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Smart Animal Agriculture: Application of Real-Time Sensors to Improve Animal Well-Being and Production

Ilan Halachmi,[1] Marcella Guarino,[2] Jeffrey Bewley,[3] and Matti Pastell[4]

[1]Laboratory for Precision Livestock Farming (PLF), Institute of Agricultural Engineering, Agricultural Research Organization, Volcani Centre, Rishon LeZion 7505101, Israel; email: halachmi@volcani.agri.gov.il

[2]Department of Environmental Science and Policy, Università degli Studi di Milano, 20122 Milan, Italy; email: marcella.guarino@unimi.it

[3]Alltech, Inc., Nicholasville, Kentucky 40356, USA; email: jbewley@alltech.com

[4]Natural Resources Institute Finland (Luke), Production Systems, FI-00790 Helsinki, Finland; email: matti.pastell@luke.fi

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Abstract

Consumption of animal products such as meat, milk, and eggs in first-world countries has leveled off, but it is rising precipitously in developing countries. Agriculture will have to increase its output to meet demand, opening the door to increased automation and technological innovation; intensified, sustainable farming; and precision livestock farming (PLF) applications. Early indicators of medical problems, which use sensors to alert cattle farmers early concerning individual animals that need special care, are proliferating. Wearable technologies dominate the market. In less-value-per-animal systems like sheep, goat, pig, poultry, and fish, one sensor, like a camera or robot per herd/flock/school, rather than one sensor per animal, will become common. PLF sensors generate huge amounts of data, and many actors benefit from PLF data. No standards currently exist for sharing sensor-generated data, limiting the use of commercial sensors. Technologies providing accurate data can enhance a well-managed farm. Development of methods to turn the data into actionable solutions is critical.

INTRODUCTION

Precision livestock farming (PLF) might be defined as "real-time monitoring technologies aimed at managing the smallest manageable production unit, otherwise known as the 'sensor-based' individual animal approach" (1, p. 1482). The first widely adopted application of PLF, years before the term PLF was coined, was the individual electronic milk meter for dairy cows in the 1970s (2) and early 1980s (3), followed by commercialized behavior-based estrus detection (4, 5), rumination tags (6–10), and online real-time milk analyzers (11). However, the dairy cow is not the only animal species in the PLF arena; it was applied to other species at approximately the same time. Undoubtedly, these technologies will continue to change the way that animals are managed. Moving forward, this technological shift provides reasons for optimism regarding improvements in both animal and farmer well-being. Producers can examine real-time data organized in reports to identify abnormal deviations from a baseline. However, the data themselves are meaningless unless they are transformed into information that can be used in a good decision-making program. Precision livestock monitoring technologies will never replace producers' intuition and management, but they may enhance it by enabling them to make better-informed decisions.

Earlier reviews did not relate PLF to technologies but examined PLF's use with particular species (12) or addressed specific questions, such as "daydream or nightmare?" (4), or commercialization issues (13). By contrast, this review analyzes PLF implementation by sensor type and then discusses its application to species. In **Table 1**, the main sensors are listed in the columns (A–K), with the main applications written in rows (1–17). The cells in **Table 1** that contain species are reviewed in this article. Callouts throughout the article refer to **Table 1**; e.g., A1 stands for body condition scoring (BCS) using a thermal camera, and B2 refers to body weight monitoring using a 3D camera.

Dairy Body Condition Scoring: Machine Vision

In modern dairy farms, BCS is applied for nutrition, health, and insemination management (14–18). However, human-observed BCS is time consuming and might be subject to personal bias owing to the observer's physical and mental state, experience, training, and previous knowledge or observation of cows. Attempts were made to quantify BCS using ultrasound (**Table 1**, cell K1) as early as the 1970s (19). However, Mizrach et al. (20) reported that the training and time required to collect reliable, repeatable ultrasonic BCS were considerably longer than for human-observed BCS. More importantly, ultrasound equipment and skilled ultrasound technicians are costly. Therefore, at the dawn of commercial digital photography, researchers (21–24) began exploring the application of these technologies to BCS (**Table 1**, cell C1). They argued that automatic digital recording of BCS could save labor and deliver unbiased quantification. Early studies applied RGB digital cameras (**Table 1**, cell C1; 21, 24), thermal cameras (**Table 1**, cell A1; 25), and high-resolution digital cameras with Fourier descriptors (**Table 1**, cell C1; 26). However, full automation of image processing was not reported until 2013 (**Table 1**, cell B1; 27). Spoliansky et al. (28) added a step forward: a low-cost 3D camera, which went beyond full automation (**Table 1**, cell C1; 27). Farm technology providers read the papers and developed a commercial system based on the 3D camera in 2017 (28). This allowed the BCS application to appear as a commercial on-the-shelf product, an accessory in almost every new commercial milking robot. The ability to collect BCS automatically may help dairy producers manage BCS at the group or herd level to improve animal health and reproduction. Additionally, examining how BCS curves change throughout lactation provides a valuable, consistently measured phenotype for genetic evaluations.

Table 1 Animal applications (rows) versus sensing technologies (columns)

		Sensors										
		A	B	C	D	E	F	G	H	I	J	K
		Machine vision (cameras)										
	Applications	Thermal	3D	RGB	Sound analysis	Response surface	Accelerometers: neck, leg, and ear tags	Positioning GPS, low-frequency RFID, UWB RFID, radar	Loadcell	Bolus	Electronic nose	Other
1	Body condition scoring	Dairy	Dairy	Dairy								Dairy
2	Body weight		Pigs Cattle		Broilers				Dairy Broiler	Dairy Beef		
3	Early detection of diseases or lameness	Dairy Poultry Horses	Dairy	Dairy Poultry	Pigs	Dairy	Dairy Pigs	Dairy	Dairy	Dairy Pigs	Dairy Poultry	
4	Quantifying pain and stress	Sheep Goats		Horses	Pigs		Dairy					
5	Feed intake and feeding behavior		Dairy	Dairy	Dairy Beef Poultry Sheep Goats			Dairy	Dairy	Cattle		
6	Water intake								Sheep Goats			Goats
7	Rumination time				Dairy		Dairy					
8	Estrus detection						Dairy Pigs	Dairy				
9	Milk yield and composition											Dairy
10	Calving detection			Horses			Dairy					
11	Body temperature	Poultry										Dairy
12	Aggressive behavior			Pigs								
13	Quantifying animal welfare				Pigs							
14	Grazing management							Beef Dairy	Cattle Reindeer			
15	Virtual fencing							Beef Dairy Sheep Goats				
16	Heart rate											Beef
17	Air quality										Dairy Beef Poultry Pigs	

Abbreviations: GPS, Global Positioning System; RFID, radio-frequency identification; RGB, red, green, blue; UWB, ultra-wideband.

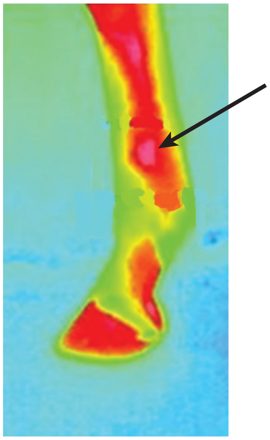

Figure 1

The thermal image reveals inflammation in the leg of a horse. The inflamed area is marked with an arrow.

The introduction of imaging technology for BCS and body weight measurements opens the door for further morphologically based image analysis, potentially providing novel measurements of body size traits and udder and leg conformation, which could standardize these traits.

Early Detection of Diseases or Lameness

Diseases often affect an animal's body temperature, and inflammation caused by infection or injury may be visible at specific spots in an animal's body (**Figure 1**). One of the challenges in measuring body temperature is the lack of a true gold standard. Each body temperature measurement location has either physical, logistical, or physiological limitations. In addition, many physiological and environmental factors affect body temperature. Thus, the inherent variation in body temperature can make detection of outliers challenging. Thermal imaging has been proven to work as a diagnostic tool for some animal diseases (**Table 1**, cell A3; 29). The temperature in the gluteal region of dairy cattle increases when an animal becomes ill; this can be detected in thermal images even before the disease is detected clinically (30). Examination for a disease using this method can be done with no physical contact with the animals.

Yanmaz et al. (31) suggested that using thermal imaging can be beneficial in detecting lameness, inflammation, and other irregularities, especially in the legs and hoofs of horses (31) (see **Figure 1** for an example of inflammation in a horse's leg). In hot weather, thermal imaging may also be used to control the climate in poultry houses (**Figure 2**). This technology could be potentially efficacious in identifying mastitis in dairy cow mammary glands (32, 33). Biomarkers within the milk may be used for disease detection. Such biomarkers may be measured using real-time spectroscopy (34) or biochemical analysis. In disease detection, the basic premise for using biomarkers centers on detecting diseases earlier than when a human observer might detect them. Early detection may lead to earlier medical treatment and an increased likelihood of success, thus reducing the impact and costs of disease. However, literature supporting the magnitude of this benefit is limited. The end user must also consider the usefulness of alerts provided by the system. The relationship of false-positive and false-negative alerts almost always challenges the usefulness of biomarkers (32). The best systems will minimize both false positives and false negatives. Missing disease occurrence (false negatives) limits the value of the system, whereas too many false

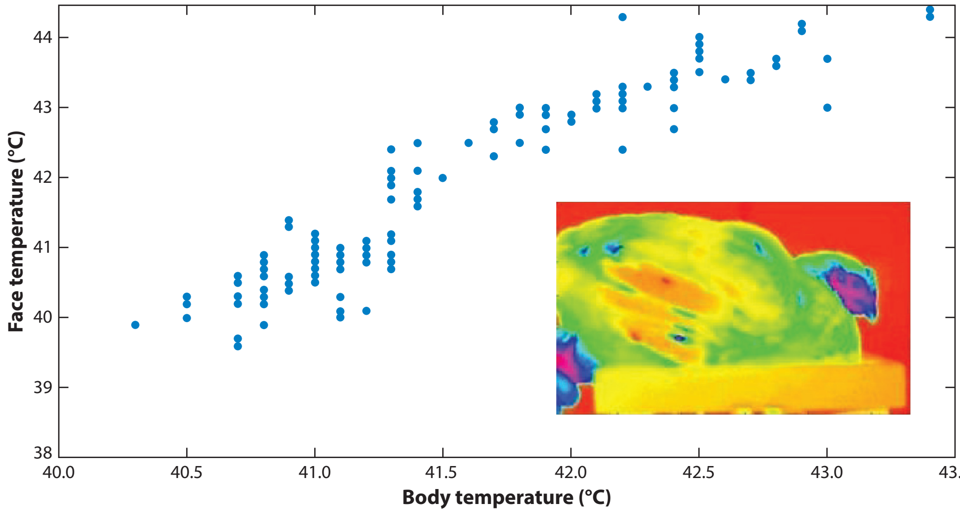

Figure 2

The face's thermal image reveals body temperature. Face maximum temperature is correlated ($r^2 = 0.93$) with body temperature. Other body parts are covered with feathers or are more affected by the environment. Figure adapted with permission from N. Barchilon, V. Bloch, S. Druyan, and I. Halachmi, manuscript under review.

positives mean the livestock producer may be forced to follow up on alerts that are not related to disease (33). Managing this balance is not always easy. In general, these challenges reflect the difference between the theoretical application of technologies and their practical and economical use in the field. While working on mastitis, Steensels et al. (32, 33, 35) addressed two crucial issues: the quality of sensor data and the ability to develop a model on one farm and validate it on another. Steensels observed that it is possible to develop a model on one farm and make it valid elsewhere in another farm—if one develops a local-calibration procedure that allows automatic adaptation to local conditions. This insight should be taken into consideration when a new PLF tool is being developed (**Table 2**).

Detection of Lameness in Dairy Cows: Response Surface and Machine Vision

Lameness is one of the most painful illnesses that dairy cows suffer, and it jeopardizes animal welfare (36, 37). Lameness is second only to mastitis in terms of its detrimental effects on herd productivity (38). The annual incidence of lameness ranges between 4 and 55 cases per 100 cows (38), depending on the farm, location, and year of study. The overall cost noted in the literature

Table 2 Early detection of diseases; developing a model in one farm and validating it in another farm (1–3)

Farm	Correct
1	83%
2	70%
3	91%
4	67%
5	77%

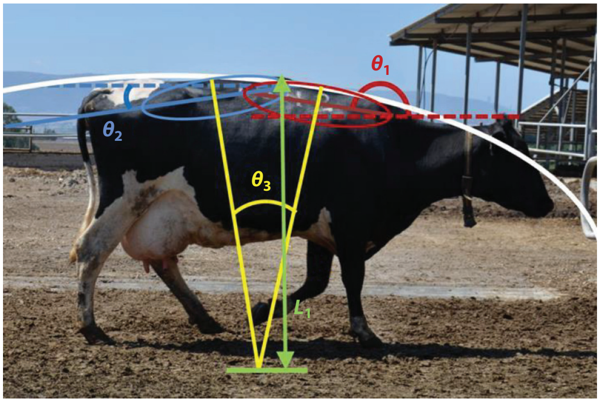

Figure 3

A picture taken in Kibutz Yefat, Israel, which intensively farms 1,200 dairy cows. The project, a collaboration between the Katholieke Universiteit Leuven (Belgium), Wageningen University (The Netherlands), DeLaval, and Agricultural Research Organization (ARO, Volcani Centre) (Israel), included a comparison of 2D versus 3D cameras and a combination of a 3D camera and animal production and behavior parameters (5).

varies, from approximately US$446 per case in the United Kingdom (39) to an average cost per case of sole ulcer, digital dermatitis, and foot rot of $216.07, $132.96, and $120.70, respectively, in the United States (40). Detection of severe lameness is relatively easy; however, by the time the animal becomes severely lame, successful treatment is often difficult. Dairy producers often miss subtle signs of lameness. A monitoring system that could detect milder, subclinical cases of lameness would be beneficial. Therefore, in 2002, at the University of Maryland, Baltimore, Rajkondawar et al. (41) hypothesized that measuring vertical ground reaction forces as animals walked over a force-plate system could provide the basis for early detection of lameness. The concept went through all the PLF development processes until a product was developed (41, 42). Marketed as the StepMetrix™ lameness detection system by BouMatic, it involved a pressure-sensor mat on which cows walked once or twice a day (43–45). Weight-distribution systems (46) were also developed for early detection of lameness, but these systems are rather expensive. In 2006 (47), a machine vision–based system was proposed (47–49) and explored in Israel (**Figure 3**). Together with other animal-related data that already exist in the farm management software, parameters correlated with lameness were drawn, including milk production and neck activity (50). A side-view concept was validated in 2013 (51) and was replaced by a 3D camera placed above the cows (52–54). Currently, the combined system—a 3D camera together with animal production– and behavior-related parameters (55)—appears to be the "winning setup" (56). A commercial product is expected to be introduced at the EuroTier exhibition in 2018. As with BCS, the long-term benefit of an automated lameness detection system includes providing a new phenotype to be used in genetic selection of animals less susceptible to becoming lame.

Feed Intake and Feeding Behavior: Machine Vision

Individual cow feed intake (**Table 1**, cells B5, C5, D5, H5) is intensively measured in research farms (**Table 1**, cell H5; 57). However, observing eating behavior (**Table 1**, cell C5; 57) via photogrammetry (**Figure 4**; **Table 1**, cell B5) may provide an accurate measurement of feed intake, providing a measurement of the individual cow's feed efficiency on commercial farms (**Table 1**, cell B5).

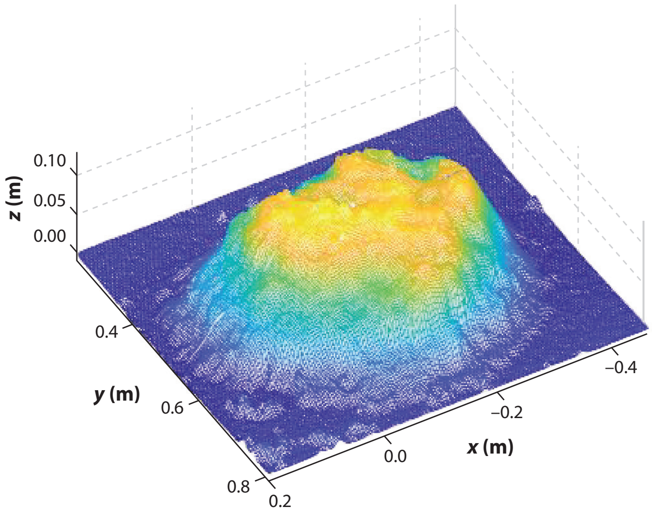

Figure 4

Monitoring cow individual feed intake applying photogrammetry. The picture was taken in the Agricultural Research Organization's Precision Livestock Farming lab (Israel) and research farm, and results were $R^2 = 0.98$ and std 0.15 kg when compared with real feed intake. Adapted with permission from V. Bloch, H. Levit, and I. Halachmi, manuscript submitted.

Accelerometers

An accelerometer measures the change in velocity and the static acceleration component of gravity (**Table 1**, column F). The position of the sensor can be determined with high accuracy when the sensor is not moving. If the sensor is moving, the position can be calculated only if the orientation of the device with respect to gravity is known. Inertial measurement units (IMUs) consisting of three-axis accelerometers and gyroscopes can be used to measure the precise movement trajectory if sufficient sample rates are used. Unlike accelerometers alone, IMUs can measure both linear and angular acceleration. Accelerometers attached to animals have seen a rise in popularity during the last 10 years, as technology has improved to the level at which reasonable battery life can be reached with sensors that are small enough to be attached to animals' legs, necks, ears, or tails; for example, accelerometers have even been attached to the dorsal fins of fish (58).

The main challenge in many research systems is that quite high sampling rates are required, which limits the system's battery life. One solution to the battery life problem is to program the device to make the calculations without transmitting or storing the data (59). However, embedded low-power devices have limited computational power, which in turn limits the complexity of algorithms that can be used. As battery technology evolves and the power consumption of electronic devices decreases, future sensors will be able to make more sophisticated analyses and measurements.

Dairy. Leg-mounted accelerometers were the first applications used with cattle; fairly accurate, they are commonly used to measure dairy cows' lying time and walking (60–62). Commercial versions are available from several manufacturers. Commercial pedometers calculate lying time, steps, and activity on the sensor; only summaries are stored and transmitted from the device (e.g., during milking, the summaries are transmitted to the farm's management software). Accelerometers have been used in the dairy industry primarily to measure activity related to estrus behavior. Activity, measured from many different locations, changes dramatically during estrus. Basic statistical processes to identify changes in activity can be applied to identify cases of estrus. These technologies have been widely and successfully adopted in the dairy industry. Monitoring lying behavior may also be useful as a proxy for cow comfort, with longer lying times often associated with more comfortable resting conditions. Monitoring lying time using an accelerometer affixed to a leg, combined with an accelerometer affixed to the head or neck, to measure head movement, may lead to quantification of sleep and rest quality.

In addition to the use of pedometers, several studies have focused on the use of accelerometers to automatically classify a wide range of behaviors. For adult dairy cows, neck- and ear-mounted accelerometers have been used to classify walking, standing, lying, panting, feeding, and ruminating (63–65), as well as grazing behavior (66). The classification models generally vary from temporal and spectral patterns of the sensor data, adapted using human observations as reference data, to bag of class posteriors (BOGP) classifiers. Use of BOGP and IMU data from 10 cows, and a simpler threshold-based classifier suitable for real applications for recognizing standing and feeding behavior, showed promising results for classification of walking, standing, lying, and ruminating (67), achieving precision and specificity of over 95% (68). The technology for measuring feeding and rumination time has progressed to a commercial level; validation papers have shown that commercial sensors have moderate to strong correlations to matching behavioral observations (69, 70). Changes in feeding and rumination time have been used to identify metabolic or digestive disturbances within dairy cattle (32, 33, 35). Such detection is particularly useful during the transition period, defined as the three weeks before and after calving. During this period, the cow is susceptible to ketosis, hypocalcemia, metritis, and displaced abomasum. Early detection of these conditions can hasten medical intervention, thus potentially reducing illness severity and recovery time. Additionally, these technologies may be used for tracking group- or herd-level changes in rumination or eating behavior to identify changes in feedstuffs and provide data for feeding management. For example, if overmatured (faulty) silage is mistakenly offered to the animals, changes in their eating behavior and consequently rumination times can be observed, and the farmer can react.

Accelerometers have also been used for direct measurements of gait to detect and analyze lameness. Chapinal et al. (71) and Pastell et al. (72) used accelerometers attached to all four legs to differentiate between sound and lame cows based on analysis of gait symmetry. Alsaaod et al. (73) developed a cow pedogram to analyze the temporal patterns related to gait and lameness using high-frequency measurements. In dairy calves, researchers have used leg-mounted accelerometers for measuring lying time (74) and locomotor play behavior (75); neck-mounted accelerometers for measuring total sleep and lying time, with an accuracy of over 90% (76); and halter-mounted sensors for measuring suckling behavior (77).

Pigs. Accelerometers have been used in similar ways in pigs as in cattle: Ear tag sensors can automatically classify sow behavior (78, 79), and sensors attached to the leg or back of the animal indicate posture (80, 81). Several projects have also focused on predicting parturition, owing to distinct increases in sow activity related to nest-building behavior when farrowing approaches. High accuracy has been achieved in detecting the activity related to nest-building behavior. Nonetheless, the exact moment of farrowing can be detected only in a 6–24-h window (82–84). Accelerometers have also been used to measure gait (85) and behavioral changes (86) associated with lameness in sows.

Quantifying Pain and Stress

Pain assessment based on physiological parameters was originally thought to be inapplicable to farms (87) (**Table 1**, row 4). Traditionally, when aiming for a clinical pain diagnosis in dairy cows, the farmer or veterinarian has observed the cow's behavior, searching for deviations from normal behavior (e.g., the time it spends lying down, standing, or ruminating or whether it is shifting its weight between its legs), which could imply that the animal is in pain (88–90). For example, individual cows with mastitis demonstrate behavioral changes, such as standing longer, eating more slowly, drinking less, and ruminating less, and have higher body temperatures (88) and decreased dry-matter intake (90). Basing pain diagnosis on behavior has its weaknesses, stemming from the stoic nature of the animal—cows do not explicitly show pain behavior (91). Moreover, the diagnosis is subjective, depending on the farmer's or veterinarian's experience, training, and familiarity with the individual cows, factors that might bias their judgment. Pain behavior assessment could greatly benefit from sensors, which could detect changes in activity, feeding, rumination, lying, and other behaviors early and quantify them (63). Such sensors include ear tag accelerometers (92, 93), neck collars (94, 95), and noseband pressure sensors to record jaw movements (95) and core body temperature sensors (96, 97). Notably, in a recent developmental venture, heart rate variability was associated with analgesia/nociception balance in anaesthetized animals undergoing surgery (98). Thus, realizing the need for improved dairy cow pain diagnosis, the assumption that pain assessment based on physiological parameters is inapplicable on farms should be challenged.

Positioning Systems

Positioning systems locate animals outside, grazing, or inside buildings in intensive farming. There is valuable information hidden in the animal location and its derivatives (velocity and acceleration) that is not yet fully explored in the PLF fields (**Table 1**, column G).

Indoor positioning. Several technological solutions have been used to locate animals inside buildings. One of the first published systems in dairy cows was based on radar technology (99). The system reached accuracy within 1 m, but the battery life of the system in continuous operation was only 24 h. Another early system (100) used Bluetooth beacons combined with a Kalman filter to track the position of cows in a barn.

After the first experiments, several commercial indoor positioning systems targeting cattle barns were introduced to the market. These systems use tags that transmit a radio signal that can be used to continuously calculate the location of the cow inside a barn. The systems typically use sampling rates close to 1 Hz. Ultra-wideband-based systems (101, 102) and low-frequency Nedap (103) systems can achieve positioning error below 1 m after filtering. The Smartbow positioning system has lower accuracy, within 3 m, 95% of the time (104).

The first studies analyzing the data from positioning systems have shown that the data can be used to measure the time that a cow spends in different functional areas (105), the effect of hoof lesions on walking distance (106), feeding time (105, 107), social networks (108), and the effect of disease and estrus on cow activity (109, 110). It is still too early to say whether the positioning data will provide significant improvements in these applications over other, e.g., accelerometer-based, systems. However, combining positioning data with other sensors to automatically measure behavior could yield higher prediction accuracy, as different behaviors with similar movement patterns are more likely to appear in different functional areas, e.g., feeding in the feeding area, drinking at the water trough, and rumination in other areas. The data from positioning systems have recently been combined with image analysis to yield improved positioning accuracy (111). The data from these systems may also be used in conjunction with environmental control systems within feedback loops to control microenvironments within livestock facilities. For example, cow panting behavior together with bolus temperature may be used to indicate that fans should be turned on in one part of a barn but not in another. Additionally, the presence of cows at the feed bunk can be used to determine whether sprinkler systems should be turned on only for the feed sections within the barn, reducing water usage.

Outdoor positioning. Global Satellite Navigation System (GNSS) can be used to track objects in outdoor environments where satellites have an unobstructed view. The current existing GNSS are the United States NAVSTAR Global Positioning System (GPS) and the Russian GLONASS. The European Union's Galileo system is expected to be completed in 2020. According to Standard Positioning Service specifications, the maximum range of error of a standard GPS receiver should not exceed 30 m (112). Higher accuracy can be obtained using various correction methods, such as Differential GPS (DGPS), which can achieve accuracy within 1–5 m, and Real-Time Kinematic (RTK) GPS, which can achieve accuracy to a centimeter. Both DGPS and RTK use an additional correction signal from a known reference point to improve the positioning accuracy, but this increases the overall cost of the system. Thus far, GPS has been used primarily to study cattle grazing behavior (113), and the data have been combined with accelerometer measurements to identify walking, resting, and eating behavior (114); GPS data have also been used with heart rate data to calculate energy expenditure (115, 116). Another interesting area where GPS could be used in the future is virtual fencing (117). A virtual fence is a boundary without a definable physical barrier. For instance, by using GPS coordinates, when an animal approaches the virtual fence line, a warning sound or an electric shock can be triggered (118). Virtual fences could save labor and physical resources and enable efficient grazing management, and potentially could be used to fetch cows from pastures to milking robots.

Heart Rate

Heart rate and heart rate variability provide information about cardiovascular system function and cardiac autonomic modulation, respectively (**Table 1**, row 16). This information can be used to estimate physiological and psychological stressors in animals. Heart rate has been used to study pain in calves (119), stress during milking (120), effect of space allowance (121), and energy expenditure and energy balance (115, 116). Electrocardiography, the process of recording the electrical activity of the heart, has been most commonly obtained with surface electrodes (122, 123), wearable belts (120), or implantable devices (124).

In recent years, optical methods for measuring heart rate have also garnered a lot of interest and technical development. In human applications, many smart watches use sensors to measure changes in the skin's absorption of light (125). The method typically requires good placement of the sensor. In cattle (126), a photonic sensor measuring movement of the skin surface can be used to measure the cow's heart and respiration rates, and its chewing patterns using a contactless setup.

If optical methods could be developed to continuously record the heart rate of cows on working farms, they could advance research significantly, enabling easier long-term data collection and ultimately allowing use of heart rate recording and analysis to improve practical farming practices.

Sound analysis: possible applications in broiler farms. One highly important indicator in a broiler farm is flock growth (**Table 1**, cell D2), because it represents the efficiency and profitability of the farm. The average weight of the flock is generally evaluated either manually (by weighing samples of birds randomly picked up in a poultry house) or by applying step-on electronic weighing scales. Manually measuring the weight of a representative number of animals in a building is time and labor intensive, because buildings may hold up to 50,000 birds. Today, many farms use step-on scales placed on the floor of the poultry house to automatically collect the average weight of the birds in the flock. However, even if the weighing system provides an accurate weight value each time a bird steps onto it, its reliability might be limited owing to several factors. For instance, heavy birds may be reluctant to visit the weighing scale (which requires the bird to climb up onto the scale) at the end of the production period (127), and the walking ability of fast-growing broilers, which decreases with age, reduces their mobility and willingness to move (128). Various studies have validated models that describe the growth rate of broiler chickens based on the peak frequency of their vocalizations (129, 130).

Feed intake and feeding behavior. Another possible application of real-time sound-processing technology in poultry houses is a system to monitor feeding behavior: meal size, meal duration, meals per day, and feeding rate. Researchers from the Catholic University of Leuven have studied this technology and its possible uses since 2013 (131, 132). In cattle (133) and free-ranging goats and sheep (134), acoustic monitoring is a promising method to quantify feeding behavior, by applying signal-processing algorithms to automatically identify and classify sound-producing jaw movements. Identification and classification of jaw movements appear to be essential to a mechanistic understanding of the feed intake process (135) (**Table 1**, cell D5).

Acoustics, sound analysis: pigs. Since the early 1990s, analysis of animal calls has played an important role in understanding livestock health, behavior, and welfare. Animal vocalizations can contain information, signaling threats, choosing mates, or alerting infants to suckle. In the case of livestock species, information contained in vocalizations or other animals' sounds could provide valuable information for the farmer (**Table 1**, cell D4). A very good example is the rich vocal repertoire of pigs (136). In 1999, Kanitz et al. (137) started to study the acoustic relationship between pig vocalizations and stress and stress hormones. Pig screams in production environments were recorded aiming to generate early-alarm systems while taking into account effects of age and maternal reactivity on the stress response.

Quantifying animal welfare. Vocal utterances of animals are the result of emotional states in specific situations. Therefore, the distress calls of pigs can be used as indicators of impaired welfare (**Table 1**, cell D13). Manteuffel et al. (138) and Schön et al. (139) introduced vocalization in livestock farms as a measurement of welfare. They began by classifying pig calls as either contact calls (grunts) or calls reflecting arousal (squeals and screams). Automatic measurement techniques and software were developed to detect these high-pitched vocalizations (140, 141). STREMODO, a patented technique that is applicable in housing systems, during transport, and in abattoirs, is the first system developed to identify stress vocalizations (142).

Early detection of diseases and lameness. Animal health (**Table 1**, row 3) is also an important issue; thus, sound analysis (**Table 1**, cell D3) is useful not only for gathering information about animal welfare but also to locate the source of a medical problem, e.g., to map the spread of coughs that can occur in a pig house (143). Some research groups have focused their studies on bioacoustics, in particular on the acoustic features of pig coughs. As one of the body's defense mechanisms against respiratory infections, a cough can be a sign of respiratory disorder or infection. In small pig houses, cough sounds are commonly assessed for diagnostic purposes, but the practice is difficult to apply in large pig houses (144). Therefore, the acoustic features of pigs' (143, 145, 146) and calves' (147) coughs have been studied, to be used as a sort of alarm system that can inform the farmer about the health of his animals. Sound technology opens possibilities of automatically and continuously monitoring animal coughs and vocalizations. One example that has recently come to market is SoundTalks, a spin-off company derived from the studies done at the University of Leuven and the University of Milan.

Electronic Nose

An electronic nose (**Table 1**, column J) is a device that acts as the human olfactory system and, thus, is able to discriminate between different odors (148). Basically designed to simulate the human sense of smell (149–154), the technique creates numerical descriptions of all profiles by detecting odor patterns (fingerprints), rather than the concentration of single compounds in a mixture. Electronic noses are now attracting increased interest from researchers because of their wide range of potential applications (155), including in drunk driving tests, hazardous gas monitoring (156), and air-quality monitoring (157–159). Several studies have explored the possibility of diagnosing pathologies in livestock via identification of volatile organic compounds (VOCs) produced by pathogens, host-pathogen interactions, and biochemical pathways (160). VOCs are present in blood, breath, stool, sweat, skin, urine, and vaginal fluids of humans and animals; their qualitative and quantitative compositions are influenced by pathophysiological responses to infections, toxins, or endogenous metabolic pathway disturbances. For instance, VOC analysis has been explored as a method to diagnose bovine respiratory disease, brucellosis, and bovine tuberculosis in cattle. In fact, several studies were able to distinguish the VOC profiles of *Mycobacterium bovis* from cattle breath samples (161, 162). Another livestock infection, *Mycobacterium avium* subsp. *paratuberculosis*, was studied in ruminants. Tentative identification of a range of breath VOCs, or a group of VOC features, has been associated with both infected and noninfected ruminants (163). In poultry, VOCs have been analyzed to evaluate air quality in sheds (164–166) but have not been used to determine if birds were affected by enteric pathologies.

Barn odors are influenced by poultry health status; in particular, enteric problems are characterized by peculiar odor properties (165, 167). Most recently, studies have shown that it is possible to discriminate between VOCs emitted by healthy broilers and those affected by enteric diseases like coccidiosis. In particular, air analyses have revealed that the discrimination is effective even at a very early stage of infection. This technique perfectly suits the methodologies and goals of PLF, which consists of noninvasive automated technologies that can support farmers with early warning systems for the identification of production, health, and welfare problems on farms (168, 169).

CONCLUSIONS

Where Are We Now?

By increasing the amount of information available, technologies providing accurate data can only enhance a well-managed system. How the data provided by these technologies are turned into actionable solutions is a crucial point for PLF success. At this point, wearable technologies dominate the market; most of the PLF applications are based on monitoring tags attached to the animal (neck, leg, or ear tags) or inside the animal (boluses). Therefore, current PLF applications are used mainly for larger animals, such as dairy cows, beef cattle, and horses. The economic value of each single large animal justifies the investment of a monitoring tag per animal, and large animals provide many places to hang sensors (**Figure 5**). A single sensor, like a camera (25, 26, 55, 56, 170) or robot (171, 172), should be sufficient for many smaller, less-valuable animals, such as small ruminants (sheep and goats). Most existing commercial applications for pigs, fish, and poultry monitor groups using cameras, sound, or data from feeding systems. New sensor systems will be introduced into the market, and will shift from primarily wearable technologies to more image- and milk-based systems. In less-value-per-animal systems, such as sheep, goat, pig, poultry, and fish, raised intensively in large herds, flocks, or schools, one sensor per herd (not a sensor per animal), such as camera or robot, will be even more common.

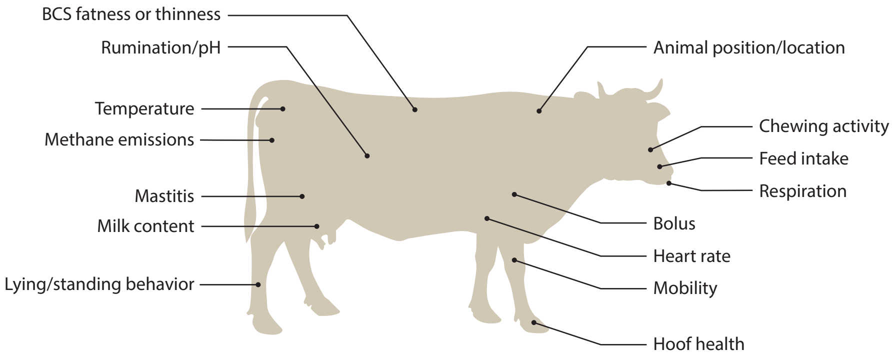

Figure 5

Key indicators, places, and sensors used in precision livestock farming. Abbreviation: BCS, body condition score.

Investment decisions should include a thorough, formal evaluation of profitability. The human factors related to successful technology adoption cannot be overlooked. Farmers are frequently skeptical of new business models, especially when new technology is involved. Often, it is difficult to convince farmers to collaborate on a digital innovation. That is one reason why collaborative business models in the livestock sector are at a relatively early stage. If scientists are able to transfer their knowledge to farmers in a reliable and transparent way, perhaps with the help of knowledge-sharing platforms and e-learning tools, there is potential to overcome such barriers to implementation and generate significant value for all parties along the value chain. Excitement about technical capabilities must be balanced with consideration of implementation challenges and economic realities. In some cases, although the technologies may be scientifically and technically sound, the economic return relative to the cost of the system limits adoption of the new technology. It is important to remember that livestock systems are, by nature, quite complex, and PLF technologies must be considered within the context of the whole system. For the most part, many of these technologies are still in the early-adoption phase. As they progress and become more mainstream, end-user demands for technology performance will increase.

What Can Be Learned?

The PLF sensors generate huge amounts of data. Many actors benefit from PLF data along the chain: The animal feed providers can design their inventory based on animal growth; the meat or milk processing factories can predict incoming quantity and quality and plan production accordingly; some consumers hope to apply objective animal welfare standards based on animal sensors; and farmers, based on the sensors' alarms, can treat those individual animals that need special care. No standards currently exist for sharing sensor-generated data, which limits the use of commercial sensors for research, animal breeding, and benchmarking purposes, among others. Data sharing needs to be enabled in a way that benefits all parties, to fully utilize sensor-generated data and the opportunities arising from combining multiple data sources for new applications.

However, at the end of the day, the farmer pays the bill—the price of installing the PLF applications on his farm. The PLF applications that are economically justified, reduce labor, are easy to use, and fit into known farm practices have a better chance to succeed commercially. Perhaps one of the most important lessons learned with these technologies thus far is that they are not a magic fix for poor management. The livestock producers who will benefit the most from the use of these technologies are the better managers.

Existing applications have focused mainly on dealing with single issues (such as diseases, estrus detection, or heat stress mitigation) and in many cases use a single data source. Clearly, detecting multiple conditions with the same sensor would be more useful, and this should be reflected in the study designs. Higher precision in anomaly detection could also be achieved by combining data from multiple sources, e.g., production, physiology, and behavior, and by incorporating existing information about risk factors into the models.

Current studies have focused more on sensor development and modeling data collected from small- to medium-scale experiments. To turn such studies into actionable solutions and obtain accurate, robust detection of anomalies in the future, more focus is needed for large-scale data collection with high-quality gold standards. This can be made possible by increasing the quantity of sensors deployed to commercial farms. More efficient use of expensive research data can also be facilitated via joint international modeling and data-sharing initiatives and by adopting a collaboration model between industry, researchers, farmers, and stakeholders. The value of data increases when (un)structured data are processed, enriched, and analyzed to create actionable insights. Operations can be further improved when farmers also share the information collected across the supply chain with relevant stakeholders, such as veterinarians, slaughterhouse operators, meat processors, and animal feed producers.

Where Are We Going?

Sustainable food production is one of today's key global challenges. According to a UN Food and Agriculture Organization report (173, 174), although meat consumption in the first world has leveled off, the share of animal products in the diet is increasing in developing countries (**Figure 6**). Between 1997–1999 and 2030, annual meat consumption in developing countries is projected to increase from 25.5 to 37 kg per person, compared with an increase from 88 to 100 kg in

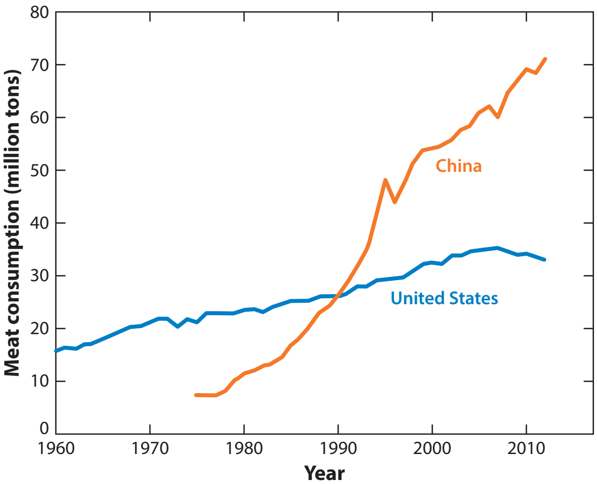

Figure 6

Meat consumption in China and the United States. The demand in first-world countries has leveled off, whereas it is rising precipitously in developing countries. Data from Food and Agriculture Organization of the United Nations (in the public domain).

industrialized countries. Consumption of milk and dairy products will rise from 45 kg/person per year to 66 kg in developing countries and from 212 to 221 kg in industrialized countries. For eggs, consumption will grow from 6.5 to 8.9 kg in developing countries but only from 13.5 to 13.8 kg in industrialized countries. In total, by 2050 an expanded world population will be consuming two-thirds more animal protein than it does today. Meat consumption is projected to rise nearly 73% by 2050; dairy consumption will grow 58% over current levels. The higher demand for animal products, together with public pressure to raise animals in compassionate ways and the concomitant decrease in available arable land, along with the desire to create smaller environmental footprints, will encourage the industry to adopt more PLF applications. Furthermore, the world continues to become more affluent, and finding labor for livestock farms is increasingly challenging. These challenges open the door for increased automation and sustainable intensification of livestock farms, consequently increasing development and use of PLF applications.

Digitalization offers the potential to make farming more sustainable. The implementation of information and communication technology in the livestock industry, and the recent use of smart networked objects and the Internet of Things, has opened a new era of communication in which things, humans, and animals are part of a data network exchange, leading to a new concept of farming. Remote or wearable sensors can be combined with smart algorithms to continuously monitor a wide range of animal responses linked to stress, health status, and welfare. The idea of real-time monitoring assumes a simple way to measure variables that can provide clear and suitable early warnings to farmers, mitigating the severity and length of medical problems and improving outcomes. The prompt reaction to any change in health, welfare, and productive status is key for reducing drug use and improving animal well-being. PLF could be considered the right environment in which to realize these goals.

SUMMARY POINTS

1. Meat consumption in the first world has leveled off, but the share of animal products in the diets of people in developing countries is increasing.
2. Early warning from sensors can enable farmers to treat those individual animals that need special care, before medical problems become serious.
3. The increasing demand for animal products, together with the desire to treat individual animals that need special care but are raised intensively in large herds, flocks, or schools, increases the development of PLF applications.
4. At this point, wearable technologies dominate the market.
5. In less-value-per-animal systems, such as sheep, goat, pig, poultry, and fish, one sensor, such as a camera or robot, per herd/flock/school will become even more common.
6. Technologies providing accurate data can only enhance a well-managed farm. How the data are turned into actionable solutions is critical.

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Errata

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