Chapter

Advanced Technologies in Sheep Extensive Farming on a Climate Change Context

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Abstract

Climate change represents a serious issue that negatively impacts the animals' performance. Sheep production from Mediterranean region is mainly characterized by extensive farming system that during summer are exposed to high temperature. The explored new technologies to monitoring animal welfare and environment could mitigate the impact of climate change supporting the sustainability of animal production and ensuring food security. The present chapter will summarize the more recent advanced technologies based on passive sensors, wearable sensors, and the combination of different technologies with the latest machine learning protocol tested for sheep farming aimed at monitoring animal welfare. A focus on the precision technologies solution to detect heat stress will be presented.

Keywords: precision sheep farming, extensive farming, animal welfare, productivity, climate change, deep learning

1. Introduction

Weather of the last years is affected by extremes climate events, characterized by period of heatwaves, droughts, and severe precipitation which are responsible for climate change [1]. The Mediterranean region is estimated to become a Hot-Spot, as one of the most responsive regions to climate change [2]. This projection is confirmed also by the IPCC [1] report which describes the prediction on how much intense will be the climate change, relatively to the increasing of temperature or intensity of precipitation (and relating period of drought), and heat weather. Therefore, the development process of future pasture-based systems will be influenced mainly by the growing of this weather instability; thus, it will affect the livestock production sustainability all over the globe [1, 3, 4]. From Mediterranean-dedicated climate-change studies, it is remarked that in the twenty-first century the Mediterranean climate would become increasingly warmer, drier, and tending, less windy [5]. Therefore, considering the actual condition of the global climate change, it could be crucial to deepen the consequence of environmental changes on the animals' physiology as well as the adaptive mechanisms orchestrated by animals to counteract the climate change [6]. The aim of this chapter is to summarize the major developed advanced technologies based on passive sensors, wearable sensors, and the combination of different technologies with the latest machine learning protocol tested to help farmers in the monitoring grazing sheep herd in the contest of climate change.

In livestock the exposition to heat stress occurs when the environmental temperature surpasses the high critical temperature, which is depended to the breed, age, and physiological state; in particular, in sheep it can vary from 25 to 31°C [7, 8]. Moreover, longer drought periods increase dramatically the resources management issues as well as water and feed supply. In general, climate change can affect animal agriculture through a modification of (1) access to feed and grain and their related price; (2) availability of pasture or forage and their quality; (3) animal health, growth, and reproduction; and (4) spreading of livestock diseases [9]. Especially in livestock production, the heat stress has direct and indirect effects. The first one is due to the increase of environmental temperatures and the frequency/intensity of heat waves [10] which determine in sheep hyperthermia, characterized by an increasing of breathing and respiration rate, and body temperature, a reduction of feed intake, and an overall alteration of metabolism of water, protein and energy metabolism, mineral balance, enzymatic reactions, and hormonal secretion [11]. The direct effects have a proportional magnitude in relation to the intensity and duration of heat stress [10]. Animals do not capable of restoring from heat stress condition are more prone to display health issue supported by immune depression condition that can cause in extreme condition the animals' death [12]. The indirect effects of heat stress are related to the reduction in quantity and quality of feedstuffs, and in the water availability, the alteration of the immune responses of the animals, and the diffusion of new vector borne diseases [10]. The mechanism of adaptation to climate change of sheep are expressed by the maintenance of hereditary functional potentiality with activation of compensatory and adaptive mechanisms which consist in the activation of behavior aimed at supporting the excess of body heat dissipation, and therefore, to tolerate the increase of heat and drought wheatear [13, 14]. On the contrary, when animals are not able to activate a compensatory mechanism to heat load, they express a physiological response that determine a condition of hyperthermia preceded by an alteration of cellular homeostasis and a failed homeorhetic adaptive response [15, 16].

A good indicator of the degree of stress caused by weather conditions is conventionally accepted to be represented by the temperature-humidity index (THI) which combines the ambient temperature (T), and relative humidity (RH). Several formulas have been proposed in order to determine the THI, that one of Kelly and Bond [17] combines the maximum temperature (expressed in °C) and the average of relative humidity (%). In lactating ewes, a THI higher than 80 and a prolonged exposure to maximum air temperature over 30°C causes heat stress exposition by decreasing milk production and quality [7, 18] and their reproductive performance [19]. Moreover, moving from THI of 60–65 to 72–75 induces a significant reduction of sheep performance by 20% [20].

A recent systematic review has emerged that the management strategies applied to restore the heat stress exposition are not effective on animal welfare and heat status when animals (cows, sheep, and goats) are exposed to severe heat stress [21]. In particular, in condition of heat stress exposition the management strategies occurred to reduce the animal performances as low as 16%. In this context the application of new technologies from precision livestock farming (PLF) could potentially offer other opportunities for the future development of strategies and improving animal welfare and productivity.

According to the definition of precision livestock farming (PLF) formulated by Berckmans [22] the objective of the PLF is the management of welfare, health status, reproductive and productive performances, and environmental impacts of single animal by using a real-time and continuous monitoring. Based on this definition the farmers can be alerted with a warning about an animal(s) health status that needs a specific attention. Several devises are used to monitor animals among which there are the camera and microphone which need images and sound analyses in real-time, and other sensors which can be mounted around or on the animals [22]. Specifically, the PLF solutions are overall based on a technological aggregation named Information and Communication Technologies (ICT) composed by sensors, information systems, decision-making algorithms, and human machine interfaces, which could provide important services to farmers by helping them in the decision-making process through an improvement of everyday tasks and herd management [23].

While on one hand the dairy cow sector offers to farmers a variety of management tools which contribute actively to increase the competitiveness of their product in the market [24], on the other, small ruminants, in particular those at pasture, are less likely to benefit from such systems. The lack of available devices is linked to the difficult of monitoring an extensive pasture environment in comparison to a closed barn, regarding to the infrastructures and communication options [25]. Animal welfare is a key factor in determining the consumers choice and the farmers profitability [26]. As reviewed by Krueger et al. [27], the implementation of sensor-based technologies will help to shift the management and welfare assessment from the farm-level manual assessment versus an automated or semi-automated continuous monitoring of individual animal [28]. Overall, the PLF systems could represent an important chance to sustain the livestock farms, also those of small ruminants in extensive farming, in terms of profit and sustainability [29, 30].

2. Methodology

According to the aim of this chapter, Google scholar (https://scholar.google.com) and Scopus (https://www.scopus.com) databases were used to conduct bibliographic research by the following main keywords "precision livestock farming" AND "extensive farming" AND "climate change" OR "heat stress". The articles selection was done including all document types among which articles, reviews, book chapters, and conference paper only in English, without year refinement. Information on latest technologies were grouped in a table to summarize data collected and gives and overview on the searched topic.

3. Major developed technologies

3.1 Animals identification and location

Currently the only technology mandatory for all sheep and goat farmers under EU legislation (Official Journal of the European Union, 9.1.2004) is the Electronic identification (EID) system, and represents an important opportunity for introduction of PLF system into extensive management systems. One of the most common technologies used to identify animals is the Radio Frequency Identification (RFID) [29]. The RFID technologies can be grouped into ear tags, boluses, and injectable glass tags; moreover, from a technological point of view, are divided in two categories; the low frequency (LF, 125–134.2 kHz,) and the high frequency (HF, 13.56 MHz). In particular, the LF 134.2 kHz, being regulated by ISO 11784 and 11,785 international standard, it is considered the international frequency for animal identification [31]. The information of the tag is transmitted to the tag reader by radiofrequency from the tag on animals to the tag reader, which needs a power source [32]. The RFID technology can store data which can be used in several decision-making process [33]. Indeed, throughout the feed- animal-food chain, the RFID technology offers to farmers a way to guarantee the traceability, and the ability to better manage individual production and feeding of each animal [23]. RFID is a cost-effective way to track and monitor animals and in combination with other PLF systems, such as the weighting scale or automatic drafter (AD), can provide information for growth performance, milk yield, reproductive efficiency, and medical treatments [33, 34]. Among the EID method based on RFID technology, the ear tags are considered the cheapest one, however, the ear application increases its possibility of loss, especially in outdoor paddocks. This disadvantage is surpassed by using ceramic boluses which are capsules, considered to be a safe choice for ruminant identification, incorporating a radio frequency transponder, they are retained in one of the first two stomachs of the ruminants [35, 36]. In lambs the retention rate of the bolus administrated after weaning period at the fifth week is of 100% [37]. Finally, the injectable glass tags or transponders can be introduced after birth [38] in different locations in relation to the animal species [39–41]. The injectable glass tags being subcutaneously inserted under the skin [42], have a possible migration and difficulty of removal in meat-producing sheep and goats in abattoir that should be considered [43, 44]. However, in field conditions it is demonstrated that the use of modern glass and silicone enclosed injectable EIDs shows poor migration patterns [45]. Apart from its limited use, a specific advantage of injectable EID is the possibility to its use as a sensor for physiological parameters and not only as passive information storage.

Besides their identification, it could be crucial for extensive sheep management to modify the animal distribution within large and fenced areas. An innovative method used is represented by the Virtual fencing (VF), which replaces the physical barriers to draw boundaries with the electronic one. In particular, the animals crossing over is avoided by using a visible and/or audible cues system in combination with an electric stimulus [46]. Animals can understand the limits of their area after a training period to the acoustic cue in which if they ignore it, receive an electric shock when touching the electronic boundaries (**Figure 1**) [47, 48].

The main scope of this system is the possibility to move the animals based on the pasture availability [48]. However, there are several disadvantages that limit VF application on a commercial point of view; firstly, due to its high cost, which is estimated in UK to be about 200,000 £ for the application to the herd of about 100 animals [46]. Secondly, sheep farms are not characterized by infrastructures with advanced technology [49]; including the network coverage and IT-related skills and understanding [50]. The last disadvantage is linked to the difficulty in developing a sufficient learning protocol to the acoustic cue and the important ethical issue due to welfare concerns caused by the electric shocks [46, 51–53].

Moreover, the flock size could influence the success of training to the acoustic cue due to individual training curve for each animal, thus, it cannot be economically feasible for large flocks [54, 55]. However, VF cannot completely replace traditional fencing and a combined use will be always needed increasing the overall cost [46, 48]. Specifically, the adoption of VF in the Mediterranean sheep farming, characterized

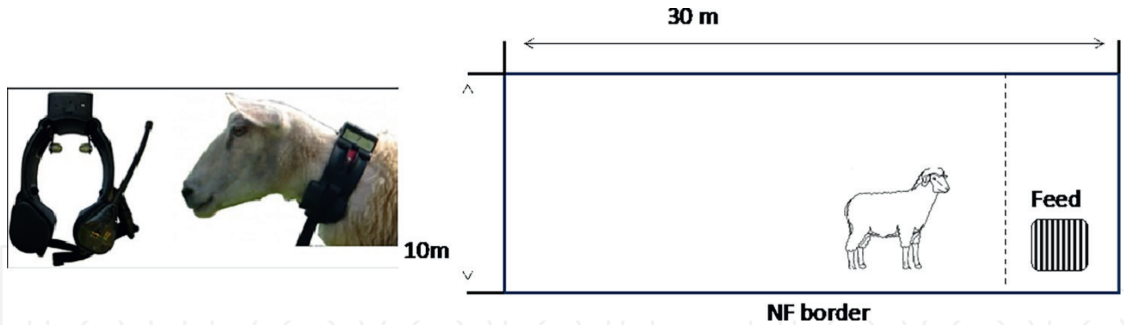

Figure 1.
a) Nofence collar photo used for testing new virtual fencing system on sheep; b) the arena used in experiment as surrounded by physical fences (black lines) and the sheep was attracted over the virtual border (dotted line) as indicated by the arrow [47].

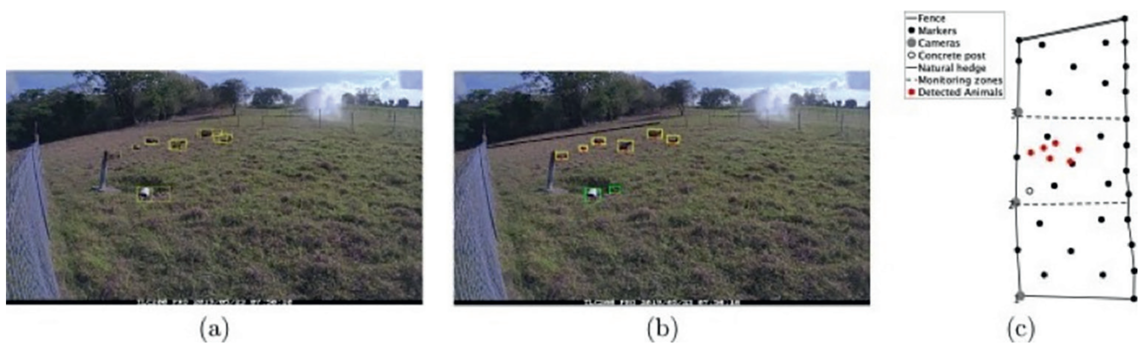

Figure 2.
Workflow of goat monitoring using animal tracking in combination with neural network and time-lapse cameras. Such an example in (a) are reported the image with yellow boxes around the objects as received by the neural network Yolo. Then, in (b) is represented the false positive correction (in green) by using a non-max suppression algorithm which merges the overlapping and operates the image classification. In (c) is presented a schematic representation of the monitored pasture with the estimated coordinates of the detected goats (red points) [57].

by grazing area of medium size (150–300 ha average), is not suitable; therefore, it is more recommendable the monitoring of animals by traditional methods (daytime shepherding, wire fences, or electrical fence) [49]. Based on previous assumption and the fact that the VF cannot completely replace all fences, because a hermetic exclusion of animal is impossible without the physical barrier [56], other devises have been tested to monitor the location of animals in pasture based on camera or video. A combination of time-lapse cameras, machine learning, and image registration represents a suitable method to a relatively low cost [57].

This specific technology applies a state of the art convolutional neural network, named You Only Look Once (Yolo) [58] to detect any object in the images and to prevent the constant change in background. Subsequently, all the detected objects are filtered in order to select only the studied animals (**Figure 2**). Obviously, the efficacy and the precision of this technique can be increased in relation to the size of the animal, the locations of the cameras, and the set-up of the pasture [57].

In Riego Del Castillo et al. [59] a camera-based system is tested to automatically detect predators in pasture-based livestock farming and distinguish them from other species, such as dog. After adopting algorithms for the objects detection by using from sv1 to v5 versions of YOLO in combination with the Single-Shot MultiBox Detector (SSD), the YOLOv5 archives prove to be the most accurate for the requirements of pasture-based systems, achieving a mean average precision of 99.49%. This system could be accounted for an additional tool for the protection of the herd [59].

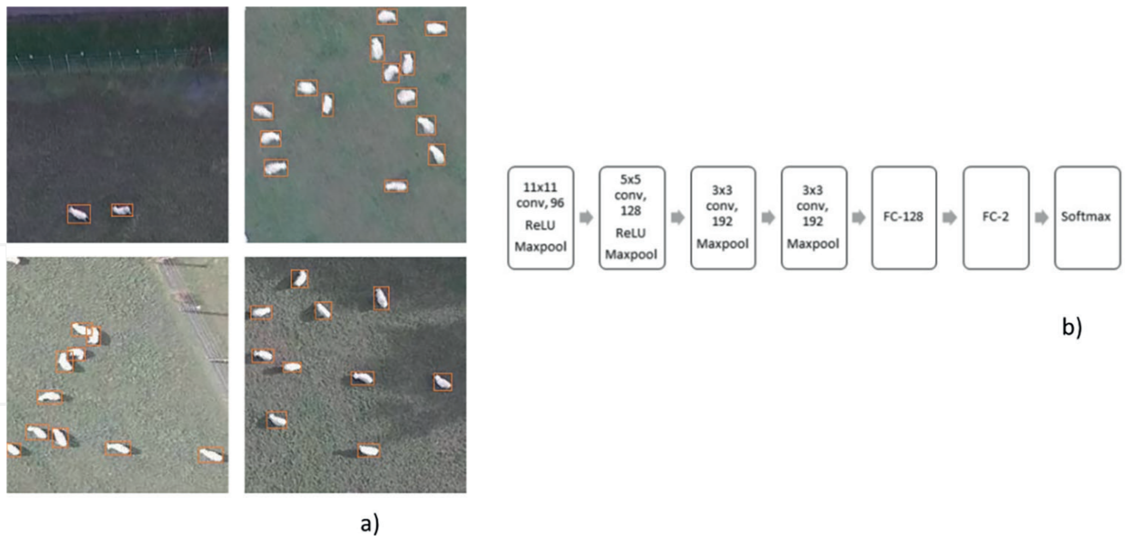

Figure 3.
a) Trained image of sheep at pasture and b) architecture of R-CNN network used for detecting and counting sheep with a convolutional neural network [63].

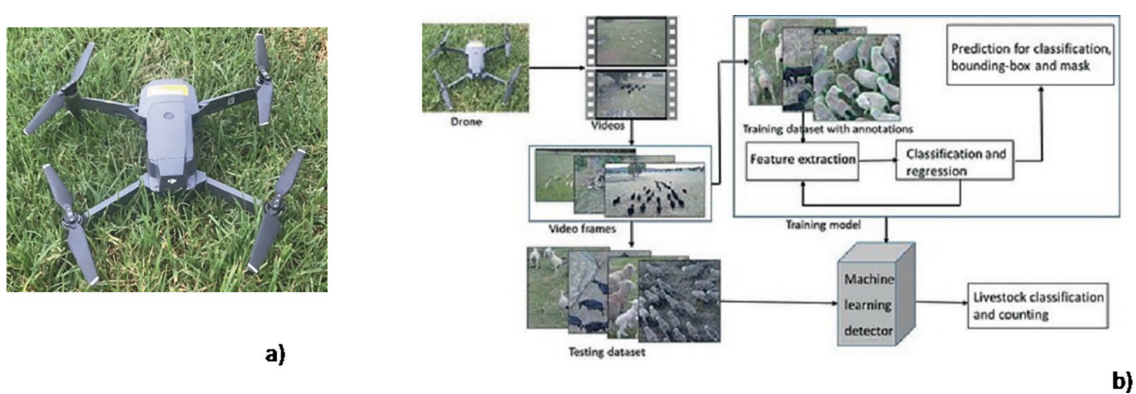

Figure 4.
a) MAVIC PRO drone, and b) architecture of the mask R-CNN network for livestock classification and counting [60].

Another feasible solution for the monitoring of small ruminants in pasture-based systems is represented by the unmanned aerial vehicles (UAVs) or drones [60–63]. UAVs system, useful to determine a live feed behavior and then the livestock monitoring, is constituted by cameras, LiDAR, multi-spectral, and obstacle avoidance sensors [64]. The hardware of UAV can be classified into two groups: the fixed-wing which requires flight planning and control using GPS digital map navigation, and the multi-rotor aerial vehicles equipped with a gateway for collecting data, on which can be mounted many sensors, having an enhanced speed and loading capacity, and time of flight [65]. In this condition, it could be given to farmers an automated animal counting, however, the use of GPS device [66] is quite expensive. For this reason, it has been developed an automated method for animal counting and detection using quadcopter system based on multiple convolutional neural network (CNN) and Region-based convolutional neural network (R-CNN) [67] on which it is possible to train the datasets of sheep detection by the captured aerial images (**Figure 3**) [62, 63].

Moreover, an additional network named Mask R-CNN algorithm (**Figure 4**) [60], which performs not only on object detection and classification but also a segmentation, by associating specific image pixels to the detected object. This system could be useful for future applications including estimation of animal pose and direction of travel to monitor abnormal behaviors [60].

Notably, as regards UAV technology useful for sheep location and monitoring, it should be considered that sheep are frightened by drones flying above. Only, the use of a small and quiet drones maintained a minimum altitude can be the best solution because they cannot be detected by the animal [30]; however, their secure application requires further research. In addition, the use of in intelligent aerial robotics includes many challenges among which computational demand and system capabilities, online learning, expedited learning time, and many others [68]. Moreover, it is important that operators need an advanced level of skill to fly drones in compliance with federal aviation regulations for UAV operations.

3.2 Wearable sensors

According to the physical relationship to the animals, the PLF sensors are commonly categorized as wearable and non-wearable [69, 70]. On animal sensors are applied directly on the individual animal and can provide information on animal's physiological conditions in real time or via data loggers downloading in key passages [22]. It is relevant for farm management the translation of data collected from sensors (movement, body position, temperature, etc.) into physiologic status such as ovulation or lameness [22]. In case of grazing sheep farming these sensors give useful information related to the grazing and resting behaviors of the flock [71]. In this sense, the wearable sensors are experimented only in controlled conditions in small scale or experimental farms [72]. Currently, the accelerometers, especially the tri-axial type, and GPS systems are the two main types of technology being tested in this field. The accelerometers, recording movement in a three-dimensional pattern in terms of the direction and speed of the sensor, give several information which are used to register movement patterns linked to animal behaviors and welfare assessment [73], also confirmed by field trials, such as resting, grazing, ruminating, moving, grazing, running/playing, lameness, mating score measurement [72, 74–79]. The **Figure 5** shows the illustration of devise used to detect sexual behavior as reported in Mozo et al. [76].

These systems can be positioned on the foot, neck, and or head of the sheep. Data recorded are firstly evaluated by the software, and then are provided to the farmer to assist him in the decision-making process [75]. The accelerometers technology can be considered robust and mature; however, the interpretation and validation of data is still under study [80]. Indeed, many challenges have to be faced that limit their application at widespread level, among which the main are the collection and management of big data as well as the correct energy to supply at the systems [81]. Therefore, the newest researchers are trying to shift the research ready prototype into commercial production [72, 82].

The second technology mainly studied for grazing animals is the GPS systems which provide data on animal movement, spatial distribution in pasture, feeding behavior, and reproductive management in extensive sheep systems [71, 83–87]. However, the high cost of application impacts its regular use in small ruminants' farms [46]. GPS are active devices that work in the ultrahigh frequencies (UHF) band (from 860 to 960 MHz) with a big energy demand to satisfy their long reading distances. The PLF systems based on GPS have mostly internet and mobile Apps such as Google maps. Indeed, other PLF solutions are based on collars equipped with sensors among which GPS that can transmit data via wireless [88].

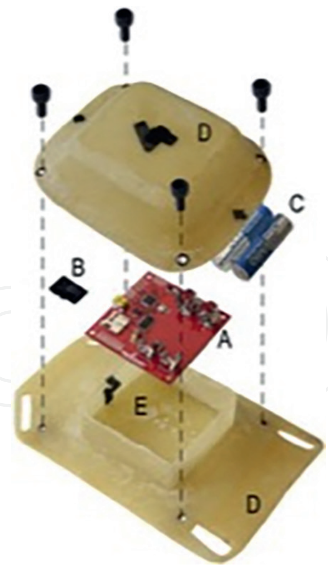

Figure 5.
Device for detecting of sexual behavior composed by a) accelerometer; b) microSD memory card; c) batteries; d) protective case; e) compartment for the accelerometer [76].

These collars allow the acquisition and transmission of data regarding animal localization (with an accuracy of 5–20 m) and behavior. In Umstätter et al. [46] is proposed a collar equipped with an automatic system based on pitch and roll tilt sensors suitable for the classification of behavior, which could be applied in extensive livestock production [89].

GPS devices can be used in combination with accelerometers and temperature sensors with the aim of informing and sending alarms on the activity and its relationship with the animal (lost device, dead animal, predator attack). Temperature values used in combination with GPS are only indicative showing a large variation based on the animal's features (e.g. long or short fleece, type of wool) and ambient conditions. The combination of GPS and tri-axis accelerometer can be a reliable method to classify livestock activity in pastures [90]. Moreover, the accelerometer is characterized by low energy requirements, and its application coupled with GPS can prolong the GPS battery lifespan leaving the active recording activity of GPS when the accelerometer detects a movement at a certain speed [88]. In addition, a GPS system equipped with a thermistor located below the vulva provide data on urination frequency, liquid and nitrogen emissions, and their spatial distribution patterns in relation to the ambient temperature changes (**Figure 6**) [91].

However, the application of these technologies meets some difficulties regarding the feasibility of these measurements in the decision-making process. In this contest the main issues are represented by the energy supply and battery duration, the lack of wireless data transmission and the accuracy and interpretation of data [80].

3.3 Technologies for heat stress data collection and analysis

The implementation of effective amelioration strategies to climate change especially related to heat stress exposition requires a deep understanding of its impacts at physiological and behavioral level on extensively grazed sheep. The measure of core temperature which reflects the temperature of the main internal organs such as the heart, brain, and viscera [92] is a reliable indicator of heat stress in livestock [93]. Even

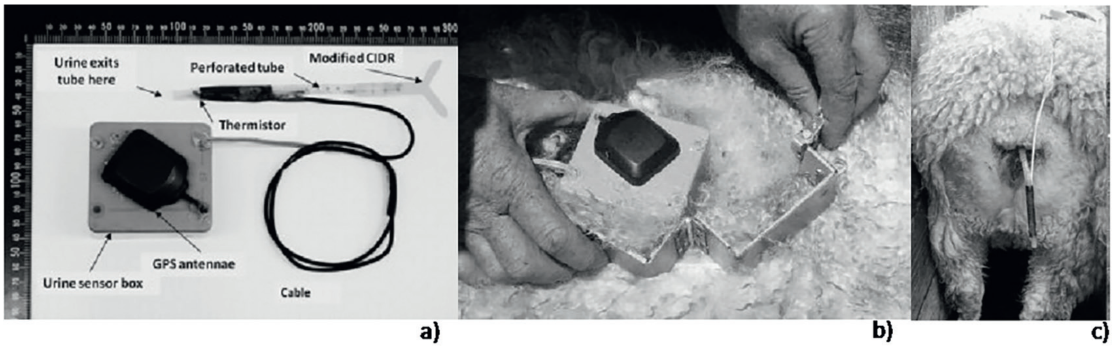

Figure 6.
a) Sheep urine sensor equipped with GPS and thermistor. The CIDR®is positioned in the vagina. The excreted urine enters in the perforated tube and flows over the thermistor. b) Electronics box positioned in sheep's fleece at the midline over the hind legs c) GPS and electronics box fitted to a sheep [91].

though the measure of core temperature can be directly associated with health [94], reproductive success [19], and overall productivity [95], the manual thermometry applied for the measure of rectal temperature (RT) [93] is not applicable when the continuous assessment of body temperature of free-range animals or in extensive grazing system is required [96]. Indeed, the RT measurement is affected by a number of limitation due to the need to handle and restrain the animal which is time consuming and labour-intensive, and the consequent intense stress to animal increased the metabolic heat production associated with the flight response that affects its reliability [97, 98]. This limitation could be covered by the introduction of indwelling thermal sensors such as rectal probes able to remotely measure temperature changes without removing animals from production and grazing [99]. However, also this technology has some instability, and the possibility of expulsion and the fecal temperature during defecation that limit its accurate data collection in sheep [96, 100]. Another common location for measuring core temperature is the vagina, in particular indwelling vaginal temperature (VT) sensors demonstrate a high correlation with RT measurements [101, 102]. Its effectiveness in measuring body temperature is demonstrated in ewe-lambs under grazing conditions [103]. As for RT, also for the VT devices it should be taken into consideration that changes in uterine and vaginal blood flows during the different stages of reproduction [104]. Indeed, in sheep, the changes in vaginal blood flow can modify the VT during gestation [105]. Moreover, also VT has several limitations, including the need of an appropriate design to prevent the loose of devices or fell out, and an advancement of technology with the integration of a full-automated data storage system. In order to overcome all of these issues, other types of devices have been developed to monitor the body temperature, such as surgically implanted devices, infrared devices, and endo-ruminal boluses equipped with temperature sensors. The subcutaneously implanted devices provide a reliable measurements of body temperature and heart rate, two important indicators that can be used for the early detection of diseases and stress, in domestic sheep freely ranged on in unfenced mountain pastures [106]. Indeed, when data collected are transmitted online, a real-time monitoring of body temperature during grazing can be possible.

The intra-ruminal insertion of temperature sensors is considered a non-invasive alternative devise to the surgical implantation [107]. This technology collects data in real-time through a wireless transmission [108], offering the chance to store data until the animal is in proximity of the receiving antenna [100]. The technology of bolus is composed by a chip, antenna, battery, and temperature sensor which is orally administered and naturally transported into the rumen [109]. The size of rumen bolus is an important issue in small ruminant studies; indeed, an ideal bolus for oral application has to be less than 20 × 100-mm and 70 g, with an optimal gravity (>2.5) which guarantees its retention in the reticulorumen [89]. Based on the ascertained possibility of using the rumen bolus sensors in small ruminants, it is applied in lactating dairy goats for the evaluation of eating-drinking behavior as a measure of heat stress exposition [110]. However, the use of bolus to evaluate the heat stress condition needs some adjustments due to differences in core temperatures and ruminal temperature, of about 2°C [111], and to the concomitant alteration of microbiota rumen profile that causes differences between ruminal temperature and core temperature [108]. In addition, in turn the microbiota rumen profile is influenced by feed intake and diet composition [112]. All these conditions must be considered when the evaluation of heat stress exposition is measured by rumen bolus. The development of best small-sized rumen boluses for small-ruminant is still ongoing [89].

One of the latest devises used in livestock useful for measuring the thermal status in a non-invasive way is based on thermal imaging camera. The infrared camera records the temperature of a certain part of animals' body returning a thermo-graphic image, which depicted the radiation emitted [113]. From the image analysis procedure, the body temperature or the changes in blood flow is determined which could be connected to stressful environmental conditions [114]. This non-invasive technology is suitable for the assessment of stress and welfare [115], and for the prediction of the heat stress exposition [116]. Moreover, different studies assess the application of infrared-thermography (IRT) to determine the thermal thresholds [117], and to predict the effects of heat stress on reproductive output in livestock [118]. Moreover, when considering the free-range grazing animals, sensors and devices should be calibrated, taking into account the possible changes in meteorological parameters that impact both the quality of the transmission and the reception of infrared waves [92]. Not to least, it is important that the body surface to be analyzed needs to be clean, because dirty or wet coats may modify the emissivity [114]. With regard to sheep, the environmental heat exchange is mainly impacted by fleece length [119] which influence heat transfer at the surface of the skin [120]. Consequently, when the peripheral temperature is measured through IRT the presence or absence of wool should be considered because skin is a thermoregulatory organ. In general, in veterinary sciences the application of IRT is used to identify infection [121, 122], lameness in horses [123], mastitis in both sheep [124] and cattle [125], scrotal temperature in buffalo [126], heat tolerance [127, 128], thermal thresholds [129], and to predict the effects of heat stress on reproductive output [118]. About the use of IRT to accurately measure body temperature, different regions of the body can result in a different degree of correlation to RT as well as association with ambient temperature [130, 131]. In Joy et al. [132] the IRT is found a good method to predict rectal temperature. However, it is important that IRT must be performed in different sites due to differences in vasoconstriction/vasodilatation activity between different parts of the body [133]. Indeed, thermal windows or different parts of the body show a direct connection with the autonomic nervous system, so infrared heat is dissipated there [134, 135]. A very recent study [136] found a different correlation between blood parameters and body temperature measured by a digital thermometer and thermography based on different parts of the body of sheep. Indeed, IRT is considered a non-invasive method to assess the stress load in sheep, especially in extensive sheep farming, founding a significant correlation between THI and the temperature of both abdomen and front legs, and the metabolic parameters. George et al. [131] experiment, conducted on using IRT using different parts of body, shows that eye temperature of hair sheep strongly correlates with VT and RT. On the contrary, the reliability of skin locations, among which eye base, eye region, and udder, even if they are considered the best thermal window, could be affected by age and stressors, as well as gender and reproductive state. Indeed, the ocular IRT images are found to correlate with RT in rams but not ewes [42]. This limitation could be due to the fact that the ocular IRT refers to ocular temperature which is lower than core temperature and not able to detect short-term changes of temperature. On the contrary, the IRT is reliable in detecting small temperature variations during different phases of the oestrous cycle in ewes using vulva and muzzle temperature (**Figure 7**) [137].

In summary the thermal imaging can be a fast and reliable method to screen many animals with little or no restraint [138] with great potentiality to be used to shift from conventional to an automated method [130]. However, as for other technologies presented here, some limitations and aspects must be taken into account when the IRT is used. Such as example, precise measurement of IRT demands an appropriate camera positioning, with consistent image angle, and distance to the subject, a constant ambient temperature, UV light, and wind speed [138], as well as it can be considered a technology with high costs and labour intensive [100, 115]. However, it is not possible to predict RT from IRT imaging; therefore, a novel innovative way to obtain a prediction of measurements could be obtained with a combination of, as an

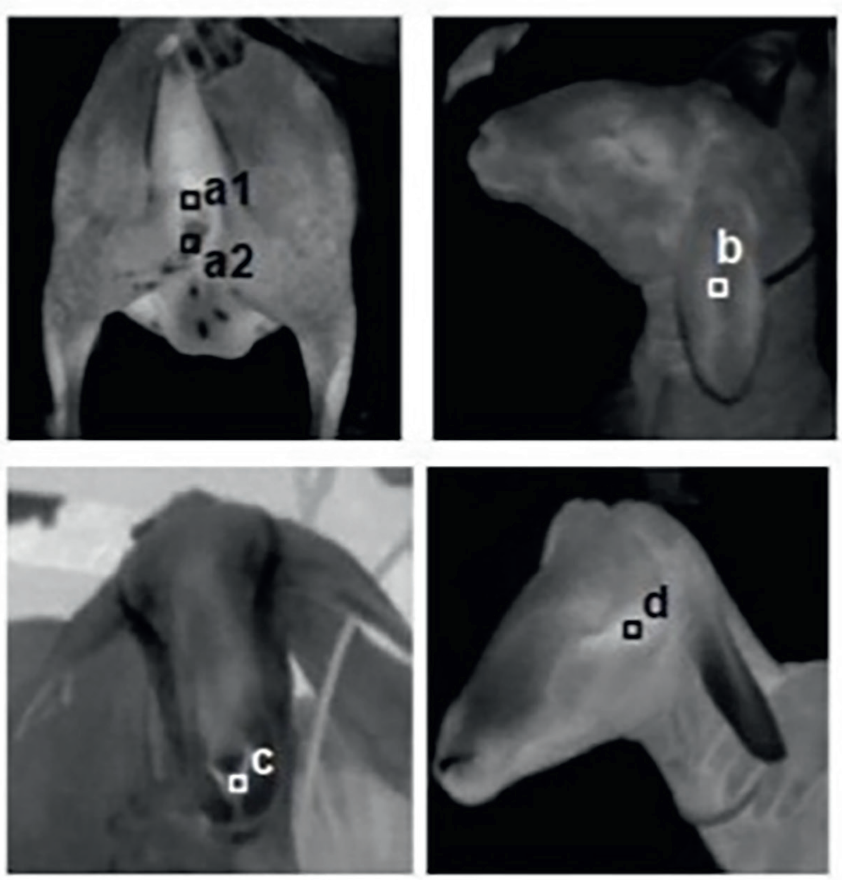

Figure 7.
Surface temperature measurenments of the following area: Around the anus (a1), in the center of the vulva (a2), ear (b), muzzle (c) and eye (d) by an infrared thermal camera (FLIR® series i50; FLIR systems Co. ltd., Shatin, Hong Kong). Warm areas appear white and cooler areas appear black [137].

example, IRT and machine learning technique [132] which provides new opportunities to non-invasively assess the behavior [139, 140], the physiology [141, 142], and the production changes [143] of farm animals. This last concept must be exploited considering the machine and deep learning procure and computer vision algorithms for model prediction development with the aim of predicting the surface temperatures of the body due to non-linearity of the relation between the inputs and the target [132]. This system is based on artificial neural networks (ANN), specifically designed to learn, and find patterns between the input data to predict specific outputs [144, 145]. The model development consists in a training procedure in which the algorithm processes automatically data by modifying weights and biases to obtain the best correlation [145].

In Jorquera-Chavez et al. [141] and Fuentes et al. [142] the implementation of ANN principle and IRT are used to analyze environmental-related stress responses in farm animals based on changes in body temperature. Recently, the deep learning approach found different application in animal behavior assessment, as presented by Kleanthous et al. [146] on deep transfer learning for activity recognition by using accelerometer data in sheep study, demonstrating that the convolutional neural network-based transfer learning is a useful approach for data capturing, data labelling, and heterogeneity of sensor devices. Moreover, with the transfer learning approach is possible the reusability (upgrading of sensor devices) and generalization of pretrained models from other applications within similar domains on unseen dataset, especially with larger datasets providing a cost-effective solution (with regard to time and resources) [146]. This last concept is essential because there is no evidence that the signal processing and classification algorithms procedure, specifically designed for one type of sensor, can be re-used on data from different types of sensors. In the **Table 1** are reported the different technologies of PLF tested in sheep field studies presented in this chapter.

4. Conclusion

The recent exploited PLF solutions give important information which support the decision process of farmers. In the context of climate change, several tools can be implemented to early detect heat stress exposition and to monitoring the welfare of animals in pasture, particularly in sheep. The technologies presented in this chapter include the animal identification and the wearable sensors, with a special focus on heat stress data collection and analysis, highlighting that all of them are characterized by several advantages and disadvantages especially when applied to sheep grazing farming system. Indeed, some devices among which ruminal bolus need to be correctly developed (i.e. dimension) for their better application in sheep studies. Moreover, most devices available for sheep are not yet validated which gives a less robust and precise data. To support this essential step new field studies on data analysis by using the latest deep learning approach used in combination with different sensors should be employed. The advancements in the field of computer science and electronics engineering, and machine intelligence are the base of monitoring efficiently and automatedly the animals' activities and welfare. The incredible opportunities derived from early detection of ewe diseases, causing a limitation of antibiotics which improve the meat and milk quality, the improvement of overall productivity, can contribute to obtain more sustainable products.

Technology	Model/type/method	Data	Aim
Accelerome-ters	AML prototype V1.0, AerobTec featuring an orthogonal three-axis MEMS accelerometer	Storage	Identification of feeding behavior in free-ranged sheep [74].
	Custom made devise based on Intel® Quark™ SE microcontroller C1000 attached to the electronic identification ear tag or to neck collar	Storage and processing by Python 3.5	Classification of grazing and ruminating behavior in sheep using various machine learning algorithms [75].
	Tri-axial accelerometer ADXL345 (Analog Devices)	Storage and analysis by a validated algorithm.	Founding a method to automatically estimate the number of mounts and services performed by rams during field mating at pasture [76].
	HOBO Pendant G data loggers	Storage	Detection of behavioral changes [77]; and sheep behavior and health status [78].
	ActiGraph GT3X sensors	Storage &wireless transmission	Prediction of lambs'birth [79].
GPS collars	UNETracker, WildTrax, EarTrax-AG, atLog-B, Perthold Engineering	Storage	Determination of sheep helter-seeking behavior [84]; grazer behavior of hill sheep [85]; sheep circadian rhythm and feeding behavior [86]; reproductive management in extensive sheep systems [87].
	CatLog-B, Perthold Engineering	Storage	Determination of sheep grazing patterns [71].
	GPS tracker collar with integrated pitch and roll tilt sensors	Storage	Behavioral classification of sheep in extensive systems [46].
GPS collar and Thermistor	CIDR® (Controlled Intra-vaginal Drug Release; InterAg)	Storage	Development of urine sensors and GPS units for the quantification of the number of daily urination events of individual animals and the determination of the pattern of urine distribution [91].
Reticulorumen boluses	Patents: Caja and Vilaseca, 1996, European Community et al., 1997.	Storage	Permanent electronic identification of sheep, goat, and cattle [35].
	Smarstock, USA	Wireless data transmission up to 200 m	Determination of Merino sheep rumen temperature [147].
Implantable devices	LifeChip ® microchips with BIO-THERM ® sensor	Storage activated through handheld receiver	Peripheral temperatures measurement [120]; determination of sheep body temperature [148].

Technology	Model/type/method	Data	Aim
Infrared Thermography	IRT Camera	Thermal image data collection	Determination of heat tolerance in lambs [128]; measure of core body temperature via eye temperature [131]; determination of vulva temperature to detect different estrous cycle [137]; determination of thermographic temperatures as good indicator of environmental and thermal comfort condition in lambs [149]; determination of lambs' response in different genetic group to the environment [150]; determination of ewes' hair coat temperatures under heat stress [151].
Vision-based system	Neural network and time-lapse camera (TLC2000)	Pre-trained convolutional neural network (Yolo)	Monitoring small ruminant location in grazing system [57].
Virtual fencing	Nofence coupled with collar GPS-based.	Storage	Learning procedure to associate a sound signal with an electrical shock in the virtual fencing system Nofence [47].
	Garmin TT15 coupled with Garmin GPS hand-held unit (Garmin Alpha 100).	Storage	Learning procedure to train sheep to a virtual fence by training collars capable of administering an audio and an electrical stimulus [53]; potentiality for virtual fencing to be used for improved grazing and natural resource management of sheep [152].
Unmanned Aerial Vehicles	Region-based Convolutional Neural Networks (R-CNN).	Not applicable	Determination of sheep detection and counting [63].
	Fully connected network (FCN) and deep convolutional neural networks (CNN).	Network-I, Network-II, U-Net, fine-tuned AlexNet, GoogLeNet, VGG16, VGG19, and ResNet50	Determination of sheep detection and counting [62].
	Mask R-CNN		Determination of classification and counting of sheep and cows [60].

Adapted by [32, 65, 153].

Table 1.
Different technologies tested in sheep field studies, including the model/type/or method, the type of data recorded, and the aim of experimentation.

Conflict of interest

The authors declare no conflict of interest.

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