabucci[a], Chiara Evangelista[b], Pedro Girotti[a], Paolo Viola[a], Raffaello Spina[a], Bruno Ronchi[a], Umberto Bernabucci[a], Loredana Basiricò[a], Luca Turini[c], Alberto Mantino[c], Marcello Mele[c] and Riccardo Primi[a]

[a]Dipartimento di Scienze Agrarie e Forestali, Università degli Studi della Tuscia, Viterbo, Italy; [b]Dipartimento per le Innovazioni nei Sistemi Biologici, Agroalimentari e Forestali, Università degli Studi della Tuscia, Viterbo, Italy; [c]Dipartimento di Scienze Agrarie, Alimentari e Agro-ambientali, Università di Pisa, Pisa, Italy

ABSTRACT
Precision Livestock Farming (PLF) represents a significant evolution in the livestock sector, promising to transform farms management improving production efficiency and sustainability, products quality, working conditions and animal welfare. While PLF is increasingly utilised under controlled condition typically linked to intensive livestock systems, its implementation in extensive livestock farms - where animals are primarily raised outdoor - is a challenge. Extensive systems, which cover approximately 67% of global agricultural land, have significant socio-economic importance worldwide, both in terms of food supply and the provision and maintenance of ecosystem services. At the farm level, Precision Livestock Extensive Farming (PLEF) - including the use of wearable sensors, environmental monitoring equipment, and remote sensing - can be widely employed in production monitoring, solving management problems, addressing logistical challenges and improving efficiency in resource management and finally in decision-making processes. Through text mining of 710 scientific articles published between 1980 and September 2024, this review identifies key trends, technologies, and gaps in current research and management approaches. Major findings highlight the prevalence of sensor technologies for monitoring animal behaviour and pasture quality, principally from Australia and United States. The review underscores the potential of PLF to enhance sustainable production in extensive systems, but also calls for more research on the integration of advanced data analytics and remote sensing technologies, including edge computing. The findings aim to guide future research and practical implementations, fostering the development of sustainable livestock farming practices globally with a view to multispecies approaches tacking into account also wildlife-livestock interactions.

ARTICLE HISTORY
Received 15 October 2024
Revised 7 March 2025
Accepted 13 March 2025

KEYWORDS
Smart farming; precision technologies; grazing; pasture quality; remote sensing

HIGHLIGHTS

- PLEF shifts livestock system management from manual to (semi-) automated.
- Text mining shows the evolution and spread of PLEF literature over the years.
- PLEF tools help address environmental and livestock system challenges.

CONTACT Riccardo Primi primi@unitus.it

Introduction

Extensive livestock farming (ELF) represents a low-input production system primarily focused on outdoor animal management (rearing), either for the entire production cycle or part of it. A variety of extensive and semi-extensive livestock systems exist worldwide, all based on ethological approaches allowing animals to express their innate behaviours, such as grazing and exploration, in more natural or semi-natural settings (Temple and Manteca 2020). According to the Food and Agriculture Organisation of the United Nations (FAO), extensive grazing occupies most of the world's agricultural lands, for the most part not easily arable, or not arable at all, covering approximately 67% of the global agricultural land (FAOSTAT 2021). Thanks to livestock production, this huge part of world's agricultural lands supports the livelihoods of millions of people converting underutilised resources into valuable food products (Nori et al. 2005, Battini et al. 2021). Therefore, ELFs are prevalent across all continents, particularly in regions, such as the drylands of Africa and the Arabian Peninsula, the highlands of Asia and Latin America, or the subpolar tundra regions (FAO. 2001).

However, ELF involves a series of variables that make it less controllable by humans and pose significant management challenges. Among the most difficult are environmental factors, which are increasingly unpredictable due to climate change, as well as the animal monitoring—including their productivity, welfare, and health—and the environmental impact (e.g. overgrazing, undergrazing, point-source pollution).

For example, although the freedom of movement afforded to animals in extensive farming is often perceived positively by consumers as a factor improving animal welfare and enhancing natural ecosystemic dynamism, it is essential to recognise that animal freedom, in terms of lack of control, does not necessarily is associate to optimal health and ecological equilibrium. Various factors, including feeding practices, water availability, overall animal density, intra- and interspecific competition, climatic conditions, diseases, and interactions with wildlife, can significantly affect animal welfare and drive undesirable ecosystemic dynamism. While in the last decades, due to advancement in animal science, many progresses have been obtained in livestock farming, the visual monitor of animals and the effective control of environmental parameters in ELF systems remains a critical issue due to the reduction of people engaged in the agricultural sector, especially in the developed countries. These challenges are even more pronounced in mountain extensive systems, where harsh conditions—such as high altitudes, steep slopes, and significant climatic variations—make access and the animal monitoring difficult. Consequently, the integration of precision technologies becomes imperative to monitor environmental parameters and to effectively manage grazing animals. Precision livestock farming (PLF) is a new multidisciplinary science based on the application of advanced technologies for enhancing farm management. The original objective of PLF was to monitor each animal, or only the lead one in the herd, in real time (Berckmans 2017). Initially, PLF emerged and was widely adopted in the context of intensive livestock systems, but recently, it has also been applied into extensive systems (Precision Livestock Extensive Farming, PLEF). PLEF offers the opportunity to transition livestock farming from manual to automated or semi-automated, improving herd management (Tzanidakis et al. 2023), pasture management, environmental control, health monitoring and feeding optimisation.

With the rapid expansion in recent years of scientific publications, there is an increasing need to discover innovative approaches for navigating and filtering through this vast array of documents (Rodrigues et al. 2014). In this regard, data mining or text mining can be specific and rapid methods for uncovering the most interesting topics in a line of research. Text mining (TM) is defined as a process of knowledge exploration, seeking to identify and analyse valuable information within large volumes of textual data that is relevant to users. It stands out for its capacity to scrutinise conceptual relationships, aiming to unearth fresh structures, patterns, or connections, and to unveil novel insights and trends (Abutridy 2000). To date, these methods have not yet been applied to PLF literature in extensive systems. In this review, we utilised, for the first time, the TM to synthesise the available knowledge regarding PLEF, with the aim of providing a guideline useful both for planning further research and for guiding and favouring the adoption of innovative monitoring and automated management systems.

Review structure

The first part of this review aimed to describe the evolution and geographical distribution of PLEF literature over the years, to identify the most investigated research topics, and to highlight the remaining gaps in knowledge. The second section had the purpose to describe the main technologies available for ELF, considering both prototype devices and commercial solutions. Precision tools had been catalogued by their usefulness in solving problems that farmers must face daily. Both environmental and management issues were discussed.

Material and methods

Dataset and text mining

The research was conducted using two main terms: 'precision' AND 'livestock', along with additional terms such as 'extensive', 'grazing' OR 'pasture', 'free ranging' OR 'rangelands', 'remote sensing', 'drone' OR 'robot', 'edge device' OR 'edge computing'. Finally, the word 'sensor' was used with 'grazing' or 'pasture'. To obtain information about interactions with wildlife, other terms were used: 'wildlife', 'carnivores' OR 'ungulates'. These terms established in agreement with the authors were used to search for publications relating to the topic in title-abstract-and keywords. The Elsevier database, called Scopus®, was used for this search. The time frame considered was from 1980 to 2024. The research was performed on 21 September 2024. The filters used in choosing the articles were: English language and subject area (the following have been flagged: agricultural and biological science, computer science, environmental science, biochemistry, genetics and molecular, veterinary, engineering, earth, and planetary sciences). The documents resulting from the individual searches (Table 1) were merged and collected in an electronic Excel workbook (Microsoft Excel®, v16.0, Redmond, WA, United States). Pre-processing was required to get a dataset ready for the final elaboration after the collection phase. The pre-processing consisted in eliminating the incomplete observations (missing abstracts, no authors, or no sources); then the duplicate observations were removed. Ultimately a reviewer independently examined all records collected in the dataset and selected them for their eligibility for final inclusion. The selection process was subsequently reviewed and confirmed by two authors to reduce subjective biases from the reviewer. The scheme of the executed pre-processing and the deleted records is shown in Figure 1. The final number of records included was 710.

Research conducted in marine environments, as well as studies focusing on intensive agriculture (such as fertiliser estimation and distribution), were excluded, along with that examining the use of milking robots in systems with limited access to pasture, which are not representative of ELF. Studies based on animal metabolism or genetics were also excluded. Furthermore, articles that focused on explaining how the technologies work and did not report the effects of these technologies on animals or the environment (i.e. pasture quality) were excluded. Ultimately, studies that were not consistent with the objective of the present research on sensors that can be used in the context of PLEF were not included.

Text mining is a technique used to extract the most frequent words in a corpus of documents and convert them into numerical information. An analysis using TM was conducted on the abstracts of the selected papers (n. 710) to identify important patterns in text data, following the methods described by Contiero et al. (2019) and Zuliani et al. (2021). Initially, pre-processing steps were performed on the text, as outlined by Sebastiani (2002). This involved removing punctuation, spaces, numerical digits, and 'stop words' which are commonly used articles, prepositions, and conjunctions. Additionally, all words were converted to lowercase. The terms used in the research, as shown in Table 1, were removed. Furthermore, a stemming algorithm was applied to reduce words to their roots, ensuring that the same word with different grammatical forms was not counted separately.

Subsequently, the term frequency-inverse document frequency (TF-IDF) technique was utilised to weigh the number of times a word appears in the adjusted summary, regardless of how common or rare the term is across all abstracts (Salton and Buckley 1988). This weight is determined by both the term's frequency within a specific document and its prevalence across the entire collection of records. By using

Table 1. List of search words and related documents.

Search words	All documents	Documents included
Precision AND livestock AND extensive	122	69
Precision AND livestock AND grazing OR pasture	331	135
Precision AND livestock AND 'free ranging' OR rangelands	54	18
Precision AND livestock AND 'remote sensing'	106	19
Precision AND livestock AND drone OR robot	155	38
Sensor AND grazing OR pasture	1,445	402
Precision AND livestock AND wildlife	36	18
Precision AND livestock AND carnivores OR ungulates	8	2
Precision AND livestock AND 'edge device' OR 'edge computing'	17	9
Total documents	2,274	710

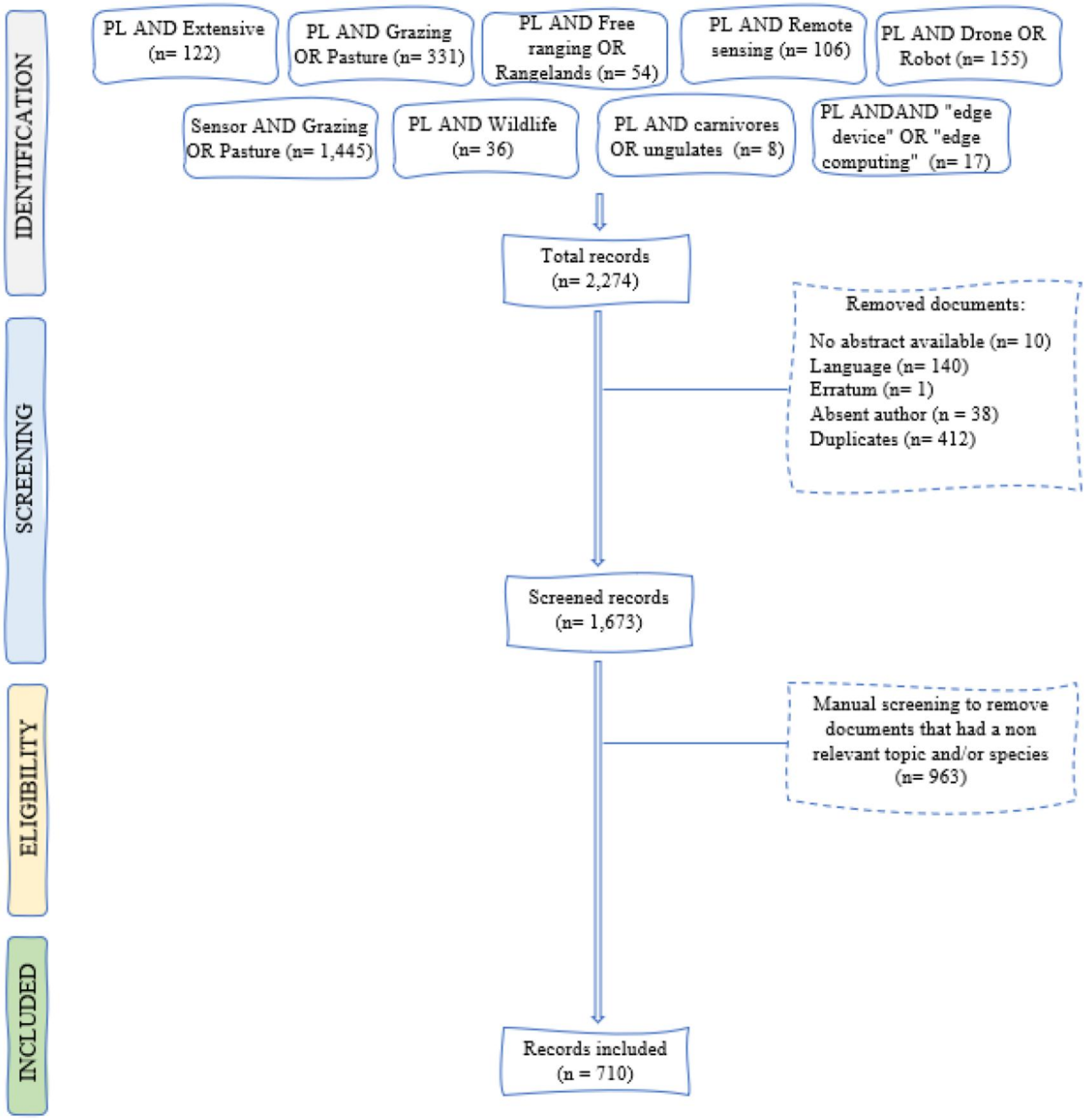

Figure 1. Flow chart illustrating the process of searching for and selecting literature on PLEF. The dashed lines indicate the quantity of excluded records and the rationale behind their removal from the study.
PL = Precision LivestockPL = Precision Livestock

TF-IDF, the importance of each term is determined not only by its frequency within a document but also by its uniqueness and significance within the broader context of the entire dataset. A threshold TF-IDF value of greater than or equal to 5.5 was applied to construct a histogram displaying the eleven most frequent words.

All steps of TM were conducted within the R studio environment using a combination of functions from the packages 'tm', 'snowballC', 'ggplot2', 'dplyr', and 'tidyverse'. Additionally, a word cloud representation (https://www.wordclouds.com/) was employed, where larger font sizes corresponded to higher TF-IDF values, thereby highlighting the most recurrent words.

Results and discussion

Figure 2 shows the trend of publications over the years (starting from 1997 to 2024) relating to the PLF in extensive systems. The first three articles that emerged from our investigation were published in 1997. Two of them concern the application of sensors for measuring the eating behaviour (intake and rumination) and non-eating behaviour (lying, standing, and walking) of grazing animals (Champion et al. 1997, Gibb et al. 1997), while the third utilises Landsat Thematic Mapper digital data to analyse variations in grazing intensity across different agricultural practices in the Southern District of Botswana (Nellis et al. 1997). Until 2018 there were not many articles published per year, the average was 10 per year. There

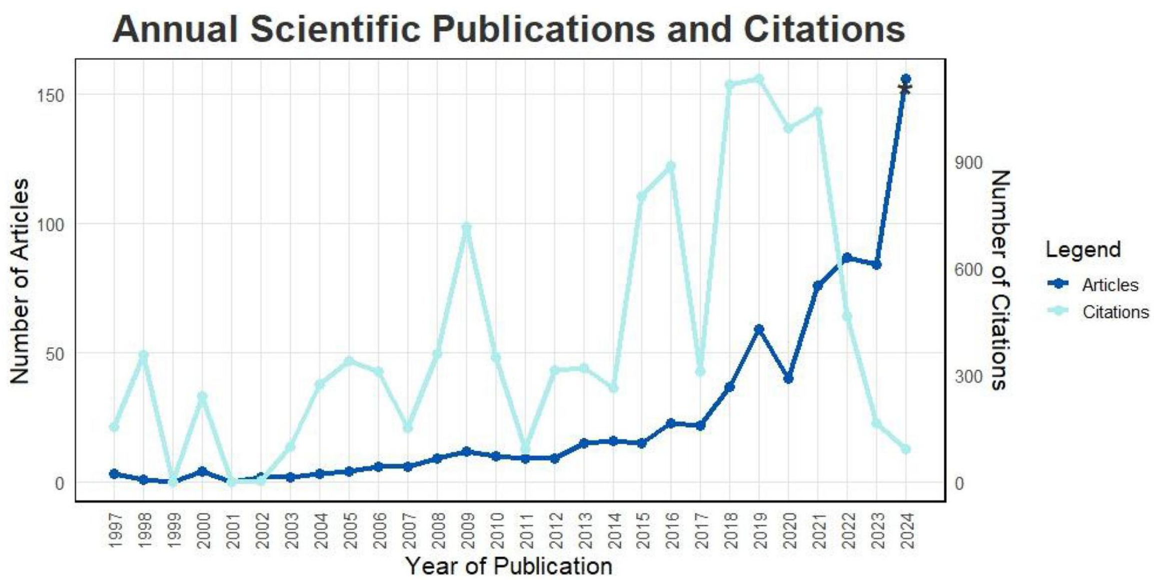

Figure 2. Annual scientific publications and citations within the period 1997–September 2024.
* Indicates that results in this year are related to the period from January to September 2024.* Indicates that results in this year are related to the period from January to September 2024.

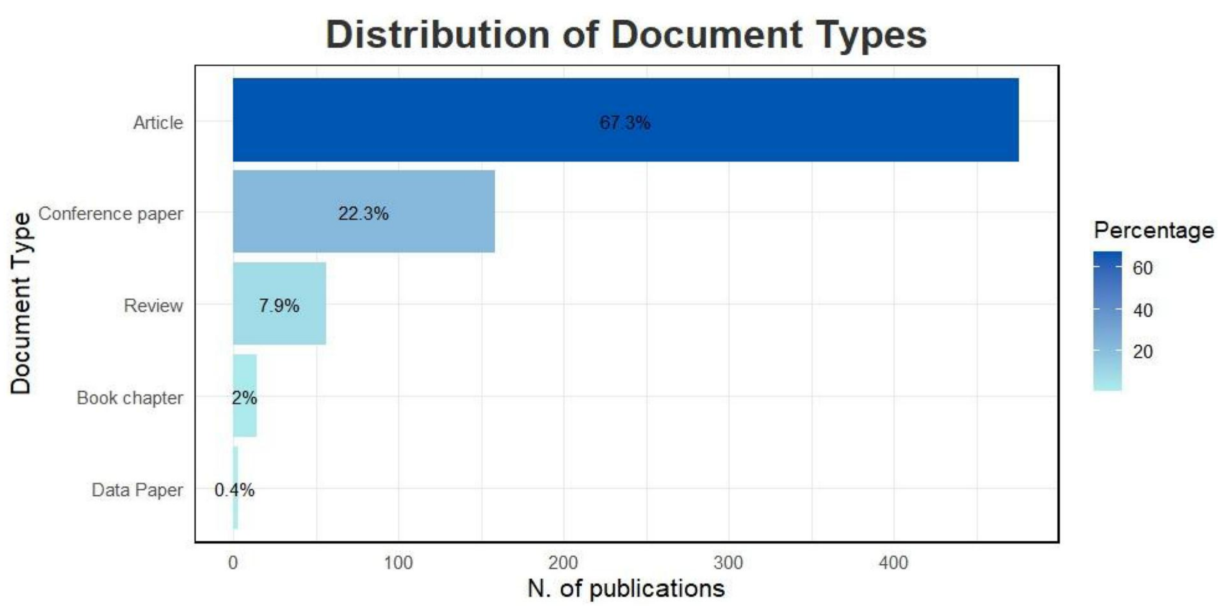

Figure 3. Distribution of document type (percentage and n. of articles).

was a peak in 2019 (with 59 articles) and then dropped again in 2020 (probably linked to the global pandemic). From 2021 it recovered with an ever-growing number of publications. For the year 2024 the search stops at September 21st, but it can be seen that the publications have more than doubled compared to 2023 (156 *vs* 83 documents, respectively). The most cited article, which describes a method for estimating fractional vegetation and soil cover in Australian tropical savannas using hyperspectral and multispectral data, was published in 2009 and has 326 citations. The average number of citations per year is 33.4.

Figure 3 shows the types of documents and their percentages. Expectedly, most documents consist of articles (67.3%, n. 478 articles), followed closely by conference papers (22.4%, n. 159). New technologies and prototypes are typically presented and discussed in conferences. Reviews are present in a smaller percentage (7.9%, n. 56), as topics are still limited and recent, making the production of reviews difficult. Following that, there are book chapters (2%, n. 14)

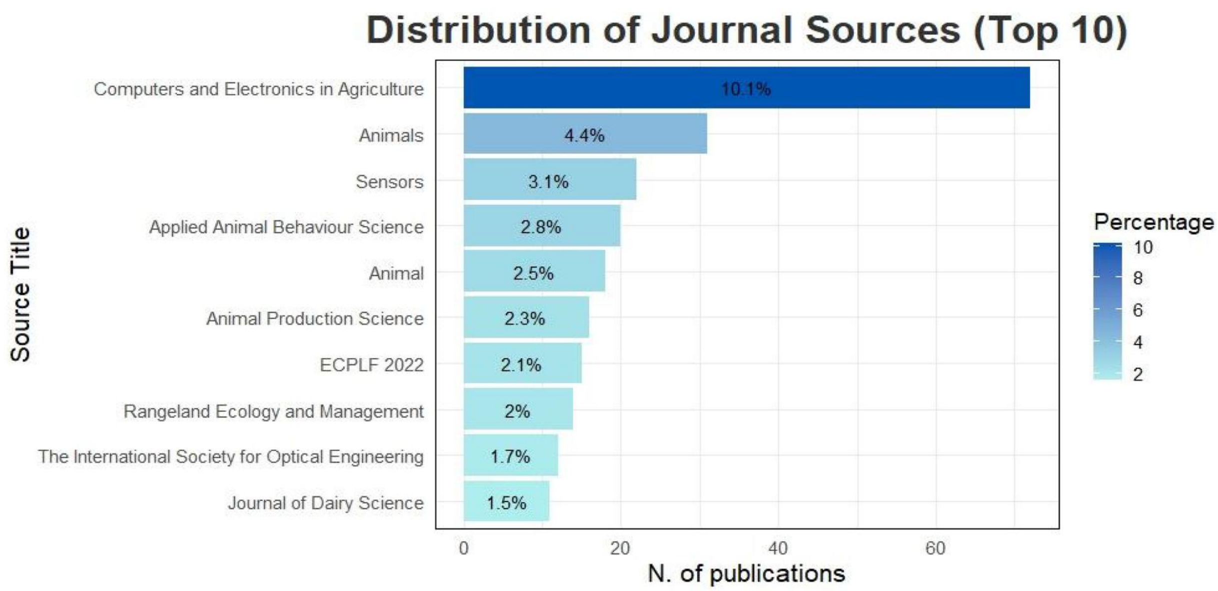

Figure 4. Top 10 of the most frequent journals (percentage and n. of articles).

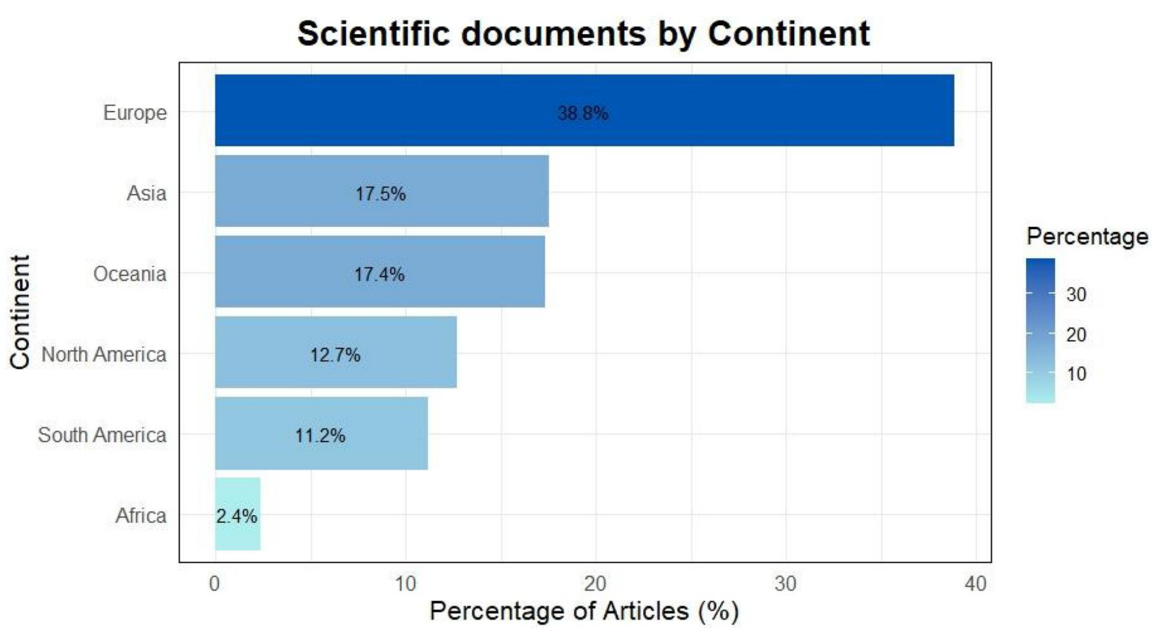

Figure 5. Graph bar of the distribution of the 710 scientific literature records selected for inclusion per continent, based on affiliation author.

and finally data papers (0.4%, n. 3), which constitute a very limited part of the research. Figure 4 shows the 10 Journals or Conferences with the highest number of publications expressed as a percentage. The journal with the highest number of publications was 'Computers and Electronics in Agriculture', in which 10.1% (72) were published, followed by 'Animals' (4.4%, n. 31); 'Sensors' (3.1%, n. 22); 'Applied Animal Behaviour Science' (2.8%, n. 20); 'Animal' (2.5%, n. 18); 'Animal Production Science' (2.3%, n. 16); 'Precision Livestock Farming, ECPLF 2022' (2.1%, n. 15); 'Rangeland Ecology and Management' (2%, n. 14); 'The International Society for Optical Engineers' (1.7%, n. 12); 'Journal of Dairy Science' (1.5%, n. 11).

The continent (Figure 5) with the highest number of publications is Europe with 38.8% (n. 276) followed by Asia 17.5% (n. 125), Oceania 17.4% (n. 123), North America 12.7% (n. 90), South America 11.2% (n. 79) and finally Africa 2.4% (n. 17). Although Africa, Asia, and Latin America have a higher prevalence of extensive livestock farming (FAO. 2001), our results show that the majority of publications on PLEF come from

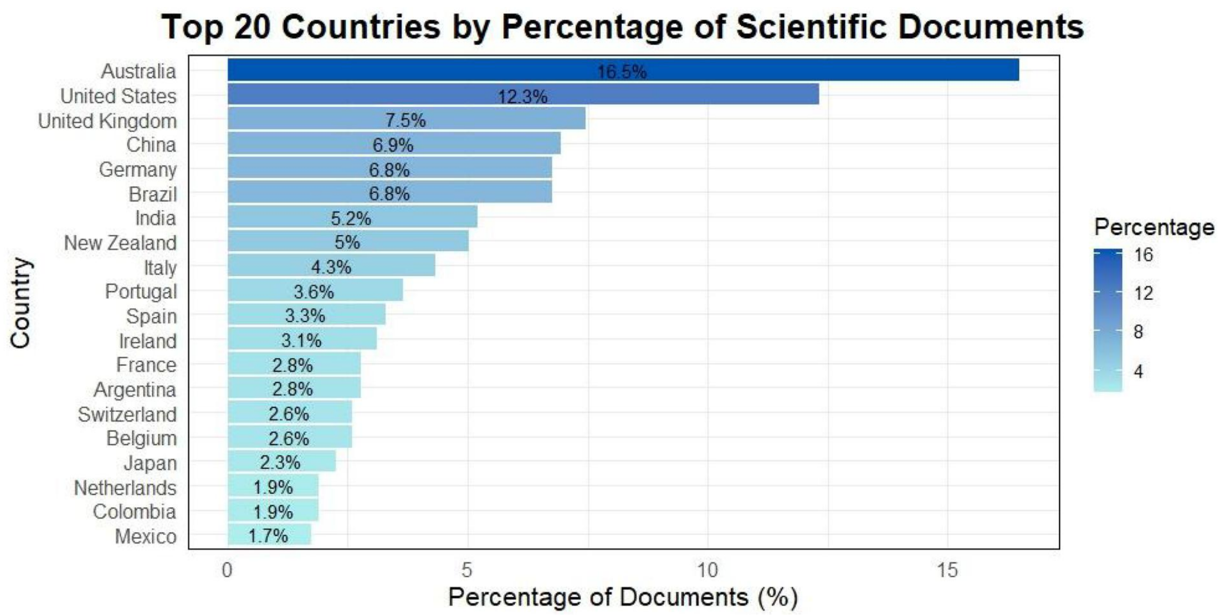

Figure 6. Graph bar of the distribution of the 710 scientific literature records selected for inclusion per country, based on affiliation author.

Europe, with Asia ranking second. This discrepancy is likely due to Europe's greater research capacity and financial resources. European countries benefit from strong governmental support and dedicated programs promoting sustainable agriculture and technological innovation, such as the Common Agricultural Policy (CAP) or research projects (e.g. Horizon 2020, ATLAS, DEMETER). In contrast, regions with a higher prevalence of extensive systems often struggle with limited research funding and technological infrastructure. This analysis highlights the need for increased research support in areas where extensive livestock systems are most prevalent.

Figure 6 displays the major countries of publication of the affiliation author. Australia is the country that has published the highest percentage of articles relating to PLEF (16.5%), followed by the United States (12.3%). All other countries have a percentage lower than 10%. This is not surprising considering that the development of early precision agriculture technologies occurred in the late 1980s, both in the United States and in Australia (Pierce and Nowak 1999, Cook and Bramley 1998). Australia might have a high number of publications on the use of sensors in PLEF primarily due to the following reasons: the vast expanses of grazing land in the country, as evidenced by the significant production of beef, sheep, and other livestock-derived products that constitute a significant portion of Australia's exports and agricultural economy. The unique environmental and climatic needs of Australia stimulate research on pasture management, while investments in agricultural and technological research, led by institutions such as the Commonwealth Scientific and Industrial Research Organisation (CSIRO), have promoted the development of new technologies to enhance pasture production and management.

The results of the TM performed on the 710 selected abstracts highlighted 1,409 terms, with a TF-IDF weight ranging from 0.20 to 9.95. Figure 7 shows the most important terms, with a TF-IDF weight greater than 5.5. The term with the greatest weight is 'cow' (9.95) followed by 'behaviour' (7.20), and then all the remaining terms have a weight less than 7: 'anim' (6.99), 'model' (6.64), 'farm' (6.46), 'cattl' (6.45), 'sheep' (6.32), 'system' (5.91), 'technolog' (5.85), 'data'(5.73), 'agricultur' (5.54). The most frequent terms 'cow' was to be expected as most of the sensors and technologies currently available in PLF were developed for cattle, particularly for dairy cows, where the highest implementation of technological systems has been observed (Odintsov Vaintrub et al. 2021). However, the most extensively farmed species, as previously mentioned, concerns sheep. In fact, the term 'sheep' is among those with the greatest weight in our analysis. Technological developments in extensive farming are only taking place in recent years and are gradually being incorporated into extensive pasture farming of cattle and small ruminants (Morgan-Davies et al. 2017). The second term 'behaviour' follows cow in order of importance. Behaviour control is one of the main objectives of the development of precision

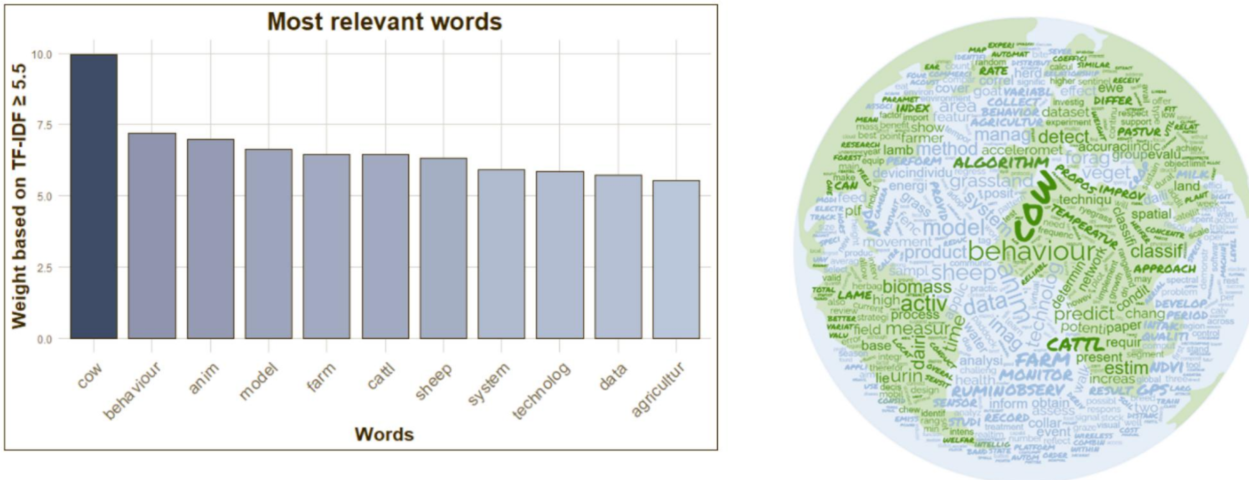

Figure 7. On the left: histogram of the most relevant words based on the term frequency-inverse document frequency (TF-IDF ≥ 5.5) of 710 records selected for inclusion in the study and their respective weights; on the right: word cloud of the 1,409 terms of the 710 records included in the study.

technologies in animal husbandry, both in intensive and in extensive system. It is fundamental because through sensors monitoring the animal's behaviour the need for visual observation of the animals is reduced (Frost et al. 1997) and it allows to obtain information on stress, diseases, lameness and daily feed consumption (Kleanthous et al. 2022). The term 'models' refers to mathematical or computational tools used to interpret data collected by sensors, encompassing parameters derived from animals (wearable sensors) and pasture characteristics. These models aid in predicting outcomes related to animal health, welfare, and productivity, thereby offering solutions to optimise management strategies. Sensors and technologies capable of measuring pasture quality parameters facilitate the development of models that can predict optimal grazing strategies, maximising forage utilisation, and improving overall pasture management, thereby promoting efficient and sustainable livestock production. In the context of our PLEF research, the term 'data' refers to the information collected by the sensors regarding various parameters concerning the animals, such as localisation (Odintsov Vaintrub et al. 2021), body weight (Brown et al. 2015), behaviour (Cabezas et al. 2022), and concerning pasture quality (Pullanagari et al. 2012).

We expected, in TM results, to find terms related to location sensors, such as 'GPS' (Global Positioning System), among the most common and used, considering it is the most prevalent system in this type of farming. However, to our surprise, this term showed a weight of 4.12 (TF-IDF value), much lower compared to the previously discussed terms.

Limits of text mining approach

Text mining approach adopted to carried out this literature review has some limitations. Firstly, papers from other databases and the 'grey literature' were not included in the search of papers, which was restricted to the Elsevier database Scopus®. Furthermore, synonyms of the main terms included in this methodology were not considered. In addition, filters were applied to limit the search to English-only abstract language or to specific subject areas. The exclusion of papers without an available abstract is another restriction. All these factors may have reduced the number of records that could have been included in the database.

Despite these limitations, this study effectively reviews the literature on PLEF, highlighting key topics in this livestock system.

PLEF applied to feed and water management

Extensive livestock farming faces a multitude of challenges, encompassing environmental concerns, increasing threats due to climate changes and technological limitations. Sustainable practices are imperative for ensuring its long-term viability. In this section, applications and related research for pasture quality, stocking rate, and other pertinent factors for sustainable land use and animal welfare are presented. Additionally, how monitoring techniques coupled with PLEF offer promising solutions to address these challenges, fostering connectivity across the animal value chain while promoting sustainability and both food security and safety are explored.

Pasture quantity and quality

The estimation of pasture quantity and quality is crucial for ensuring the nutritional requirements and productivity of livestock in extensive farming systems. Traditional methods for estimating pasture quantity, such as exclusion cages and plate metres, have evolved significantly. Modern techniques now include Unmanned Aerial Vehicles (UAVs), satellite imagery, and LiDAR technology, which provide comprehensive and accurate assessments of pasture conditions (Trukhachev et al. 2019, Weiss et al. 2020). Additionally, on-animal sensors have been explored for real-time pasture biomass estimation in rotational grazing systems, providing an alternative to ground-based assessments (Edwards et al. 2024). Mathematical models also play a pivotal role in these estimations, helping to predict pasture biomass availability and growth patterns under varying environmental conditions (Defalque et al. 2024). Recent advancements integrate remote sensing with deep learning models, allowing for automated pasture biomass predictions from UAV imagery (Barbedo et al. 2019). Regarding qualitative aspects, the composition and chemical-nutritional parameters of forage are essential indicators of pasture nutritive value. However, pasture quality, which encompasses both nutritive value and forage palatability, is more complex to assess. This complexity increases in agroforestry and silvopastoral systems, where tree cover and the presence of non-herbaceous forage sources interfere with satellite-based vegetation indices, requiring hybrid approaches combining spectral analysis and LiDAR (González et al. 2014, Ahmad et al. 2016). Moreover, forage quality differs significantly between open pastures and shaded areas under trees, as plant competition for light, water, and nutrients influences biochemical composition (Ripamonti et al. 2023, Tramacere et al. 2024).

Among remote sensing indices, Normalised Difference Vegetation Index (NDVI) remains the most widely used parameter for assessing pasture productivity, as it provides insights into vegetation density and biomass (Chen et al. 2006, Zhang et al. 2022). Recent studies suggest that integrating LiDAR height measurements with NDVI improves biomass estimation, achieving $R^2 = 0.76$ in mixed pastures (Schaefer and Lamb 2016). UAV applications have also demonstrated strong correlations between NDVI-derived values and pasture biomass, with $R^2 = 0.80$ (Insua et al. 2019). In a recent study covering 100 sites, multispectral UAV imagery showed strong correlations with key nutritional parameters such as dry matter (DM), crude protein (CP), and digestibility, yielding R^2 values of 0.676 for DM and 0.653 for CP (Gao et al. 2019). Another promising approach integrates Synthetic Aperture Radar (SAR) data with multispectral imaging, achieving 93.12% accuracy in large-scale pasture monitoring, improving previous models by 7.61% in accuracy and 0.11 in F1-score (Wang et al. 2022).

Despite these advancements, several challenges hinder the application of these technologies in ELF. Tree cover and pasture heterogeneity affect satellite data accuracy, while UAV and LiDAR technologies remain costly and require specialised skills (González et al. 2014, Rossi et al. 2019). Additionally, data integration remains complex, as multi-sensor approaches lack standardisation, and climate variability further complicates pasture productivity modelling (Tedeschi et al. 2021).

Future research should focus on integrating multi-sensor data fusion (e.g. UAVs, LiDAR, NDVI, SAR) to refine biomass estimates, developing adaptive Artificial Intelligence (AI) models for pasture productivity prediction under varying environmental conditions, and standardising remote sensing workflows to improve data integration and accessibility. By addressing these limitations, PLF technologies can optimise pasture management, ensuring sustainable livestock production and ecosystem resilience.

Precision pasture management

The management of pastures to prevent overgrazing or undergrazing is essential in ELF; new technologies can help to address these challenges. Overgrazing can cause soil erosion, degradation of water quality, loss of biodiversity, and the proliferation of undesirable plant species due to selective grazing and the degradation of palatable forage species. Conversely, undergrazing can lead to the accumulation of unpalatable, low-quality forage, reduced pasture regeneration, and an increased risk of wildfires (Karr et al. 2021). The adoption of advanced technologies is particularly relevant in ELF, where large grazing areas make traditional fencing and manual monitoring challenging. Virtual fencing (VF) systems, in particular, allow farmers to create dynamic boundaries using GPS, sensors, and communication devices, optimising grazing patterns and preventing over- or undergrazing (McSweeney et al. 2020; Waterhouse 2023) avoiding physical fences. These systems typically involve wearable devices or collars equipped with GPS and sensors that monitor the location and the behaviour of livestock. When an animal approaches or crosses a virtual boundary, it receives stimuli such as auditory signals, vibration or mild electric pulses to redirect its movement, effectively guiding it back into the desired area or preventing it from entering restricted zones (Waterhouse 2023). Virtual fencing offers several advantages, including flexibility in pasture management, the possibility of rotational grazing, reduced infrastructure costs compared to traditional fencing, and the potential to improve animal welfare by allowing for more natural movement and grazing patterns while still maintaining effective control over livestock (Lomax et al. 2019). As technology advances, VF continues to evolve, offering promising solutions for modernising livestock management practices.

A study by Confessore et al. (2022) on the effectiveness of VF in managing grazing Limousin cattle demonstrated that cattle learn to interact positively with the system through three trial sessions. Progressive learning was evidenced by the gradual reduction of stimuli and a decrease in escape events from the virtual grazing area. Furthermore, no significant differences were observed in hair cortisol levels before and after VF application, suggesting a neutral impact on animal stress. These results confirm the potential of VF in managing livestock in grazing systems, with positive implications for animal welfare and operational efficiency (Confessore et al. 2022). A study by Lee and Campbell (2021) highlighted that VF can effectively contain cattle and reduce the labour costs associated with physical fencing. This technology also uses audio stimuli followed by electrical pulses to create a virtual boundary, which livestock learn to avoid. Another study by Bishop-Hurley et al. (2007) demonstrated that cattle can be trained to respond to a combination of auditory, visual, and tactile stimuli, improving the management of grazing systems. Those authors found that these stimuli, when combined with VF technology, effectively controlled livestock movement and behaviour. Additionally, research by Campbell et al. (2020a) showed that VF can be used to manage cattle and sheep, optimising pasture utilisation and reducing the need for physical herding. A further study by Lomax et al. (2019) evaluated the application of VF in dairy cattle and found that the system contained cattle within designated grazing areas in 99% of the cases. The study also reported no significant differences in stress indicators, such as cortisol levels, between the VF and traditional electric fence periods, suggesting that VF does not adversely affect cattle welfare (Verdon et al. 2021). Another study by Jeffus et al. (2021) reported similar findings, showing that VF systems did not lead to significant increases in cortisol concentrations or behavioural stress indicators in beef cattle.

Recent research by Fuchs et al. (2023, 2024) supports these findings, indicating that dairy cows well adapted to VF showed no adverse effects of VF on milk yield, body weight, or feed intake. The study also noted that cows learned to respond to VF stimuli quickly, with most cows adapting within the first three days of exposure. Also, goats can successfully adapt to VF, with a gradual improvement in success rate over the days (Eftang et al. 2022). In this study, inexperienced goats reduced the number of auditory and electric stimuli received, going from 22 escapes on the first day to none by the fifth day. Instead, goats accustomed to VF moved to new areas and adapted to the new pasture earlier; hence, the VF system builds associations between audio cues and electric stimuli, rather than purely conditioning for place avoidance. Eftang et al. (2022) highlighted the importance of predictability and controllability of the system, as well as functioning collars, for the success of VF in commercial pastures. This insight indicates that VF can be used both in regular grazing areas and in rotational grazing.

Despite their potential, the implementation of PLEF tools faces several challenges. High initial investment costs, technical expertise requirements, and limited infrastructure in remote grazing areas may hinder widespread adoption (Heins et al. 2023). Moreover, data integration and farmer training are key factors in ensuring successful implementation. Future research should focus on developing cost-effective solutions and improving interoperability between different PLEF technologies to enhance pasture management (McSweeney et al. 2020; Waterhouse 2023).

Water monitoring and management

Access to clean water is essential for livestock health and productivity. Each grazing area should be equipped with one or more natural or artificial water supply station to ensure that livestock have access to adequate water supply during grazing periods (Yu et al. 2024). Vogel et al. (2011) have shown that cattle can lose about 5.2% of their body weight in just 36 h of water deprivation under condition of moderate temperatures. This weight loss was associated with increased serum concentrations of various electrolytes and stress hormones, indicating dehydration and physiological stress (Vogel et al. 2011). Moreover, 72 h of water deprivation caused significant reductions in body weight and feed intake in livestock, with notable physiological impacts such as increased body temperature and altered blood chemistry (Alamer 2006). Consequently, breeders usually check livestock water frequently (once every 1–3 days) depending on weather conditions and water storage (Bailey et al. 2021). Tang et al. (2021) implemented an advanced monitoring system to track individual livestock water intake, using water level sensors, Radio Frequency Identification (RFID) systems for animal identification, and cameras. The results demonstrated the accurate monitoring of water consumption, animal identification, and water temperature recording. The integrate system recorded the drinking behaviour of 29 cows over a two-week duration, providing valuable data on water intake patterns and helping in identifying animals with abnormal drinking behaviours. The study highlights potential benefits for livestock management and wildlife conservation, with quantified benefits including improved monitoring accuracy and early detection of water-related health issues. However, future improvements are needed to optimise system reliability and functionality (Tang et al. 2021).

Sensors can also be used to monitor water levels in drinkers and storage tanks (e.g. SCADALink SAT110, Bentek Systems, Calgary, AB, Canada, https://www.scadalink.com/products/satscada/livestock-water-supply-monitoring/) and the data can be transmitted to ranch headquarters directly or *via* the internet using mobile phone or satellite technologies (Bailey et al. 2018). These systems are particularly useful in ELF, where water points are scattered over large areas and manual inspections can be time-consuming. Real-time data from remote sensors allow farmers to detect water shortages or system failures quickly, preventing dehydration risks for livestock in remote grazing areas.

Furthermore, Wade et al. (2024) utilised GPS collars to monitor animal distribution, revealing significant hotspots surrounding water sources, indicating a profound influence of water location on animal movement and the possible occurrence of local animal overload with negative effects on the soil structure and grass productivity.

The use of real-time monitoring technologies, such as GPS and accelerometers, can promptly detect failures in livestock water distribution systems. During periods of water access restriction, livestock exhibited distinctive behaviours by staying closer to the water source and showing higher levels of activity. These behavioural changes were detected through analysis of both GPS and accelerometer data. The study quantified the benefit of these technologies by demonstrating that movement intensity was significantly greater on days of simulated water failure compared with control days, and cows remained closer to the water source. This precise monitoring can reduce the time for managers to repair the water system, improving animal welfare by preventing extended periods of dehydration (Tobin et al. 2021).

Machine learning models can significantly enhance farmers' ability to monitor water quality and quantity, ensuring that livestock have adequate access to this vital resource. These models utilise data from various sensors to predict water quality and quantity parameters effectively. Machine learning algorithms have been applied to predict water consumption on dairy farms, showing significant improvements in accuracy over traditional methods (Shine et al. 2018). Additionally, supervised machine learning algorithms have shown potentiality in predicting water quality indices, helping to ensure better water management practices (Ahmed et al. 2019).

PLEF applied to animal management

In ELF there are many management challenges that the farmers must face every day and that require a great deal of time and work. Precision tools have been developed to improve this condition, making herd management simpler and more functional.

Below, the main management issues are addressed by proposing some of the most important technologies, which are summarised in Table 2.

Animal location and tracking

Animal location and tracking are crucial for studying the environmental impact of grazing animals and improving farm management efficiency (Mancuso et al. 2023). However, this has long been a challenge in ELF due to the vast and rugged terrain where herds roam. Unlike enclosed barns, extensive pasture environments present difficulties in infrastructure and communication (Morgan-Davies et al. 2018). Today, there are several devices available for remotely monitoring herds, reducing human effort. The most used non-invasive sensors for animal monitoring are GPS devices, which can be attached to various parts of the animals' body, such as neck collars or ear tags, to track and record their real-time locations (Odintsov Vaintrub et al. 2021). Manning et al. (2017) showed that wearing these devices does not alter normal animal behaviour, and Rivero et al. (2021) suggested that a training period is not required for cattle. These GPS sensors utilise radio signals from satellites orbiting the Earth

Table 2. List of the main technologies available for extensive livestock systems organised by measurable parameters.

Parameter	Technology	Species	Sensor location	Status	Reference
Location	GPS	Cows, sheep, goats, horses	On-animal	C	Buerkert and Schlecht (2009) Hampson et al. (2010) Manning et al. (2017) Odintsov Vaintrub et al. (2021) Rivero et al. (2021)
	Virtual Fencing	Cows, sheep, goats, horses	Off-animal	C	Marini et al. (2018) Janicka et al. (2022) Eftang et al. (2022) Goliński et al. (2022)
	UAV	Cows, sheep, goats, horses, yak	Off-animal	C	Vayssade et al. (2019) Webb et al. (2017) Inoue et al. (2019) Xu et al. (2020) Abdulai et al. (2021) Ji et al. (2023)
	UAVs + YOLOv5	Cows	Off-animal	P	Luo et al. (2022)
Identification	RFID	Cow, sheep, goat, horse	On-animal	C	Odintsov Vaintrub et al. (2021) Kang et al. (2022)
	SmartGlove	Sheep	Off-animal	P	Pinna et al. (2023)
Body weight	WOW	Cows, sheep	Off-animal	C	Brown et al. (2014) González et al. (2014) González-García et al. (2018)
Body Condition Score	Image analysis	Cows, sheep, goats, horses	Off-animal	P	Aquilani et al. (2022)
Behaviour	Accelerometers	Cows, sheep, goats	On-animal	C	Moreau et al. (2009) Kuźnicka and Gburzyński (2017) Barwick et al. (2018a) Kour et al. (2018) Ikurior et al. (2020)
	Accelerometers + GPS	Cows	On-animal	C	Cabezas et al. (2022)
	EquiWatch System	Horses	On-animal	P	Weinert et al. (2020)
	YOLOv8	Cows	Off animal	P	Li et al. (2024)
Lameness	Accelerometers	Sheep	On-animal	P	Barwick et al. (2018b)
	Accelerometers + GPS	Cows	On-animal	P	Riaboff et al. (2021)
Oestrus	Pedometers	Cows, sheep, goats	On-animal	C	Rutten et al. (2013)
	Accelerometers	Cows, sheep, goats	On-animal	C	Rutten et al. (2013)
	GNSS	Sheep	On-animal	P	Fogarty et al. (2015)
	Alpa-Detector	Sheep	On-animal	C	Alhamada et al. (2016)
Parturition	GPS-CAL	Cows	On-animal	P	Calcante et al. (2014)
	GNSS	Cows	On-animal	C	Williams et al. (2022) Chang et al. (2024) García García et al. (2023)
	Accelerometers	Cow, sheep, horses	On-animal	C	Chang et al. (2024) Sohi et al. (2022) Jung et al. (2022)
	WOW	Cow	Off-animal	C	Aldridge et al. (2017)
Pedigree	Pedigree Matchmaker	Cow, sheep	On-animal	C	Morris et al. (2012) Scott and Blore (2019)
	Bluetooth Technology	Sheep	On-animal	C	Sohi et al. (2017)
Environmental impact	Open path laser	Cow	Off-animal	C	Tomkins and Charmley (2015)
	GPS + Urine sensor	Sheep	On-animal	P	Betteridge et al. (2010)
	Acoustic urine sensor	Cow	On-animal	P	Shorten and Welten (2022)
	Virtual Fencing	Cow	Off-animal	C	Campbell et al. (2020b)

GPS = Global Positioning System; UAV = Unmanned Aerial Vehicle; RFID = Radio Frequency Identification; GNSS = Global Navigation Satellite System; GPS-CAL = GPS-Calving Alarm; WOW = Walk-Over-Weigh.
C = Commercial; P = Prototype.

to triangulate the location of tagged animals, requiring signals from at least four satellites (Ramesh et al. 2021). The Internet of Things (IoT) has experienced significant growth in both industry and research communities, facilitating the seamless exchange of data between application devices and sensors (Hassija et al. 2019). This surge in IoT adoption has led to a proliferation of applications spanning various domains such as precision agriculture, smart cities, asset tracking, healthcare, and extensive livestock systems (Lee and Lee 2015). Many of these applications require long-range, low-data-rate communication with minimal deployment and management costs. This demand has catalysed the emergence of many licenced and unlicensed LPWAN (Low Power Wide Area Network) technologies, among which the most emergent technologies are LoRaWAN, DASH7, Sigfox, and NB-IoT (Ayoub et al. 2019). An important issue to be considered is the power consumption of these sensors, which is influenced by GPS data transmission, the most power intensive activity for a device (Handcock et al. 2009). Battery replacement or recharging affects the logistics of animal handling. Therefore, it is essential to estimate battery lifetime to develop a more appropriate maintenance schedule for these networks (Aquino et al. 2023).

Furthermore, UAVs have rapidly emerged as valuable tools in extensive livestock systems, capable of locating herds and counting grazing animals (Xu et al. 2020). There may be concerns about stress caused by UAVs flying close to animals; this depends on factors such as species, gender and age (Abdulai et al. 2021), as well as the type of UAV used (Mulero-Pázmány et al. 2017). Webb et al. (2017) and Abdulai et al. (2021) found no effects of UAV on physiological or behavioural parameters in cows and observed that the animals quickly adapted to UAV. Moreover, UAV systems can be combined with GPS sensors for herd location, and there has been a significant increase in the use of UAVs capable of acquiring geo-referenced sensor data (Gonzalez et al. 2016).

Luo et al. (2022) tested an UAV equipped with an AGX Xavier high-performance computing unit, which ran the improved YOLOv5 algorithm through edge computing. They successfully achieved individual identification and positioning of cattle during actual flight.

Ji et al. (2023) utilised georeferencing and image recognition with UAVs to track yak movements in typical household pastures on the Qinghai-Tibetan Plateau.

Animal identification

Animal identification systems can be grouped into three categories: permanent methods (ear notching, ear tattooing, hot iron branding, freeze branding), temporary methods (ear tagging) and electrical methods (Awad 2016). Electronic identification (EID) systems are a key component that have far surpassed classic identification systems and are the only technology currently mandatory under EU laws for small ruminants (Official Journal of the European Union 9.1.2004). Generally, the most used technology is the RFID that consists of three components: RFID tag, RFID reader, and antennas. The RFID tag, attached to the animal, are passive sensors that can store a large amount of data (Awad 2016). By using a RFID reader, data can be transferred to a computer, where are stored and analysed later (Bodkhe et al. 2018) for decision making. There are several types of RFID technologies, such as: ear tags, ruminal boluses, and microchips implant.

Ear tags are the cheapest EID method, and the most widespread sensor in ELF, but the presence of bushes, tree branches etc. increase the possibilities of its loss. Ruminal boluses also have a widespread use, especially for small ruminants, and they have the advantage of very low malfunction and loss rate (Odintsov Vaintrub et al. 2021). These devices can also monitor vital parameters such as rumen temperature and pH, but currently, boluses capable of measuring these parameters are not commercially available for small ruminants.

Pinna et al. (2023) developed and tested on sheep the SmartGlove, a wearable framework that can link RFID animal tags and augmented reality smart glasses *via* a Bluetooth connection, allowing the visualisation of specific animal data directly in the field. Currently, the SmartGlove is in the prototype stage, so more advancements are required, with a particular focus on the hardware's downsizing and the creation of a more ergonomic tool shape.

Microchip implants are the most used tags for equids identification and its use in livestock animals is very limited for the difficult to remove the EID in the slaughterhouse, but this injectable EID has the advantage that it can also be used as a sensor to detect physiological parameters (Odintsov Vaintrub et al. 2021). Kang et al. (2022) used a percutaneous thermal sensing microchip, implanted in different foals' body sites to monitor body temperature. They state that the pectoral muscle showed the best potential to implant microchip because it had the highest correlation and the least differences with rectal temperature. Fuchs et al. (2019) tested an implanted subcutaneous and abdominal sensor in sheep and lambs to monitor body temperature and heart rate and compared them with gold standard instruments. Ninety percent of the measurements had an appropriate measurement quality. However, this study showed an important issue due to the loss of 27% of the heart rate and 20% of the body temperature sensors.

Body weight and body condition score

The liveweight of grazing animals is a fundamental parameter for the evaluation of the health and nutritional status, the adequacy of feeding resources, and the achievement of the target weight for slaughter in the beef livestock system. However, in extensive systems traditional weighing methods are laborious, time consuming and stress-inducing (Parsons et al. 2023). To facilitate this operation, automatic 'Walk-over-Weigh' (WOW) systems have been developed, which can be equipped with solar panels for energy autonomy and transmission systems for remotely sending recorded data to the office computer.

These tools can be supplemented by individual animal identification through RFID tags and readers, enabling daily individual weight assignment and record. After the data is filtered by an algorithm to exclude illogical records (e.g. two animals on the scale at the same time, only a portion of an animal on the scale, etc.), livestock managers can next evaluate and interpret the results (Brown et al. 2014, 2015; Parsons et al. 2023).

To properly weight the animals, they must pass over the scale slowly, otherwise the data is not detected; for this reason, a period of training to the routine of using the WOW is necessary. As shown by Brown et al. (2014) and González-García et al. (2018), an adaptation period of about 2–3 weeks can increase data quality and data collection frequency. At least 5 to 10 individual measurements are required to obtain reliable weight records (Aquilani et al. 2022). Furthermore, to encourage the animals to pass over the WOW, this is placed in an obligatory passage e.g. at the entrance to areas where attractants are placed. González et al. (2014) used water and minerals as attractants for beef cattle and obtained satisfactory results. González-García et al. (2018) have demonstrated that this technique is also highly effective for sheep.

The WOW system can also be used to identify animals with gastrointestinal parasite infection by measuring weight gain anomalies. In this way it is possible to apply individually the targeted selective treatments (TST) to the infected animal within the group (Charlier et al. 2014). Pasture-borne parasites are a constant threat, particularly on permanent pastures, that can both impair animal health and decrease weight gain (Segerkvist et al. 2020). The TST could be a valued alternative to the traditional method (i.e. mass deworming) for reducing the use of anthelmintics and avoiding the onset of anthelmintic-resistant nematode populations.

Another important parameter to evaluate animals' health and nutritional status is the Body Condition Score (BCS) that can be estimated with the image analysis based on 2D and 3D cameras. But this technique has primarily been tested in indoor systems because the variable environmental conditions, animal motion and the challenge of maintaining the ideal position in front of the camera in extensive systems reduce the data quality (Aquilani et al. 2022).

Behaviour monitoring

The oldest method of monitoring animal behaviour is still visual observation; however, it can be challenging at times, particularly in ELFs. Nowadays, smart tools, like accelerometers, can identify the animals' movements and associate them with a specific behaviour, such as resting, grazing, rumination, walking etc. Accelerometers can be placed to different animal body parts (Odintsov Vaintrub et al. 2021) (e.g. leg, neck, ears, rumen) and by measuring the accelerations in 1, 2 or 3 axes, based on the accelerometer type, can record activity data. The accuracy and sensitivity of detecting animal behaviour can be increased by combining these sensors with a GPS unit (Herlin et al. 2021).

Numerous studies have been carried out over the years to assess and test the tools' ability to monitor the animals' behaviour. Cabezas et al. (2022) using a low cost 3–D accelerometers and GPS sensors, attached to the cattle's neck, observed a good accuracy for behaviour classification with the highest value (0.93) for grazing and the lowest (0.881) for ruminating. Barwick et al. (2018a) compared different accelerometers, attached simultaneously to the leg, the ear, and the neck, to monitor grazing, standing and walking behaviour in sheep. The ear tag demonstrated high classification accuracies, with 94, 96 and 99% for grazing, standing, and walking, respectively. The other two devices also showed high classification accuracies for grazing and walking, but low accuracy for standing (54% for the collar and 56% for the leg device).

Additionally, calves' and lamb's suckling behaviour can be monitored. Kour et al. (2018), in a pasture-based system, estimated the duration and occurrence of more than 95% of suckling episodes in calves. Using a neck-mounted accelerometer, Kuźnicka and Gburzyński (2017) were able to accurately identify the suckling behaviour in lambs with a 95% accuracy rate.

Furthermore, Weinert et al. (2020) assessed the performance of the EquiWatch System (EWS), an automated chew sensor-based remote monitoring device, in detecting equines' feeding behaviour in grazing systems. They observed a high correlation between visual observations and system-recorded grazing time with 0.997 concordance correlation coefficient (CCC). They also observed a high agreement between the sum of manually counted bites and chews and total chew counts reported by the EWS with 0.979 CCC.

By quantifying the time animals spent on each behaviour, it is possible to assess their health status. Unusual resting behaviours, abnormal stance and gaits, the absence of vertical or horizontal neck movements or the observation of too slow displacements can provide key signals of possible ongoing diseases (Cabezas et al. 2022).

Barwick et al. (2018b) showed that a tri-axial accelerometer deployed in the ear-tag can successfully discriminate lame walking activity from normal grazing, standing, and walking behaviours in sheep. Riaboff et al. (2021) detected lameness cows using an accelerometer with GPS sensor and found that severely lame animals spent 4.5 less time grazing and almost twice in resting, especially in the lying position. Additionally, moderately or severely lame cows exhibited lower exploratory attitude travelling 1.2 and 1.7 times less distance, respectively.

Ikurior et al. (2020) demonstrated that gastrointestinal nematode (GIN) infection may have an impact on animal activity measured by a tri-axial accelerometer. Sheep infected with GIN exhibited less activity than the others.

An innovative approach is the monitoring IoT system for real-time animal activity detection. Li et al. (2024) proposed a non-invasive recognition algorithm based on video analysis called YOLOv8n_BiF_DSC (Fusion of Dynamic Snake Convolution and BiFormer Attention). The aim of the study was to increase the accuracy of beef cattle behaviour identification. This algorithm achieved a recognition accuracy of 93.6%; particularly, they obtained an average accuracy of 98.9% when it comes to identifying the lying posture of beef cattle.

Several studies have assessed the accuracy of these tools in monitoring animal behaviour, but their applicability in ELF still presents some challenges. Battery life, device resistance to harsh environmental conditions, and data transmission reliability in remote areas remain critical limitations, as highlighted by Riaboff et al. (2021). Moreover, while low-cost sensors such as accelerometers and GPS have shown good performance (Cabezas et al. 2022), large-scale implementation is limited by the need for data processing infrastructure. Despite these challenges, combining different technologies and integrating them with IoT systems and AI could enhance the reliability and practicality of these tools on farms.

Feeding behaviour

Feeding behaviour in animals is a crucial indicator of their overall health, but it is also influenced by external factors, such as environmental conditions, forage quality and availability. Embedded sensors, such as accelerometers and microphones can effectively monitor feeding behaviour and masticatory activity, which, in turn, can facilitate the estimation of dry-matter intake, classification of jaw movements, and identification of activity such as grazing and rumination. Over time, algorithms for analysing feeding sounds evolved (Zhang et al. 2022; Defalque et al. 2020; Martinez-Rau et al. 2023). However, in some cases, these algorithms have been integrated into resource-limited electronic devices, restricting their functionality to a singular task: either classifying jaw movements or identifying feeding activities such as grazing and rumination (Martinez-Rau et al. 2024).

Yu et al. (2022) proposed a recognition method of cow feeding behaviour based on DRN-YOLO algorithm and edge computing technology, achieving accurate and fast detection of cow feeding behaviour in farm feeding environments. Although originally designed for dairy free-stall barns, implementing this system at the grazing level in extensive livestock farms presents an interesting perspective.

Martinez-Rau et al. (2024) introduced an acoustic monitoring system designed to analyse the feeding behaviour of grazing cattle across various scales. This embedded system offers predictor variables to estimate dry-matter intake, classifies jaw movements, and identifies grazing and rumination bouts, with results transmitted remotely *via* LoRa (long-range) communication. Two versions of the system were developed on a Raspberry Pi Pico board, based on a low-power ARM Cortex-M0+ microcontroller. Both versions employ techniques to reduce energy consumption, such as direct memory access, sleep mode, and clock-gating. The first deployment achieved an 87.3% accuracy rate for classifying jaw movements and 87.0% for feeding activities, while the second deployment achieved scores of 84.1% for jaw movements and 83.5% for feeding activities.

Oestrus detection

Reproductive efficiency is a key factor improvable by detecting oestrus promptly. At this scope automated oestrus detection systems have been developed. These technologies, designed primarily for intensive systems, involved different sensors including pedometers, activity metres, 3–dimensional-accelerometers, sensors for mounting behaviour, video cameras, microphones for vocalisation, sensors for body temperature, progesterone sensors (Rutten et al. 2013) and GNSS (Global Navigation Satellite System) tools (Fogarty et al. 2015). Pedometers and accelerometers are the two most widely studied and used technologies for oestrus detection (Rutten et al. 2013) by monitoring the animals' activity. All these technologies can be used either individually or in combination (Firk et al.

2002; Peralta et al. 2005) and it is necessary to employ these tools in conjunction with an electronic identification device.

Fogarty et al. (2015) tested the UNETracker II GNSS system to monitor oestrus and improve reproductive management in extensive sheep farming systems. GNSS devices were attached to ewes' neck collars following hormonal oestrus synchronisation. Ewes demonstrated an increase in speed of movement in the early hours of the morning (01:00–03:00 and 07:00–08:00) on the day of oestrus compared to non-oestrus periods. Additionally, ewes that increased their speed of movement by 0.05 m/s received 1.4 to 28.4 times more mounts, depending on the hour of the day. Furthermore, ewes that received at least one mount showed an apparent increase in activity in the hours leading up to and during the period of maximum sexual activity. This study suggested that the onset of sexual activity can be identified as a period of increased speed of movement followed by a return to 'normal' activity.

Alhamada et al. (2016) obtained good results with an Alpha-Detector (AD) system for oestrus identification in sheep. The system consists of transponders placed in females' rump and an RFID reader on the rams, which is triggered during mounting. Two trials were conducted. In trial 1, visual observations were compared to data from two rams monitoring twelve ewes over two oestrus cycles: hormonally induced and natural. The AD identified 100% of ewes in oestrus, with a 94% match for standing oestrus. Additionally, a significant difference in male activity was observed. In trial 2, thirteen ewes tagged with a caudal transponder were naturally sired by a ram equipped with AD. Oestrus events were consistently spread over time, with all ewes showing oestrus during the first cycle. Lambing dates confirmed the conception timing detected by AD.

Parturition event

The health and survival of animals can be significantly impacted by parturition events, particularly in ELF where it is challenging to promptly act when issues like dystocia or risk of predator attack can happen.

Calcante et al. (2014) designed and tested a GPS-Calving alarm (GPS-CAL) to identify the onset of calving and notify the farmer *via* SMS. The message contains the date and hour of the birth event, the animal's ID and the geographical coordinates of the calving location. Field tests confirmed that this system was both extremely reliable and cost-effective for the farmer, as each device could be utilised to monitor 10 calvings/year at a unit cost of 31.50 €/birth, a value sustainable by the farmer who can take advantage of a sort of low-cost 'insurance' for cow and calf. Additionally, GNSS equipment can be helpful in tracking the isolating behaviour that typically takes place before calving. According to several studies, the isolation behaviour can be shown up already 24 h before the parturition events (Chang et al. 2024; Williams et al. 2022; García García et al. 2023). Accelerometers can also be used to measure rumination time and walking activity which is known to decrease significantly on the day before calving (Chang et al. 2024). Moreover, various commercial accelerometers are available to detect tail raising, such as Alert'Vel (ALB Innovation, Montbrison, France), Calving Alert Set (Patura, Laudenbach, Germany), SmartVel (Evolution XY, Noyal-sur-Vilaine, France), MooCall Sensor (MooCall, Dublin, Ireland) (García García et al. 2023), which identify characteristic tail movement patterns linked to the onset of labour and alert farmers in real time *via* mobile applications or GSM. However, these systems are mainly designed for intensive livestock systems, where calving occurs in confined spaces. In ELF, challenges such as power supply, sensor robustness, and long-range data transmission in remote areas limit their effectiveness (García García et al. 2023).

Aldridge et al. (2017) investigated a WOW system that could be used to determine the calving day and found the onset of calving was properly identified in 59% of cases. Chang et al. (2024) suggested to integrate data from several sensors for increasing the likelihood of detecting the onset of calving. However, useful devices are not widespread available and accessible because of their cost is still high and energy requirements for data acquisition and transmission should be optimised (Chang et al. 2024). Anyhow, it is expected that the commercialisation of GNSS tools will increase in the coming years as the cost of microelectronics continues to decline and data coverage in rural areas improves (Bailey et al. 2018).

Pedigree determination

In ELF, identifying the correct maternal parentage can be difficult to assess, especially for small ruminants. Expensive and labour-intensive mothering-up measures, which are impractical under an extensive grazing system, can be avoided using technologies such as Pedigree Matchmaker (PMM) (Morris et al. 2012). The PMM is a walk-by system that estimates the association between ewes and their lambs using recorded RFID data. This system requires all lambs and dams to be equipped with RFID tags and calculates the frequency with which a particular lamb follows a dam past the RFID reader during several weeks of data recording to determine parentage. Based on the frequency of specific lamb/dam combinations and associations, the PMM software estimates the probability that lamb and dam are related. The PMM could be integrated with the WOW system, where an RFID reader is installed. Scott and Blore (2019) showed that it is possible to match cows and calves using PMM. With effective attractants, it was found that 56% and 94% of animals were matched after 15 and 30 days, respectively. In addition, for recording cow details, calves as young as 1 month of age and up to 6 months of age were successfully recorded through the PMM equipment.

Sohi et al. (2017) proposed the application of Bluetooth (BT) technology (ActiGraph wGT3X-BT, Pensacola, Florida, USA) for determining maternal pedigree and ewe-lamb spatial relationships in extensive farming systems. In this study, thirty-five ewes and twenty-three labs, aged 1 to 3 weeks, were equipped with BT activity monitors: ewes with beacons and lambs with receivers. Ewe beacons emitted BT signals four times per second, while lamb receivers collected these signals every minute. The BT signals received by lambs were subsequently downloaded using the ActiGraph software. Maternal pedigree was determined as the ewe from which the lamb received the most BT signals. The system achieved 100% accuracy in determining maternal pedigree within 15 min of returning animals to pasture. The number of maternal signals received by lambs varied with age and light conditions, with over 90% of signals within 2 metres originating from the mother. BT sensor must be combined with a form of animal identification (e.g. RFID) because it is not possible to maintain animals' identity when BT device is removed from the animal (Sohi et al. 2017).

Environmental impact monitoring

The environmental impact of animals in ELF is poorly investigated, mainly due to the difficult environmental conditions and the remote locations, which complicate measurements. Key issues include manure management, which can affect soil quality and lead to nutrient losses, as well as the emission of greenhouse gases (GHG) (Sakadevan and Nguyen 2017). Addressing these issues is crucial for improving the sustainability of ELF. Tomkins and Charmley (2015) tested the open-path laser technique to estimate the methane emission in extensively managing cattle and state that the lasers can be successfully deployed in extensive grazing conditions to directly measure methane emissions from cattle at a herd scale.

To determine the urine distribution, Betteridge et al. (2010) combined GPS technology with urine sensors to quantify the daily urination rates for cow and sheep. The system employed a thermistor placed below the vulva to continuously measures ambient temperature, which increases to near body temperature when urine pass over it. Field validation showed that 85% of urination events detected by sheep sensors and 78% of those detected by cattle sensors were confirmed by visual observation. The authors suggested that this integrated approach could support the identification of potential critical Nitrogen (N) emissions source sites, allowing mitigation strategies at the within-paddock level. For sheep, there was a strong correlation ($r = 0.82$) between time spent in an area and the number of urination events, but the correlation was weaker ($r = 0.54$) for cattle. However, the authors suggested that to enhance this information, the sensor's capacity to estimate the N load in each urination event should be improved.

Shorten and Welten (2022) utilised non-invasive acoustic sensors, attached to 100 grazing cows, to detect the time and duration of urination events. Significant variations were observed among cows in urination frequency, duration, and N load per event, with coefficients of variation of 10–30%. Two divergent cow groups (Low and High N load per event) were identified. Although the two groups excreted similar total daily amounts of urine-N, they differed by 23% in the average amount of N per urination event, primarily due to a 37% increase in urination frequency. This finding demonstrates that more widespread urination could reduce N leaching by 10% at the paddock level and indicates the potential to select and manage cows that excrete a lower N load per urination event by reducing the volume per urination event and increasing urination frequency.

PLEF applied to monitor interactions between livestock and wildlife

In ELF wildlife-livestock interactions can pose significant challenges, such as changes in behaviour and spatial use, additive grazing intensity, disease transmission and predator conflicts (Viola et al. 2021; Aquilani et al. 2022; Spencer et al. 2024) and the use of smart technologies can be crucial in monitoring and managing them.

Grazing intensity

Studies on sustainable grazing intensity, often expressed as Animal Unit (AU) (Allen et al. 2011), generally lack to assess wildlife (Cai et al. 2022; Rodríguez et al. 2024) as possible source of additive or complementary grazing. In extensive grazing systems, wildlife and livestock adjust spatial behaviour and activity patterns based on resources availability, competition and predation risk (Treves et al. 2004; Di Virgilio et al. 2018; Gaynor et al. 2019; Cai et al. 2022; Spencer et al. 2024), potentially determining local over- or under-grazing. At the state, studies based on satellite monitoring, suggest a substantial shifting of wild herbivores distribution towards sectors characterised by low livestock presence, suggesting complementarity and compensative forage utilisation. Brivio et al. (2022), reported that, in a study conducted in Sardinia (Italy), mouflons move away from their preferred feeding sites when livestock are closer than 650 metres. Spencer et al. (2024) used GPS data to examine the movements of 19 white-tailed deer as part of a cattle breeding experiment conducted in Texas, USA. The study area spanned on 7502 ha of range land divided into 10 pastures, enclosed by 1.3–meter-tall wire fences. Cattle were introduced into six of the ten pastures, with stocking densities varying between 0 and 15.6 AU/km^2. Movements of ungulates were analysed for a period of 30 days before and 30 days after the stand event. The GPS collars collected an average of 239 location points both before and after the introduction of the livestock. After the cattle introduction, 76% of the deer locations occurred in areas with low or no presence/abundance of livestock. This study allowed an assessment of how the presence of livestock affected deer movements. Despite deer reduced their movement speed by 1.4% per 1 AU/km^2 increase in cattle density, likely to minimise interactions, their home range remained consistent before and after the introduction of cattle (86.3 SE = 7.87 vs. 86.0 SE = 5.87).

Despite these findings, research on wildlife-livestock interactions remains limited. Further studies are needed to better understand the extent to which wildlife contributes to overall grazing pressure and how their foraging behaviour interacts with livestock grazing dynamics.

Transmission of disease

Wildlife can drive disease transmission to livestock or human as effective reservoir of many pathogens, threatening economy or public health (Kukielka et al. 2013; Triguero-Ocaña et al. 2019; Corti et al. 2022; Ferrara et al. 2024). Triguero-Ocaña et al. (2019) demonstrated, tracking 6 red deer, 6 wild boar, 8 Iberian pigs and 3 cattle by GPS in a Spanish extensive pig farm, that wild boars and deer, in particular, frequently and directly interact with livestock identifying water sources as crucial key hotspots for pathogen spread.

In the Basque Country (Spain), however, Varela-Castro et al. (2021), studied the interactions between sympatric wildlife and livestock deploying for twenty-three camera traps in pastures, bushy edges between pastures, farm buildings, and a pine forest, applying an overall effort of 2741 trapping days (119 days per camera trap). In contrast to the previous finding, only 23 direct encounters with livestock have been observed out of a total of 1293 events: foxes (8), small rodents (6), wild boar (6), badgers (2), and roe deer (1). No direct interactions were observed among other wild mammals. On the base of this result, the authors suggested that mycobacteria transmission occurs mainly through indirect interactions. The most prone habitats for interspecies transmission appear to be cattle pastures, while badger latrines could be a critical point for mycobacteria circulation between badgers, wild boars, foxes, and cattle.

Predation of livestock

The use of precision technologies is crucial in improving wildlife management in livestock systems. In addition to predictive risk model based on satellite telemetry data (Clark et al. 2020), GPS collars and accelerometers exhaustively reviewed by Aquilani et al. (2022), recent advancements have led to the development of technologies capable of detecting predator threats in real time (acoustic monitoring systems and AI-based surveillance).

In a recent study, Primi et al. (2024) reported performance and limits of a prototype for predator defence using a microphone connected to an alert system. This innovative device, powered by an Arduino-based system, was designed to detect anomalous acoustic signals near barns or pens, identifying potential threats such as wolves or stray dogs. The system integrates an Arduino UNO board and a GSM Shield V2 module, which process and analyse audio signals captured by a directional microphone. The system has been calibrated to distinguish among routine sounds such as common flock movement, normal barking of guard dogs, rumbling or engine sound and anomalous noises attributable to flock agitation and defensive barking. When the noise surpasses a predetermined threshold, the Arduino microcontroller triggers an alert, successfully sending an automatic SMS warning to a designated recipient. Setting the noise threshold is a crucial challenge because of background variations from vehicles or dogs. However, the flexibility of Arduino allows for continuous calibration, which makes it a cost-effective and open-source solution for real-time predator detection.

Instead, a study by Dede et al. (2023) used surveillance cameras and AI-based algorithms to mitigate conflicts between wolves and livestock integrating advanced technologies in pasture management. Images and videos of surrounding pasture areas have been passively acquired and automatically analysed for detecting potential predators and triggering acoustic, visual, and other deterrents. However, implementing AI poses significant challenges, particularly in hardware and software configuration. Indeed, algorithms should detect animals in natural environments even when partially visible, and under varying weather and environmental conditions and the training process requires extensive collection of images from different scenarios, making it lengthy and complex.

Main limitations to PLEF's diffusion

Precision Livestock Farming offers numerous advantages, and its application in ELF is crucial for supporting farmers in overcoming daily challenges, improving herd management, and reducing workloads and environmental impact. Despite these benefits, the adoption of precision technologies in extensive grazing systems remains limited (Bahlo et al. 2019). PLEF adoption can be significantly influenced by internet access and connectivity, as they facilitate real-time monitoring and data analysis (Greig et al. 2023). However, limited internet connectivity in rural areas can hinder the adoption of new technologies (Vogels 2021). Moreover, in open areas the use of GPS technology to trace animal position is energy consuming, limiting the application of real time monitoring application. Additionally, the financial status of farms poses another barrier to the diffusion of PLEF. According to a survey conducted across several European countries, smaller and less profitable farms are hesitant to invest in new precision technologies (Knierim et al. 2018). Moreover, the availability of technical assistance, training, and knowledge sharing significantly influences the adoption process (Läpple and Kelley 2013). Studies have shown that more technical support and education programs from technology providers promote the adoption of precision technologies (Barnes et al. 2019; Drewry et al. 2019;). These resources help farmers to understand the benefits, manage the complexities, and effectively integrate new technologies into their farming practices. Networks and forums for sharing experiences and best practices can enhance farmers' confidence in using precision technologies. For instance, Rose et al. (2016) found that social learning and peer-to-peer networks significantly improve the dissemination and uptake of innovative farming practices. Cultural and demographic factors also impact PLEF adoption. The average age of farmers and their conservatism towards new technologies can impede the adoption process. For instance, Odintsov Vaintrub et al. (2021) highlighted that, in the Mediterranean region, older farmers, averaging 60 years of age, are reluctant to invest in new technologies due to perceived financial risks and cultural dynamics. Conversely, younger farmers and those with higher educational levels are more likely to adopt precision farming technologies (Paustian and Theuvsen 2017). Farms with larger land areas and those that use agricultural contractor services are also more inclined to implement these technologies due to their higher capacity to absorb the costs and benefits associated with precision farming (Paustian and Theuvsen 2017).

Vecchio et al. (2020) indicated that farmers who perceive net benefits and have confidence in using precision farming technologies are more likely to adopt them. Adrian et al. (2005) found that attitudes of confidence towards using precision agriculture technologies, perceptions of net benefit, farm size, and educational levels positively influence the adoption of these technologies. Their study revealed that the perception of usefulness significantly influences the perception of net benefit, which in turn affects the adoption decision.

Further evidence by Thompson et al. (2019) suggests that farmers' perceptions of increased yields, reduced production costs, and increased convenience drive the adoption of precision agriculture technologies. Their study indicated that the perceived benefits of precision farming were heterogeneous among farmers but crucial for adoption decisions.

Future perspectives and conclusions

Developing an integrated system combining multiple sensors is crucial to maximise the added value of each component, thereby enhancing the overall potential

PLF technologies (Lovarelli and Guarino 2021). The integration of various sensors and data sources, such as biometric tools, environmental monitors, and wearable devices, can provide a comprehensive overview of animal health, behaviour, and environmental conditions. This holistic approach allows for more precise and timely interventions, ultimately improving animal welfare and farm productivity.

Moreover, edge computing can play a significant role in this context by enabling local data processing, and reducing latency, making it ideal for real-time responsiveness (Shumba et al. 2022), reducing bandwidth usage, and battery consumption, which are critical factors in ELF. Edge detection algorithms can also be employed to analyse sensor data in real time, identifying critical changes in animal behaviour or environmental conditions that require immediate action. Additionally, the integration of PLF technologies with big data analytics and blockchain can revolutionise livestock farming improving decision-making, ensuring secure and transparent traceability of animal products from farm to table, addressing concerns about food safety and animal welfare (Neethirajan and Kemp 2021).

In conclusion, while these technological advancements offer promising opportunities, their economic feasibility in ELF remain largely unexplored. Future research should focus on cost-benefit analyses to assess their financial viability and support decision-making for farmers.

Acknowledgements

This study was carried out within the Agritech National Research Center and received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR)—MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4—D.D. 1032 17/06/2022, CN00000022). This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

Disclosure statement

The authors confirm that there are no relevant financial or non-financial competing interests to report.

Funding

Università degli Studi della Tuscia and Ambito Territoriale di Caccia Roma 2 funded the fellowship of G. Bernabucci. PON - Research and Innovation 2014–2020 (DM 1016/2021) funded the PhD fellowship of C. Evangelista, and PNRR—Mission 4 C1. Inv. 3.4 Doctoral fellowships in Digital and Environmental Transitions (DM no. 118/2023) funded the PhD fellowship of P. Girotti.

ORCID

Gloria Bernabucci http://orcid.org/0009-0000-0698-5769
Chiara Evangelista http://orcid.org/0000-0002-3004-3365
Pedro Girotti http://orcid.org/0000-0002-6729-8847
Paolo Viola http://orcid.org/0000-0003-4465-3380
Raffaello Spina http://orcid.org/0009-0004-0716-2894
Bruno Ronchi http://orcid.org/0000-0002-9405-2949
Umberto Bernabucci http://orcid.org/0000-0002-8126-3042
Loredana Basiricò http://orcid.org/0000-0002-4738-3622
Luca Turini http://orcid.org/0000-0002-4164-8263
Alberto Mantino http://orcid.org/0000-0002-1087-0056
Marcello Mele http://orcid.org/0000-0002-7896-012X
Riccardo Primi http://orcid.org/0000-0003-0109-9404

Data availability statement

Data available on request from the authors.

References

Abdulai G, Sama M, Jackson J. 2021. A preliminary study of the physiological and behavioral response of beef cattle to unmanned aerial vehicles (UAVs). Appl Anim Behav Sci. 241:105355. doi: 10.1016/j.applanim.2021.105355.

Abutridy JA. 2000. Text mining: principles and applications. Revista Facultad de Ingenieria. 7:57–62. https://www.redalyc.org/articulo.oa?id=11400708.

Adrian A, Norwood S, Mask P. 2005. Producers' perceptions and attitudes toward precision agriculture technologies. Comput Electron Agric. 48(3):256–271. doi: 10.1016/j.compag.2005.04.004.

Ahmad T, Sahoo PM, Jally SK. 2016. Estimation of area under agroforestry using high resolution satellite data. Agroforest Syst. 90(2):289–303. doi: 10.1007/s10457-015-9854-2.

Ahmed U, Mumtaz R, Anwar H, Shah AA, Irfan R, García-Nieto J. 2019. Efficient water quality prediction using supervised machine learning. Water. 11(11):2210. doi: 10.3390/w11112210.

Alamer M. 2006. Physiological responses of Saudi Arabia indigenous goats to water deprivation. Small Rumin Res. 63(1-2):100–109. doi: 10.1016/j.smallrumres.2005.02.004.

Aldridge MN, Lee SJ, Taylor JD, Popplewell GI, Job FR, Pitchford WS. 2017. The use of walk over weigh to predict calving date in extensively managed beef herds. Anim Prod Sci. 57(3):583–591. doi: 10.1071/AN15172.

Alhamada M, Debus N, Lurette A, Bocquier F. 2016. Validation of automated electronic oestrus detection in sheep as an alternative to visual observation. Small Rumin Res. 134:97–104. doi: 10.1016/j.smallrumres.2015.12.032.

Allen VG, Batello C, Berretta EJ, Hodgson J, Kothmann M, Li X, McIvor J, Milne J, Morris C, Peeters A, et al. 2011. An international terminology for grazing lands and grazing animals. Grass Forage Sci. 66(1):2–28. doi: 10.1111/j.1365-2494.2010.00780.x.

Aquilani C, Confessore A, Bozzi R, Sirtori F, Pugliese C. 2022. Review: precision Livestock Farming technologies in pasture-based livestock systems. Animal. 16(1):100429. doi: 10.1016/j.animal.2021.100429.

Aquino AT, Barboza Júnior JAL, de Araújo Moreira N, Praça PP. 2023. Impacts of GPS module on energy consumption and machine-learning based battery lifetime estimation. Proceedings of the 10th International Workshop on ADVANCEs in ICT Infrastructures and Services (ADVANCE 2023); Feb 2023; Fortaleza-Jerricoacoara, Brazil: Federal University of Ceara, University of Evry. doi: 10.48545/advance2023-fullpapers-3_3.

Awad AI. 2016. From classical methods to animal biometrics: a review on cattle identification and tracking. Comput Electron Agric. 123:423–435. doi: 10.1016/j.compag.2016.03.014.

Ayoub W, Samhat AE, Nouvel F, Mroue M, Prevotet J-C. 2019. Internet of mobile things: overview of LoRaWAN, DASH7, and NB-IoT in LPWANs standards and supported mobility. Proceed IEEE Commun Surv Tutorials. 21(2):1561–1581. doi: 10.1109/COMST.2018.2877382.

Bahlo C, Dahlhaus P, Thompson H, Trotter M. 2019. The role of interoperable data standards in precision livestock farming in extensive livestock systems: a review. Comput Electron Agric. 156:459–466. doi: 10.1016/j.compag.2018.12.007.

Bailey DW, Trotter MG, Knight CW, Thomas MG. 2018. Use of GPS tracking collars and accelerometers for rangeland livestock production research. Transl Anim Sci. 2(1):81–88. doi: 10.1093/tas/txx006.

Bailey DW, Trotter MG, Tobin C, Thomas MG. 2021. Opportunities to apply precision livestock management on rangelands. Front Sustain Food Syst. 5:611915. doi: 10.3389/fsufs.2021.611915.

Barbedo JGA, Koenigkan LV, Santos TT, Santos PM. 2019. A study on the detection of cattle in UAV images using deep learning. Sensors (Basel). 19(24):5436. doi: 10.3390/s19245436.

Barnes AP, Soto I, Eory V, Beck B, Balafoutis A, Sánchez B, Vangeyte J, Fountas S, van der Wal T, Gómez-Barbero M. 2019. Exploring the adoption of precision agricultural technologies: a cross regional study of EU farmers. Land Use Pol. 80:163–174. doi: 10.1016/j.landusepol.2018.10.004.

Barwick J, Lamb DW, Dobos R, Welch M, Trotter M. 2018a. Categorising sheep activity using a tri-axial accelerometer. Comput Electron Agric. 145:289–297. doi: 10.1016/j.compag.2018.01.007.

Barwick J, Lamb D, Dobos R, Schneider D, Welch M, Trotter M. 2018b. Predicting lameness in sheep activity using tri-axial acceleration signals. Animals (Basel). 8(1):12. doi: 10.3390/ani8010012.

Battini M, Renna M, Giammarino M, Battaglini L, Mattiello S. 2021. Feasibility and reliability of the AWIN Welfare assessment protocol for dairy goats in semi-extensive farming conditions. Front Vet Sci. 8:731927. doi: 10.3389/fvets.2021.731927.

Berckmans D. 2017. General introduction to precision livestock farming. Anim Front. 7(1):6–11. doi: 10.2527/af.2017.0102.

Betteridge K, Hoogendoorn C, Costall D, Carter M, Griffiths W. 2010. Sensors for detecting and logging spatial distribution of urine patches of grazing female sheep and cattle. Comput Electron Agric. 73(1):66–73. doi: 10.1016/j.compag.2010.04.005.

Bishop-Hurley G, Swain D, Anderson D, Sikka P, Crossman C, Corke P. 2007. Virtual fencing applications: implementing and testing an automated cattle control system. Comput Electron Agric. 56(1):14–22. doi: 10.1016/j.compag.2006.12.003.

Bodkhe J, Dighe H, Gupta A, Bopche L. 2018. Animal identification. Proceedings of the International Conference on Advanced Computation and Telecommunication (ICACAT); Dec 8-9. Bhopal, India. IEE. doi: 10.1109/ICACAT.2018.8933624.

Brivio F, Ciuti S, Pipia A, Grignolio S, Apollonio M. 2022. Livestock displace European mouflon from optimal foraging sites. Eur J Wildl Res. 68:30 doi: 10.1007/s10344-022-01581-y.

Brown DJ, Savage DB, Hinch GN. 2014. Repeatability and frequency of in-paddock sheep walk-over weights: implications for individual animal management. Anim Prod Sci. 54(2):207–213. doi: 10.1071/AN12311.

Brown DJ, Savage DB, Hinch GN, Hatcher S. 2015. Monitoring liveweight in sheep is a valuable management strategy: a review of available technologies. Anim Prod Sci. 55(4):427–436. doi: 10.1071/AN13274.

Buerkert A, Schlecht E. 2009. Performance of three GPS collars to monitor goats' grazing itineraries on mountain pastures. Comput Electron Agric. 65(1):85–92. doi: 10.1016/j.compag.2008.07.010.

Cabezas J, Yubero R, Visitación B, Navarro-García J, Algar MJ, Cano EL, Ortega F. 2022. Analysis of accelerometer and GPS data for cattle behaviour identification and anomalous events detection. Entropy (Basel). 24(3):336. doi: 10.3390/e24030336.

Cai Z, Song P, Wang J, Jiang F, Liang C, Zhang J, Gao H, Zhang T. 2022. Grazing pressure index considering both wildlife and livestock in Three-River Headwaters, Qinghai-Tibetan Plateau. Ecol Indic. 143:109338. doi: 10.1016/j.ecolind.2022.109338.

Calcante A, Tangorra FM, Marchesi G, Lazzari M. 2014. A GPS/GSM based birth alarm system for grazing cows. Comput Electron Agric. 100:123–130. doi: 10.1016/j.compag.2013.11.006.

Campbell DLM, Marini D, Lea J, Keshavarzi H, Dyall T, Lee C. 2020a. The application of virtual fencing technology effectively herds cattle and sheep. Anim Prod Sci. 61(13):1393–1402. doi: 10.1071/AN20525.

Campbell DLM, Ouzman J, Mowat D, Lea JM, Lee C, Llewellyn RS. 2020b. Virtual fencing technology excludes beef cattle from an environmentally sensitive area. Animals (Basel). 10(6):1069. doi: 10.3390/ani10061069.

Champion RA, Rutter SM, Penning PD. 1997. An automatic system to monitor lying, standing and walking behaviour of grazing animals. Appl Anim Behav Sci. 54(4):291–305. doi: 10.1016/s0168-1591(96)01210-5.

Chang AZ, Swain DL, Trotter MG. 2024. A multi-sensor approach to calving detection. Inf Process Agric. 11(1):45–64. doi: 10.1016/j.inpa.2022.07.002.

Charlier J, Morgan ER, Rinaldi L, Van Dijk J, Demeler J, Höglund J, Hertzberg H, Van Ranst B, Hendrickx G, Vercruysse J, et al. 2014. Practices to optimise gastrointestinal nematode control on sheep, goat and cattle farms in Europe using targeted (selective) treatments. Vet Rec. 175(10):250–255. doi: 10.1136/vr.102512.

Chen XL, Zhao HM, Li PX, Yin ZY. 2006. Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. Remote Sens Environ. 104(2):133–146. doi: 10.1016/j.rse.2005.11.016.

Clark PE, Chigbrow J, Johnson DE, Larson LL, Nielson RM, Louhaichi M, Roland T, Williams J. 2020. Predicting spatial risk of wolf-cattle encounters and depredation. Rangel Ecol Manag. 73(1):30–52. doi: 10.1016/j.rama.2019.08.012.

Confessore A, Aquilani C, Nannucci L, Fabbri MC, Accorsi PA, Dibari C, Argenti G, Pugliese C. 2022. Application of virtual fencing for the management of Limousin cows at pasture. Livest Sci. 263:105037. doi: 10.1016/j.livsci.2022.105037.

Contiero B, Cozzi G, Karpf L, Gottardo F. 2019. Pain in pig production: text mining analysis of the scientific literature. J Agric Environ Ethics. 32(3):401–412. doi: 10.1007/s10806-019-09781-4.

Cook SE, Bramley RGV. 1998. Precision agriculture opportunities, benefits and pitfalls of site-specific crop management in Australia. Aust J Exp Agric. 38(7):753–763. doi: 10.1071/EA97156.

Corti P, Collado B, Salgado M, Moraga CA, Radic-Schilling S, Tejeda C, Ruiz-Aravena M. 2022. Dynamic of Mycobacterium avium subspecies paratuberculosis infection in a domestic–wildlife interface: domestic sheep and guanaco as reservoir community. Transbound Emerg Dis. 69(4):e161–e174. doi: 10.1111/tbed.14277.

Dede J, Wewetzer D, Förster A. 2023. AI in the wild: challenges of remote deployments. Proceedings of the INFORMATIK 2023—Designing Futures: Zukünfte Gestalten. Bonn (Germany): Gesellschaft für Informatik e.V. p. 1583–1589. ISBN: 978-3-88579-731-9. doi: 10.18420/inf2023_161.

Defalque G, Santos R, Yoshimura VL, Alves FV. 2020. Ingestive behaviour activities based on bioacoustic signals in grazing cattle. Int J Agric Environ Inf Syst. 11(4):69–83. doi: 10.4018/IJAEIS.2020100105.

Defalque G, Santos R, Bungenstab D, Echeverria D, Dias A, Defalque C. 2024. Machine learning models for dry matter and biomass estimates on cattle grazing systems. Comput Electron Agric. 216:108520. doi: 10.1016/j.compag.2023.108520.

Di Virgilio A, Morales JM, Lambertucci SA, Shepard ELC, Wilson RP. 2018. Multi-dimensional Precision Livestock Farming: a potential toolbox for sustainable rangeland management. PeerJ. 6(6):e4867. doi: 10.7717/peerj.4867.

Drewry JL, Shutske JM, Trechter D, Luck DB, Pitman L. 2019. Assessment of digital technology adoption and access barriers among crop, dairy and livestock producers in Wisconsin. Comput Electron Agric. 165:104960. doi: 10.1016/j.compag.2019.104960.

Edwards JP, Qasim M, Bryant RH, Thomas C, Wright-Watson C, Zobel G, Neal MB, Eastwood CR. 2024. On-animal sensors may predict paddock level pasture mass in rotationally grazed dairy systems. Comput Electron Agric. 219:108779. doi: 10.1016/j.compag.2024.108779.

Eftang S, Vas J, Holand Ø, Bøe KE. 2022. Goats are able to adapt to virtual fencing; A field study in commercial goat herds on Norwegian farms. Appl Anim Behav Sci. 256:105755. doi: 10.1016/j.applanim.2022.105755.

FAO. 2001. Animal Production and Health Paper. Pastoralism in the new millennium. 150. Rome (Italy): Food and Agriculture Organization of the United Nations. https://www.fao.org/3/Y2647E/y2647e00.htm#toc. (accessed 18 January 2024)

FAOSTAT. 2021. FAOSTAT database. https://www.fao.org/faostat/en/#data/RL. (accessed 25 January 2024).

Ferrara G, Piscopo N, Pagnini U, Esposito L, Montagnaro S. 2024. Detection of selected pathogens in reproductive tissues of wild boars in the Campania region, southern Italy. Acta Vet Scand. 66(1):9. doi: 10.1186/s13028-024-00731-3.

Firk R, Stamer E, Junge W, Krieter J, Krieter K. 2002. Automation of oestrus detection in dairy cows: a review. Livest Prod Sci. 75(3):219–232. doi: 10.1016/S0301-6226(01)00323-2.

Fogarty ES, Manning JK, Trotter MG, Schneider DA, Thomson PC, Bush RD, Cronin GM. 2015. GNSS technology and its application for improved reproductive management in extensive sheep systems. Anim Prod Sci. 55(10):1272–1280. doi: 10.1071/AN14032.

Frost A, Schofield C, Beaulah S, Mottram T, Lines J, Wathes C. 1997. A review of livestock monitoring and the need for integrated systems. Comput Electron Agric. 17(2):139–159. doi: 10.1016/S0168-1699(96)01301-4.

Fuchs B, Sørheim KM, Chincarini M, Brunberg E, Stubsjøen SM, Bratbergsengen K, Hvasshovd SO, Zimmermann B, Lande US, Grøva L. 2019. Heart rate sensor validation and seasonal and diurnal variation of body temperature and heart rate in domestic sheep. Vet Anim Sci. 8(8):100075. doi: 10.1016/j.vas.2019.100075.

Fuchs P, Stachowicz J, Schneider M, Probo M, Bruckmaier R, Umstätter C. 2023. PSVI-16 conditioning dairy cows to a virtual fencing system is compatible with animal welfare. J Anim Sci. 101(Supplement_3):334–335. doi: 10.1093/jas/skad281.400.

Fuchs P, Stachowicz J, Schneider MK, Probo M, Bruckmaier RM, Umstätter C. 2024. Stress indicators in dairy cows adapting to virtual fencing. J Anim Sci. 102:1–17. doi: 10.1093/jas/skae024.

Gaynor KM, Brown JS, Middleton AD, Power ME, Brashares JS. 2019. Landscapes of fear: spatial patterns of risk perception and response. Trends Ecol Evol. 34(4):355–368. doi: 10.1016/j.tree.2019.01.004.

Gao R, Kong Q, Wang H, Su Z. 2019. Diagnostic feed values of natural grasslands based on multispectral images acquired by small unmanned aerial vehicle. Rangel Ecol Manag. 72(6):916–922. doi: 10.1016/j.rama.2019.06.005.

García García MJ, Maroto Molina F, Pérez Marín CC, Pérez Marín DC. 2023. Potential for automatic detection of calving in beef cows grazing on rangelands from Global Navigate Satellite System collar data. Animal. 17(8):100901. doi: 10.1016/j.animal.2023.100901.

Gibb MJ, Huckle CA, Nuthall R, Rook AJ. 1997. Effect of sward surface height on intake and grazing behaviour by lactating Holstein Friesian cows. Grass Forage Sci. 52(3):309–321. doi: 10.1111/j.1365-2494.1997.tb02361.x.

Goliński P, Sobolewska P, Stefańska B, Golińska B. 2022. Virtual fencing technology for cattle management in the pasture feeding system—a review. Agriculture. 13(1):91. doi: 10.3390/agriculture13010091.

González LA, Bishop-Hurley G, Henry D, Charmley E. 2014. Wireless sensor networks to study, monitor and manage cattle in grazing systems. Anim Prod Sci. 54(10):1687–1693. doi: 10.1071/AN14368.

Gonzalez LF, Montes GA, Puig E, Johnson S, Mengersen K, Gaston KJ. 2016. Unmanned aerial vehicles (UAVs) and artificial intelligence revolutionizing wildlife monitoring and conservation. Sensors (Basel). 16(1):97. doi: 10.3390/s16010097.

González-García E, Alhamada M, Pradel J, Douls S, Parisot S, Bocquier F, Menassol JB, Llach I, González LA. 2018. A mobile and automated walk-over-weighing system for a close and remote monitoring of liveweight in sheep. Comput Electron Agric. 153:226–238. doi: 10.1016/j.compag.2018.08.022.

Greig J, Cavasos K, Boyer C, Schexnayder S. 2023. Diffusion of innovation, internet access, and adoption barriers for precision livestock farming among beef producers. Adv Ag Dev. 4(3):103–116. doi: 10.37433/aad.v4i3.329.

Hampson BA, Morton JM, Mills PC, Trotter MG, Lamb DW, Pollitt CC. 2010. Monitoring distances travelled by horses using GPS tracking collars. Aust Vet J. 88(5):176–181. doi: 10.1111/j.1751-0813.2010.00564.x.

Handcock RN, Swain DL, Bishop-Hurley GJ, Patison KP, Wark T, Valencia P, Corke P, O'Neill CJ. 2009. Monitoring animal behaviour and environmental interactions using wireless sensor networks, GPS collars and satellite remote sensing. Sensors (Basel). 9(5):3586–3603. doi: 10.3390/s90503586.

Hassija V, Chamola V, Saxena V, Jain D, Goyal P, Sikdar B. 2019. A survey on IoT security: application areas, security threats, and solution architectures. IEEE Access, 7:82721–82743. Institute of Electrical and Electronics Engineers Inc. doi: 10.1109/ACCESS.2019.2924045.

Heins BJ, Pereira G, Sharpe K. 2023. Precision technologies to improve dairy grazing systems. JDS Commun. 4(4):318–323. doi: 10.3168/jdsc.2022-0308.

Herlin A, Brunberg E, Hultgren J, Högberg N, Rydberg A, Skarin A. 2021. Animal welfare implications of digital tools for monitoring and management of cattle and sheep on pasture. Animals (Basel). 11(3):829. doi: 10.3390/ani11030829.

Ikurior SJ, Pomroy WE, Scott I, Corner-Thomas R, Marquetoux N, Leu ST. 2020. Gastrointestinal nematode infection affects overall activity in young sheep monitored with tri-axial accelerometers. Vet Parasitol. 283:109188. doi: 10.1016/j.vetpar.2020.109188.

Inoue S, Yamamoto S, Ringhofer M, Mendonça RS, Pereira C, Hirata S. 2019. Spatial positioning of individuals in a group of feral horses: a case study using drone technology. Mamm Res. 64(2):249–259. doi: 10.1007/s13364-018-0400-2.

Insua JR, Utsumi SA, Basso B. 2019. Estimation of spatial and temporal variability of pasture growth and digestibility in grazing rotations coupling unmanned aerial vehicle (UAV) with crop simulation models. PLoS ONE. 14(3):e0212773. doi: 10.1371/journal.pone.0212773.

Janicka W, Wilk I, Próchniak T, Janczarek I. 2022. Can sound alone act as a virtual barrier for horses? A preliminary study. Animals (Basel). 12(22):3151. doi: 10.3390/ani12223151.

Jeffus J, Reuter R, Wagner K, Goodman L, Parker T. 2021. 5 Effects of virtual fencing on cortisol concentrations and behavior of beef cattle. J Anim Sci. 99(Supplement_3):1–2. doi: 10.1093/jas/skab235.001.

Ji W, Luo Y, Liao Y, Wu W, Wei X, Yang Y, He XZ, Shen Y, Ma Q, Yi S, et al. 2023. UAV assisted livestock distribution monitoring and quantification: a low-cost and high-precision solution. Animals (Basel). 13(19):3069. doi: 10.3390/ani13193069.

Jung Y, Chang H, Yoon M. 2022. Development of a foaling alarm system using an accelerometer. J Anim Sci Technol. 64(6):1237–1244. doi: 10.5187/jast.2022.e75.

Kang H, Sole-Guitart A, Mellor VA, Gaughan JB, Zsoldos RR. 2022. The use of percutaneous thermal sensing microchips for non-invasive measurement of body temperature in foals during summer seasons in a subtropical region. Animal. 16(9):100620. doi: 10.1016/j.animal.2022.100620.

Karr S, Houtman A, Interlandi J. 2021. Environmental Science for a Changing World (4th ed.). New York (NY): W.H. Freeman and Company.

Kleanthous N, Hussain A, Khan W, Sneddon J, Liatsis P. 2022. Deep transfer learning in sheep activity recognition using accelerometer data. Expert Syst Appl. 207:117925. doi: 10.1016/j.eswa.2022.117925.

Knierim A, Borges F, Lee Kernecker M, Kraus T, Wurbs A. 2018. What drives adoption of smart farming technologies? Evidence from a cross-country study. Proceedings of the European IFSA Symposium; 2018 Jul 1–5; Chania, Greece. Theme 4—Smart technologies in farming and food systems.

Kour H, Patison KP, Corbet NJ, Swain DL. 2018. Validation of accelerometer use to measure suckling behaviour in Northern Australian beef calves. Appl Anim Behav Sci. 202:1–6. doi: 10.1016/j.applanim.2018.01.012.

Kukielka E, Barasona JA, Cowie CE, Drewe JA, Gortazar C, Cotarelo I, Vicente J. 2013. Spatial and temporal interactions between livestock and wildlife in South Central Spain assessed by camera traps. Prev Vet Med. 112(3–4):213–221. doi: 10.1016/j.prevetmed.2013.08.008.

Kuźnicka E, Gburzyński P. 2017. Automatic detection of suckling events in lamb through accelerometer data classification. Comput Electron Agric. 138:137–147. doi: 10.1016/j.compag.2017.04.009.

Läpple D, Kelley H. 2013. Understanding the uptake of organic farming: accounting for heterogeneities among Irish farmers. Ecol Econ. 88:11–19. doi: 10.1016/j.ecolecon.2012.12.025.

Lee C, Campbell DLM. 2021. A multi-disciplinary approach to assess the welfare impacts of a new virtual fencing technology. Front Vet Sci. 8:637709. doi: 10.3389/fvets.2021.637709.

Lee I, Lee K. 2015. The Internet of Things (IoT): applications, investments, and challenges for enterprises. Bus Horiz. 58(4):431–440. doi: 10.1016/j.bushor.2015.03.008.

Li G, Shi G, Zhu C. 2024. Dynamic serpentine convolution with attention mechanism enhancement for beef cattle behavior recognition. Animals (Basel). 14(3):466. doi: 10.3390/ani14030466.

Lomax S, Colusso P, Clark C. 2019. Does virtual fencing work for grazing dairy cattle? Animals (Basel). 9(7):429. doi: 10.3390/ani9070429.

Lovarelli D, Guarino M. 2021. Zootecnia sempre più smart ma le criticità sono numerose. Terra e Vita. IoT e Meccatronica. 22:2021. https://terraevita.edagricole.it/nova/nova-allevamento-zootecnia/zootecnia-sempre-piu-smart-ma-le-criticita-sono-numerose/. (accessed 14 May 2024).

Luo W, Zhang Z, Fu P, Wei G, Wang D, Li X, Shao Q, He Y, Wang H, Zhao Z, et al. 2022. Intelligent grazing UAV based on airborne depth reasoning. Remote Sens. 14(17): 4188. doi: 10.3390/rs14174188.

Mancuso D, Castagnolo G, Porto SMC. 2023. Cow behavioural activities in extensive farms: challenges of adopting automatic monitoring systems. Sensors (Basel). 23(8):3828. doi: 10.3390/s23083828.

Manning JK, Cronin GM, González LA, Hall EJS, Merchant A, Ingram LJ. 2017. The effects of global navigation satellite system (GNSS) collars on cattle (Bos taurus) behaviour. Appl Anim Behav Sci. 187:54–59. doi: 10.1016/j.applanim.2016.11.013.

Marini D, Llewellyn R, Belson S, Lee C. 2018. Controlling within-field sheep movement using virtual fencing. Animals (Basel). 8(3):31. doi: 10.3390/ani8030031.

Martinez-Rau LS, Adin V, Giovanini LL, Oelmann B, Bader S. 2023. Real-Time acoustic monitoring of foraging behaviour of grazing cattle using low-power embedded devices. Proceedings of the 2023 IEEE Sensors Applications Symposium (SAS); 2023 Jul 18–20; Ottawa, ON, Canada. p. 1–6. doi: 10.1109/SAS58821.2023.10254175.

Martinez-Rau LS, Chelotti JO, Giovanini LL, Adin V, Oelmann B, Bader S. 2024. On-device feeding behaviour analysis of grazing cattle. IEEE Trans Instrum Meas. 73:1–13. doi: 10.1109/TIM.2024.3376013.

McSweeney D, O'Brien B, Coughlan NE, Férard A, Ivanov S, Halton P, Umstatter C. 2020. Virtual fencing without visual cues: design, difficulties of implementation, and associated dairy cow behaviour. Comput Electron Agric. 176: 105613. doi: 10.1016/j.compag.2020.105613.

Moreau M, Siebert S, Buerkert A, Schlecht E. 2009. Use of a tri-axial accelerometer for automated recording and classification of goats' grazing behaviour. Appl Anim Behav Sci. 119(3–4):158–170. doi: 10.1016/j.applanim.2009.04.008.

Morgan-Davies C, Wilson R, Waterhouse T. 2017. Impacts of farmers' management styles on income and labour under alternative extensive land use scenarios. Agric Syst. 155: 168–178. doi: 10.1016/j.agsy.2017.04.011.

Morgan-Davies C, Lambe N, Wishart H, Waterhouse T, Kenyon F, McBean D, McCracken D. 2018. Impacts of using a precision livestock system targeted approach in mountain sheep flocks. Livest Sci. 208:67–76. doi: 10.1016/j.livsci.2017.12.002.

Morris JE, Cronin GM, Bush RD. 2012. Improving sheep production and welfare in extensive systems through precision sheep management. Anim Prod Sci. 52(7):665–670. doi: 10.1071/AN11097.

Mulero-Pázmány M, Jenni-Eiermann S, Strebel N, Sattler T, Negro JJ, Tablado Z. 2017. Unmanned aircraft systems as a new source of disturbance for wildlife: a systematic review. PLoS One. 12(6):e0178448. doi: 10.1371/journal.pone.0178448.

Neethirajan S, Kemp B. 2021. Digital Livestock Farming. Sens Bio-Sens Res. 32:100408. doi: 10.1016/j.sbsr.2021.100408.

Nellis MD, Bussing CE, Coleman TL, Nkambwe M, Ringrose S. 1997. Spatial and spectral dimensions of rural lands and grazing systems in the southern district of Botswana. Geocarto Int. 12(1):41–47. doi: 10.1080/10106049709354572.

Nori M, Switzer J, Crawford A. 2005. Herding on the brink: towards a global survey of pastoral communities and conflict. An occasional working paper from the IUCN Commission on Environmental, Economic and Social Policy. International Institute for Sustainable Development. https://www.iisd.org/system/files/publications/security_herding_on_brink.pdf. (accessed 18 June 2024).

Odintsov Vaintrub M, Levit H, Chincarini M, Fusaro I, Giammarco M, Vignola G. 2021. Review: precision livestock farming, automats and new technologies: possible applications in extensive dairy sheep farming. Animal. 15(3): 100143. doi: 10.1016/j.animal.2020.100143.

Parsons IL, Norman DA, Karisch BB, Webb SL, Stone AE, Proctor MD, Street GM. 2023. Automated walk-over-weigh system to track daily body mass and growth in grazing steers. Comput Electron Agric. 212:108113. doi: 10.1016/j.compag.2023.108113.

Paustian M, Theuvsen L. 2017. Adoption of precision agriculture technologies by German crop farmers. Precision Agric. 18(5):701–716. doi: 10.1007/s11119-016-9482-5.

Peralta OA, Pearson RE, Nebel RL. 2005. Comparison of three estrus detection systems during summer in a large commercial dairy herd. Anim Reprod Sci. 87(1–2):59–72. doi: 10.1016/j.anireprosci.2004.10.003.

Pierce FJ, Nowak P. 1999. Aspects of precision agriculture. Adv Agron. 67:1–85. doi: 10.1016/S0065-2113(08)60513-1.

Pinna D, Sara G, Todde G, Atzori AS, Artizzu V, Spano LD, Caria M. 2023. Advancements in combining electronic animal identification and augmented reality technologies in digital livestock farming. Sci Rep. 13(1):18282. doi: 10.1038/s41598-023-45772-2.

Primi R, Viola P, Girotti P, Danieli PP, Ronchi B, Spina R. 2024. Performance evaluation of a prototype for the defence against wolf attacks on livestock animals. Acta IMEKO. 13(1):1–7. doi: 10.21014/acta_imeko.v13i1.1650.

Pullanagari RR, Yule IJ, Tuohy MP, Hedley MJ, Dynes RA, King WM. 2012. In-field hyperspectral proximal sensing for estimating quality parameters of mixed pasture. Precision Agric. 13(3):351–369. doi: 10.1007/s11119-011-9251-4.

Ramesh G, Sivaraman K, Subramani V, Vignesh PY, Bhogachari SVV. 2021. Farm Animal Location Tracking System Using Arduino and GPS Module. Proceedings of the 2021 International Conference on Computer Communication and Informatics (ICCCI); 2021 Jan 7–9; Coimbatore, India. doi: 10.1109/ICCCI50826.2021.9402610.

Riaboff L, Relun A, Petiot CE, Feuilloy M, Couvreur S, Madouasse A. 2021. Identification of discriminating behavioural and movement variables in lameness scores of dairy cows at pasture from accelerometer and GPS sensors using a partial least squares discriminant analysis. Prev Vet Med. 193:105383. doi: 10.1016/j.prevetmed.2021.105383.

Ripamonti A, Mantino A, Annecchini F, Cappucci A, Casarosa L, Turini L, Foggi G, Mele M. 2023. Outcomes of a comparison between pastoral and silvopastoral management on beef cattle productivity, animal welfare and pasture depletion in a Mediterranean extensive farm. Agroforest Syst. 97(6):1071–1086. doi: 10.1007/s10457-023-00848-w.

Rivero MJ, Grau-Campanario P, Mullan S, Held SDE, Stokes JE, Lee MRF, Cardenas LM. 2021. Factors affecting site use preference of grazing cattle studied from 2000 to 2020 through GPS tracking: a review. Sensors (Basel). 21(8): 2696. doi: 10.3390/s21082696.

Rodrigues S, Van Eck N, Waltman L, Jansen F. 2014. Mapping patient safety: a large-scale literature review using bibliometric visualisation techniques. BMJ Open. 4(3): e004468. doi: 10.1136/bmjopen-2013-004468.

Rodríguez V, Marino A, Schroeder N. 2024. Grazing distribution of wild guanacos and livestock in Patagonian rangelands: an ecological approach to assess mixed carrying capacity and overgrazing risk in extensive pastoral systems. Landsc Ecol. 39(2):14. doi: 10.1007/s10980-024-01800-8.

Rose DC, Sutherland WJ, Parker C, Lobley M, Winter M, Morris C, Twining S, Ffoulkes C, Amano T, Dicks LV. 2016. Decision support tools for agriculture: towards effective design and delivery. Agric Syst. 149:165–174. doi: 10.1016/j.agsy.2016.09.009.

Rossi M, Niedrist G, Asam S, Tonon G, Tomelleri E, Zebisch M. 2019. A comparison of the signal from diverse optical sensors for monitoring alpine grassland dynamics. Remote Sens. 11(3):296. doi: 10.3390/rs11030296.

Rutten CJ, Velthuis AGJ, Steeneveld W, Hogeveen H. 2013. Invited review: sensors to support health management on dairy farms. J Dairy Sci. 96(4):1928–1952. doi: 10.3168/jds.2012-6107.

Sakadevan K, Nguyen ML. 2017. Chapter four—livestock production and its impact on nutrient pollution and greenhouse gas emissions. Adv Agron. 141:147–184. doi: 10.1016/bs.agron.2016.10.002.

Salton G, Buckley C. 1988. Term-weighting approaches in automatic text retrieval. Inf Process Manag. 24(5):513–523. doi: 10.1016/0306-4573(88)90021-0.

Schaefer MT, Lamb DW. 2016. A combination of plant NDVI and LiDAR measurements improve the estimation of pasture biomass in tall fescue (Festuca arundinacea var. Fletcher). Remote Sens. 8(2):109. doi: 10.3390/rs8020109.

Scott N, Blore C. 2019. Final report - Pedigree MatchMaker for beef. https://www.mla.com.au/contentassets/508206e28e024e21b44d29e3d850d9b6/l.pds.1803_-_e.pds.1410_pedigree_matchmaker.pdf. (accessed 08 May 2024).

Sebastiani F. 2002. Machine learning in automated text categorization. ACM Comput Surv. 34(1):1–47. doi: 10.48550/arXiv.cs/0110053.

Segerkvist KA, Höglund J, Österlund H, Wik C, Högberg N, Hessle A. 2020. Automatic weighing as an animal health monitoring tool on pasture. Livest Sci. 240:104157. doi: 10.1016/j.livsci.2020.104157.

Shine P, Murphy M, Upton J, Scully T. 2018. Machine-learning algorithms for predicting on-farm direct water and electricity consumption on pasture based dairy farms. Comput Electron Agric. 150:74–87. doi: 10.1016/j.compag.2018.03.023.

Shorten PR, Welten BG. 2022. An acoustic sensor technology to detect urine excretion. Biosyst Eng. 214:90–106. doi: 10.1016/j.biosystemseng.2021.12.004.

Shumba AT, Montanaro T, Sergi I, Fachechi L, De Vittorio M, Patrono L. 2022. Leveraging IoT-aware technologies and AI techniques for real-time critical healthcare applications. Sensors (Basel). 22(19):7675. doi: 10.3390/s22197675.

Sohi R, Trompf J, Marriott H, Bervan A, Godoy BI, Weerasinghe M, Desai A, Jois M. 2017. Determination of maternal pedigree and ewe–lamb spatial relationships by application of bluetooth technology in extensive farming systems. J Anim Sci. 95(11):5145–5151. doi: 10.2527/jas2017.1887.

Sohi R, Almasi F, Nguyen H, Carroll A, Trompf J, Weerasinghe M, Bervan A, Godoy BI, Ahmed A, Stear MJ, et al. 2022. Determination of ewe behaviour around lambing time and prediction of parturition 7 days prior to lambing by tri-axial accelerometer sensors in an extensive farming system. Anim Prod Sci. 62(17):1729–1738. doi: 10.1071/AN21460.

Spencer BD, DeYoung RW, Foley AM, Hewitt DG, Ortega SJA, Schofield LR, Campbell TA, Cherry MJ. 2024. Understanding an ecological tug of war: disentangling competition between native and domesticated ungulates. Ecosphere. 15(4):e4850. doi: 10.1002/ecs2.4850.

Tang W, Biglari A, Ebarb R, Pickett T, Smallidge S, Ward M. 2021. A smart sensing system of water quality and intake monitoring for livestock and wild animals. Sensors (Basel). 21(8):2885. doi: 10.3390/s21082885.

Tedeschi LO, Greenwood PL, Halachmi I. 2021. Advancements in sensor technology and decision support intelligent tools to assist smart livestock farming. J Anim Sci. 99(2):skab038. doi: 10.1093/jas/skab038

Temple D, Manteca X. 2020. Animal welfare in extensive production systems is still an area of concern. Front Sustain Food Syst. 4:545902. doi: 10.3389/fsufs.2020.545902.

Thompson N, Bir C, Widmar D, Mintert J. 2019. Farmer perceptions of precision agriculture technology benefits. J Agric Appl Econ. 51(1):142–163. doi: 10.1017/aae.2018.27.

Tobin C, Bailey DW, Trotter MG. 2021. Tracking and sensor-based detection of livestock water system failure: a case study simulation. Rangel Ecol and Manag. 77:9–16. doi: 10.1016/j.rama.2021.02.013.

Tomkins NW, Charmley E. 2015. Herd-scale measurements of methane emissions from cattle grazing extensive sub-tropical grasslands using the open-path laser technique. Animal. 9(12):2029–2038. doi: 10.1017/S1751731115001688.

Tramacere LG, Antichi D, Mele M, Ragaglini G, Mantino A. 2024. Effects of intercropping on the herbage production of a binary grass-legume mixture (Hedysarum coronarium L. and Lolium multiflorum Lam.) under artificial shade in Mediterranean rainfed conditions. Agroforest Syst. 98(6): 1445–1460. doi: 10.1007/s10457-024-01012-8.

Treves A, Naughton-Treves L, Harper EK, Miladenoff DJ, Rose RA, Sickley TA, Wydeven AP. 2004. Predictiong human-carnivore conflict: a spatial model derived from 25 years of data on wolf predation on livestock. Conserv Biol. 18(1): 114–125. doi: 10.1111/j.1523-1739.2004.00189.x.

Triguero-Ocaña R, Barasona JA, Carro F, Soriguer RC, Vicente J, Acevedo P. 2019. Spatio-temporal trends in the frequency of interspecific interactions between domestic and wild ungulates from Mediterranean Spain. PLoS One. 14(1):e0211216. doi: 10.1371/journal.pone.0211216.

Trukhachev V, Oliinyk S, Mikhailenko I, Timoshin VN, Lesnyak T. 2019. Estimation of condition of cultivated pastures under remote sensing of earth. Eng Rural Dev. doi: 10.22616/ERDev2019.18.N472.

Tzanidakis C, Tzamaloukas O, Simitzis P, Panagakis P. 2023. Precision livestock farming applications (PLF) for grazing animals. Agriculture. 13(2):288. doi: 10.3390/agriculture13020288.

Varela-Castro L, Sevilla IA, Payne A, Gilot-Fromont E, Barral M. 2021. Interaction patterns between wildlife and cattle reveal opportunities for mycobacteria transmission in farms from north-eastern atlantic iberian peninsula. Animals (Basel). 11(8):2364. doi: 10.3390/ani11082364.

Vayssade JA, Arquet R, Bonneau M. 2019. Automatic activity tracking of goats using drone camera. Comput Electron Agric. 162:767–772. doi: 10.1016/j.compag.2019.05.021.

Vecchio Y, Agnusdei G, Miglietta P, Capitanio F. 2020. Adoption of Precision Farming Tools: the Case of Italian Farmers. Int J Environ Res Public Health. 17(3):869. doi: 10.3390/ijerph17030869.

Verdon M, Langworthy A, Rawnsley R. 2021. Virtual fencing technology to intensively graze lactating dairy cattle II: effects on cow welfare and behavior. J Dairy Sci. 104(6):7084–7094. doi: 10.3168/jds.2020-19797.

Viola P, Adriani S, Rossi CM, Franceschini C, Primi R, Apollonio M, Amici A. 2021. Anthropogenic and environmental factors determining local favourable conditions for wolves during the cold season. Animals (Basel). 11(7):1895. doi: 10.3390/ani11071895.

Vogel K, Claus J, Grandin T, Oetzel G, Schaefer D. 2011. Effect of water and feed withdrawal and health status on blood and serum components, body weight loss, and meat and carcass characteristics of Holstein slaughter cows. J Anim Sci. 89(2):538–548. doi: 10.2527/jas.2009-2675.

Vogels EA. 2021. Some digital divides persist between rural, urban and suburban America. Pew Research Center. https://www.pewresearch.org/short-reads/2021/08/19/some-digital-divides-persist-between-rural-urban-and-suburban-america/. (accessed 4 June 2024).

Wade C, Trotter M, Chang A, Steele C, Prihodko L, Bailey DW. 2024. Use of global positioning system tracking to assess landscape distribution in extensive small ruminant operations. Rangel Ecol Manag. 94:29–37. doi: 10.1016/j.rama.2024.01.010.

Wang W, Ma Q, Huang J, Feng Q, Zhao Y, Guo H, Chen B, Li C, Zhang Y. 2022. Remote sensing monitoring of grasslands based on adaptive feature fusion with multi-source data. Remote Sens. 14(3):750. doi: 10.3390/rs14030750.

Waterhouse T. 2023. Virtual fencing systems: balancing production and welfare outcomes. Livestock. 28(5):227–234. doi: 10.12968/live.2023.28.5.227.

Webb P, Mehlhorn S, Smartt P. 2017. Developing protocols for using a UAV to monitor herd health. Proceedings of the 2017 ASABE Annual International Meeting; 2017 July 16–19; Spokane, WA, USA. doi: 10.13031/aim.201700865.

Weinert JR, Werner J, Williams CA. 2020. Validation and implementation of an automated chew sensor–based remote monitoring device as tool for equine grazing research. J Equine Vet Sci. 88:102971. doi: 10.1016/j.jevs.2020.102971.

Weiss M, Jacob F, Duveiller G. 2020. Remote sensing for agricultural applications: a meta-review. Remote Sens Environ. 236:111402. doi: 10.1016/j.rse.2019.111402.

Williams TM, Costa DFA, Wilson CS, Chang A, Manning J, Swain D, Trotter MG. 2022. Sensor-based detection of parturition in beef cattle grazing in an extensive landscape: a case study using a commercial GNSS collar. Anim Prod Sci. 62(11):993–999. doi: 10.1071/AN21528.

Xu B, Wang W, Falzon G, Kwan P, Guo L, Chen G, Tait A, Schneider D. 2020. Automated cattle counting using Mask R-CNN in quadcopter vision system. Comput Electron Agric. 171:105300. doi: 10.1016/j.compag.2020.105300.

Yu Z, Liu Y, Yu S, Wang R, Song Z, Yan Y, Li F, Wang Z, Tian F. 2022. Automatic detection method of dairy cow feeding behaviour based on YOLO improved model and edge computing. Sensors (Basel). 22(9):3271. doi: 10.3390/s22093271.

Yu T, Yan R, Zhang C, Chen S, Zhang Z, Guo LF, Hu T, Jiang C, Wang M, Bai K, et al. 2024. How does grazing pressure affect feed intake and behavior of livestock in a meadow steppe in northern China and their coupling relationship. Sci Total Environ. 908:168472. doi: 10.1016/j.scitotenv.2023.168472.

Zhang J, Khoshbakht M, Liu J, Gou Z, Xiong J, Jiang M. 2022. A clustering review of vegetation-indicating parameters in urban thermal environment studies towards various factors. J Therm Biol. 110:103340. doi: 10.1016/j.jtherbio.2022.103340.

Zuliani A, Contiero B, Schneider MK, Arsenos G, Bernués A, Dovc P, Gauly M, Holand Ø, Martin B, Morgan-Davies C, et al. 2021. Topics and trends in mountain livestock farming research: a text mining approach. Animal. 15(1):100058. doi: 10.1016/j.animal.2020.100058.