Sci

MDPI

Review

Precision Livestock Farming as a Strategic Tool for Mitigating and Adapting to the Consequences of Climate Change in Farm Animals

Lampros Fotos [1], Georgios I. Papakonstantinou [1], Aris Pourlis [2], Irene Valasi [3], Georgios Michailidis [4], Zisis Tsiropoulos [5], Ioannis Kaimakamis [6] and Vasileios G. Papatsiros [1,*]

[1] Clinic of Medicine, Faculty of Veterinary Medicine, University of Thessaly, 43100 Karditsa, Greece; lfotos@uth.gr (L.F.); geopapak@vet.uth.gr (G.I.P.)
[2] Laboratory of Anatomy, Histology and Embryology, Faculty of Veterinary Medicine, University of Thessaly, 43100 Karditsa, Greece; apourlis@vet.uth.gr
[3] Laboratory of Physiology, Faculty of Veterinary Medicine, University of Thessaly, 43100 Karditsa, Greece; evalasi@uth.gr
[4] Laboratory of Physiology of Reproduction of Farm Animals, Department of Animal Production, School of Agriculture, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece; michageo@agro.auth.gr
[5] Department of Agrotechnology, School of Agricultural Sciences, University of Thessaly, 41500 Larissa, Greece; ztsiropoulos@uth.gr
[6] Independent Researcher, 55133 Thessaloniki, Greece; i.kaimakamis@kaimakamis.com
* Correspondence: vpapatsiros@vet.uth.gr

Abstract

Livestock production occupies a paradoxical position with respect to climate change: farm animals are highly vulnerable to heat stress, feed and water scarcity, and climate-sensitive disease, while the sector contributes an estimated 14.5% of anthropogenic greenhouse gas emissions, most of which is biogenic methane from enteric fermentation. This review evaluates the evidence for precision livestock farming (PLF)—continuous, automated, real-time monitoring of individual animals' health, welfare, production and environmental impact—across dairy and beef cattle, small ruminants, pigs, and poultry. For mitigation, precision feeding and additive-dosing strategies have been associated with enteric methane reductions of approximately 10–25%; for adaptation, wearable and non-invasive sensors have been reported to detect heat-stress-related behavioural changes before productivity losses become apparent, and smart climate-control systems have been associated with housing energy-use reductions of roughly 5–10%. Much of this evidence derives from single-farm, small-sample or short-duration studies and should be read as indicative rather than generalisable. Adoption remains constrained by high investment costs, limited interoperability, insufficient technical support, and uneven applicability to extensive and smallholder systems. We conclude that PLF is a valuable enabling technology that, combined with genetic, nutritional, and management strategies, can strengthen the resilience and environmental sustainability of livestock systems under a changing climate.

Keywords: greenhouse gas emissions; heat stress; enteric methane; animal welfare; sensors; smart farming; intelligent agriculture; digital twin; sustainability; livestock resilience

Check for updates

Academic Editor: João Miguel Dias

Received: 6 August 2026
Revised: 29 August 2026
Accepted: 3 September 2026
Published: 7 September 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

The global demand for animal-source foods continues to rise in parallel with population growth, urbanisation, and rising incomes, with the world population projected

to reach approximately 9.7 billion by 2050 [1]. Meeting this demand while remaining within safe environmental limits is one of the central challenges facing the livestock sector today. Two decades of assessments by the Food and Agriculture Organization of the United Nations (FAO) have shown that livestock supply chains are a substantial source of anthropogenic greenhouse gas (GHG) emissions: an initial estimate of approximately 18% of global emissions [2] was later revised to around 14.5%, or 7.1 gigatonnes of CO_2-equivalent per year, once methodologies and global warming potential values were updated [3]. Cattle raised for beef and milk account for roughly two-thirds of this total, mainly through methane (CH_4) produced during enteric fermentation [3,4]. A complementary assessment from the Food and Agriculture Organization of the United Nations, based on 2015 activity data, places livestock agrifood-system emissions at approximately 6.2 gigatonnes of CO_2-equivalent per year (around 12% of all anthropogenic GHG emissions), with cattle (meat and milk) contributing approximately 62% of the livestock total, pigs 14%, chickens 9%, buffaloes 8%, and small ruminants (sheep and goats) 7% [5], underlining that although cattle dominate the sector's emissions profile, other species make materially significant contributions that precision livestock farming (PLF) applications must also address. More recent assessments, including the IPCC Sixth Assessment Report, confirm agriculture, forestry and other land uses as a major anthropogenic emissions source while emphasising that enteric methane is part of a biogenic carbon cycle—carbon previously fixed from the atmosphere by photosynthesis—rather than fossil-derived carbon, a distinction that is important when comparing livestock emissions with fossil-fuel sources [6].

Before turning to PLF specifically, it is worth situating it within the wider portfolio of mitigation strategies already recognised in the livestock literature. These include improving feed conversion and overall production efficiency; genetic selection and breeding for lower-emission animals; sustainable intensification of livestock systems; nutritional strategies and feed additives; improved manure management practices; enhanced housing conditions and thermal comfort; animal health and welfare improvements; and reproductive efficiency and herd management. PLF does not replace these approaches; rather, it provides the monitoring, individualisation and decision-support layer that helps farmers implement, verify and optimise them in practice.

At the same time, farm animals are themselves highly vulnerable to the consequences of the climate they help to shape. Rising ambient temperatures, more frequent and prolonged heat waves, altered rainfall patterns, and extreme weather events intensify physiological and behavioural stress in livestock, reducing feed intake, milk and meat yield, reproductive performance, and overall welfare [7]. This creates a bidirectional relationship in which livestock are simultaneously a driver of, and a casualty of, climate change—a relationship that conventional, herd-level management practices are poorly equipped to address, since they rely on periodic observation rather than continuous, individualised information.

Two further technological developments have materially expanded the feasibility of PLF adoption in recent years. First, advances in big-data analytics now allow the integration and processing of large volumes of farm-level information that were previously underused or discarded because of limited storage and computational capacity, transforming raw sensor output into actionable management information. Second, the ongoing expansion of satellite-based internet services is rapidly improving connectivity in rural and remote areas worldwide, enabling real-time data collection, transmission and processing from farms located far from conventional broadband infrastructure [8]. Together, these developments have removed a major practical barrier to digital livestock farming.

Precision livestock farming (PLF) has been proposed as a technological response to this gap. PLF was defined by Berckmans as the management of individual animals through continuous, automated, real-time monitoring of health, welfare, production and

reproduction, and environmental impact [7]. Enabled by advances in low-cost sensors, wireless connectivity, computer vision, and machine learning, PLF systems can generate high-frequency data streams on individual animals and their surrounding environment, supporting earlier and more precise management decisions than are possible through visual inspection alone [9,10]. This review is substantially distinct in scope and structure from the authors' earlier publication on PLF [11], which surveyed PLF technology broadly alongside general animal-welfare challenges, transportation stress, food-chain sustainability, and the EU legislative framework governing animal welfare, with climate change treated as one of several contextual pressures. The present review is instead organised entirely around a climate mitigation/adaptation framework: it quantifies reported mitigation and adaptation effect sizes across studies (Sections 5 and 6), introduces a three-component Digital Twin architecture coupling PLF sensor data with climate reanalysis products (Section 4), and provides a systematic, species-by-species breakdown of climate-relevant PLF applications (Section 7) that the earlier publication did not include. It does not revisit the EU legislative or general-welfare material covered previously and cites the earlier publication only where its content on general PLF challenges is directly relevant.

This article reviews the evidence for PLF as a tool to address climate change in farm animal production along two complementary axes: mitigation, referring to interventions that reduce the emission of GHGs per animal or per unit of animal product, and adaptation, referring to interventions that help animals maintain health, welfare and productivity under increasingly variable and stressful climatic conditions. The review covers the main PLF technology categories, summarises applications reported for dairy and beef cattle, small ruminants, pigs and poultry, and discusses the practical barriers that currently limit widespread adoption. This is a non-systematic narrative review rather than a formally registered systematic review. The review design, literature search strategy, eligibility criteria, and synthesis approach are described in full in Section 2.

2. Materials and Methods

This is a narrative, non-systematic review of the literature on PLF in relation to climate change mitigation and adaptation in farm animal production, following established guidance for writing and reporting narrative literature reviews for peer-reviewed journals [12]; no PRISMA protocol was formally registered and no exhaustive, quantitatively reported search log was maintained. Relevant literature was identified through targeted searches of PubMed, Scopus and Web of Science, combining PLF-related terms ("precision livestock farming," "smart farming," "sensor," "decision-support system," "digital twin") with climate-related terms ("climate change," "greenhouse gas," "methane," "heat stress") and species-specific terms ("dairy cattle," "beef cattle," "sheep," "goats," "pigs," "poultry"), supplemented by citation-tracking (snowballing) of key reviews and primary studies; search emphasis was placed on literature published from the mid-2010s onward, with most cited sources published between 2019 and 2026. Searches were conducted iteratively between March 2025 and July 2026, using illustrative Boolean strings such as ("precision livestock farming" OR "smart farming" OR sensor*) AND ("climate change" OR "greenhouse gas*" OR methane OR "heat stress") AND (species term), adapted to the syntax of each database. Screening proceeded in two informal stages—title/abstract relevance screening followed by full-text assessment against the inclusion criteria below; because this is a narrative rather than a systematic review, per-database record counts and a formal PRISMA-style flow diagram were not centrally logged, a limitation acknowledged in Section 8. Studies were included if they described or reviewed a PLF technology applied to one of the target species with a demonstrated or explicitly discussed link to a climate-relevant outcome (enteric methane, precision feeding, manure management, genomic

selection, heat-stress detection, or environmental control); non-peer-reviewed sources were generally excluded, with one explicitly flagged exception discussed in Sections 5.2 and 8. Quality was considered qualitatively rather than through a formal risk-of-bias instrument, with particular attention to study design, sample size and peer-review status; where the evidence base for a claim was limited to a small number of studies or a single research group, this is stated explicitly at the relevant point in the text and revisited in Section 8 (Challenges and Limitations).

Generative Artificial Intelligence (GenAI) was used exclusively for the preparation of visual material accompanying this review and played no role in the literature search, data extraction, analysis, or drafting of the manuscript text. Specifically, ChatGPT (OpenAI, GPT-4o, May 2024 version) was used to generate the graphical abstract and Figures 1–7, based on content, data summaries, and layout specifications prepared by the authors. For each figure, the authors supplied the underlying information (categories, values, and structure) drawn from the literature reviewed in this article, and the tool was used only to render this information into a visual format. All AI-generated visual outputs were subsequently reviewed, checked for factual accuracy against the source literature, and edited by the authors, who take full responsibility for their final content, consistent with the statement provided in the Acknowledgments section. A full list of the primary and review sources cited throughout this manuscript, including author(s), year, country/region, and livestock species addressed, is provided in Table S1 (Supplementary Materials).

3. The Bidirectional Relationship Between Climate Change and Livestock Production

This section establishes the central argument that motivates the rest of the review: livestock production and climate change are linked by a two-way relationship rather than a one-directional cause-and-effect chain. Section 3.1 summarises the evidence that livestock is a significant source of GHG emissions; Section 3.2 summarises the evidence that livestock is simultaneously a casualty of the climate it helps to shape. Taken together, these two strands establish a 'double dividend' rationale, developed at the end of this section, for treating PLF as a technology that must be evaluated on both its mitigation and its adaptation performance, which is the structure followed in Sections 5 and 6.

3.1. Livestock as a Source of Greenhouse Gas Emissions

Livestock-related GHG emissions arise from several distinct pathways: enteric fermentation in ruminants (methane, CH_4), storage and application of manure (methane and nitrous oxide, N_2O), feed production including fertiliser use and land-use change (carbon dioxide, CO_2, and N_2O), and on-farm energy consumption for housing, ventilation and processing [3]. Because methane has a substantially higher short-term warming potential than CO_2, enteric fermentation from ruminants—particularly dairy and beef cattle—is typically identified as the single largest emission source within livestock supply chains [3,4]. As already noted in the Introduction, the sector's precise contribution to global anthropogenic emissions (approximately 14.5% in the most-cited current estimate, revised down from an earlier 18% figure) depends on the assessment year, system boundaries, and the global warming potential metric applied, underlining both the scale of the issue and the genuine scientific debate over how best to quantify it [2,3].

3.2. Livestock as a Casualty of Climate Change

Farm animals possess a species-specific thermoneutral zone outside of which they must invest energy in thermoregulation, typically through increased respiration rate, reduced feed intake, altered posture and activity, and, in dairy cattle, measurable declines

in milk yield and composition [7,13]. As heat waves become more frequent, more intense and longer in duration, the cumulative physiological burden on livestock increases, with consequences that extend to reproductive performance, immune competence and, in severe cases, mortality [7]. These effects are not confined to intensive systems: extensive and pastoral livestock enterprises face compounding pressures from reduced and more erratic rainfall, degraded pasture quality, and greater exposure to climate extremes, while typically having the least capacity to buffer these impacts through infrastructure such as shade, cooling or supplementary feeding [14].

This bidirectional relationship implies that interventions capable of simultaneously improving production efficiency and animal resilience carry a double dividend: any strategy that reduces the resources required per unit of animal product, or that helps animals maintain productivity under thermal or nutritional stress, tends to lower both the emission intensity and the climate vulnerability of the system at the same time [4,13]. This convergence is the central rationale for examining PLF through both a mitigation and an adaptation lens rather than treating the two as separate problems. This bidirectional relationship is summarised schematically in Figure 1.

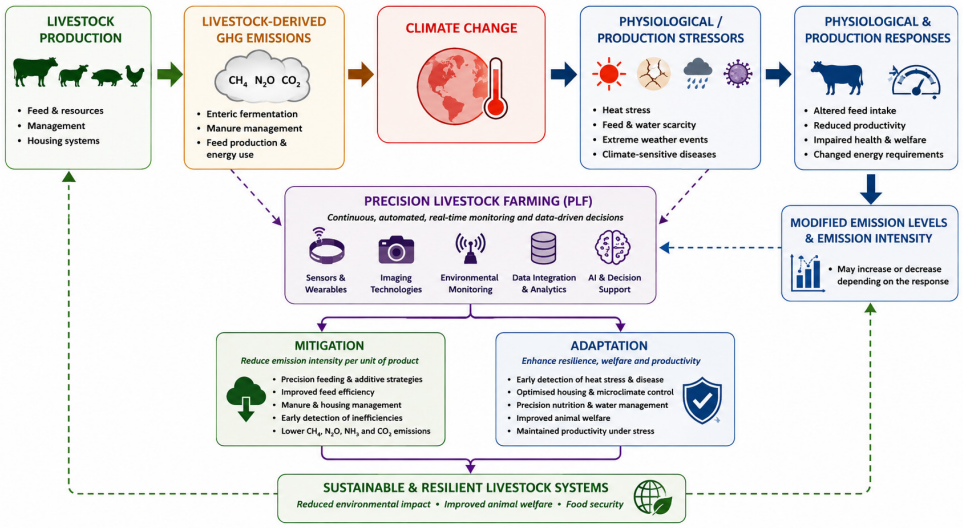


Figure 1. Conceptual framework showing livestock-derived emissions as an intrinsic driver of climate change, and climate change as a modifier of physiological and production responses—and hence of emission levels and intensity—in farm animals; precision livestock farming (PLF) is positioned to reduce emission intensity (mitigation) and to buffer animal stressors and strengthen resilience (adaptation), with both pathways feeding back to reduced pressure on the climate system. Sources: [3,4] (climate-emissions relationship); [7] (heat-stress pathway); [9–11] (PLF sensing and decision-support framework); [14–17] (mitigation applications); [7,10,13,18] (adaptation applications).

Solid arrows indicate the primary causal chain, from livestock production through GHG emissions, climate change, physiological/production stressors, and production responses to modified emission levels, which feeds back into livestock production. Dashed arrows indicate the points at which precision livestock farming (PLF) monitors and receives feedback from this chain: from GHG emissions and from physiological/production stressors into PLF, and from modified emission levels back into PLF; the dashed green arrow at the base indicates the feedback loop by which sustainable and resilient outcomes reduce future pressure on livestock production.

4. Precision Livestock Farming: Concept and Technological Framework

PLF technologies are commonly classified according to where and how data are collected relative to the animal. On-animal (wearable) sensors are physically attached to or

implanted in the animal, and include accelerometer-based ear tags and collars, rumen boluses, and implantable temperature loggers [19]. Near-animal (non-invasive) sensors capture information without physical attachment, most notably cameras coupled with computer-vision algorithms [20], microphones for vocalisation analysis, and infrared thermography. Off-animal (environmental) sensors monitor the surrounding microclimate and air quality, including temperature, relative humidity, ventilation rate and concentrations of gases such as ammonia (NH_3), carbon dioxide (CO_2) and methane (CH_4) [9–11]. A further, product- and sample-based sensing approach analyses animal-derived biological samples—milk, faeces, and blood—for biomarkers of health status, nutritional status, production quality, and disease occurrence; when combined with the physical sensor layers above, these measurements provide clinically and physiologically grounded information that on-animal, near-animal, and environmental sensors cannot capture directly [21]. Data from these layers are integrated through decision-support systems (DSS) that apply statistical models, machine learning or rule-based algorithms to translate raw sensor output into actionable alerts for the farmer, such as early warnings of heat stress, disease, or suboptimal ventilation [10,22,23]. As illustrated in Figure 2, this architecture links four functional layers: the sensing layer (on-animal, near-animal, environmental, and product/sample-based devices), a wireless IoT communication layer (e.g., LoRaWAN, Wi-Fi, Bluetooth, 4G/5G) that transmits raw signals, a data storage and AI/machine-learning processing layer that cleans and analyses the incoming streams, and a decision-support layer that converts model outputs into concrete farm-level actions such as adjusting ventilation, triggering cooling, or flagging an animal for veterinary attention.

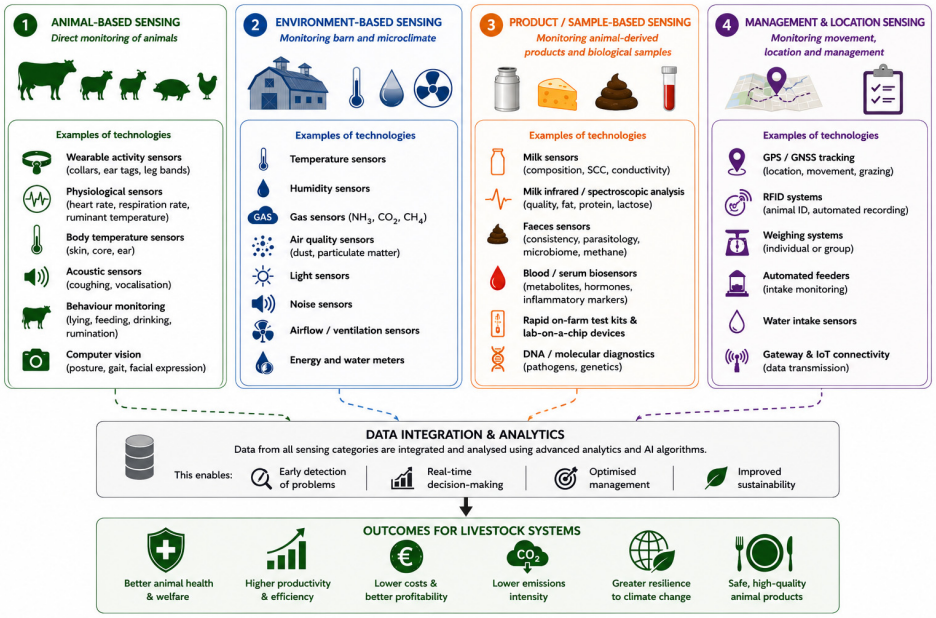


Figure 2. Precision Livestock Farming (PLF) architecture for climate-smart livestock production, showing the integration of on-animal, near-animal, environmental, and product/sample-based (milk, faeces, blood) sensing with wireless IoT communication, AI/machine learning, and decision-support systems that translate continuous data acquisition into automated management actions (ventilation, cooling, feeding, health interventions). The four numbered panels shown correspond to: (1) animal-based sensing (on-animal, wearable devices); (2) environment-based sensing (off-animal, barn/microclimate monitoring); (3) product/sample-based sensing (milk, faeces, and blood); and (4) management and location sensing (e.g., GPS/GNSS tracking, RFID identification, automated weighing and feeding, and water-intake monitoring).

Table 1 summarises the main categories of PLF technology, representative devices, the parameters they monitor, and their principal relevance to climate change mitigation or adaptation. This framework underpins the applications discussed in Sections 5 and 6. The four sensor categories introduced here (on-animal, near-animal, environmental, and methane-specific) are applied differently across species; a species-organised breakdown of representative tools and their mitigation/adaptation relevance is given in Table 2 and discussed further in Section 7.

Table 1. Overview of precision livestock farming (PLF) technology categories, representative devices, monitored parameters, and their relevance to climate change mitigation and adaptation.

Sensor Category	Representative Devices	Monitored Parameters	Primary Climate-Related Relevance	Key Refs.
On-animal (wearable)	Accelerometer ear tags/collars; rumen boluses; implantable temperature loggers	Activity, rumination, lying time, core/rumen temperature, pH	Adaptation (early heat-stress detection); Mitigation (rumination-linked feed efficiency)	[10,11,18,19]
Near-animal (non-invasive)	RGB/thermal cameras; microphones; infrared thermography	Body condition, gait, respiration rate, surface temperature, vocalisation	Adaptation (behavioural and thermal stress indicators); welfare screening	[9,20,24]
Off-animal (environmental)	Anemometers; thermo-hygrometers; gas sensors (CH_4, NH_3, CO_2)	Ambient temperature, humidity, ventilation rate, gas concentration	Mitigation (emission monitoring); Adaptation (housing microclimate control)	[10,24]
Individual methane sensing	GreenFeed stations; sniffer analysers; laser methane detectors	Eructed/exhaled CH_4 concentration or flux	Mitigation (methane phenotyping, additive dosing, genetic selection)	[14,15,25]
Precision feeding systems	Automated feeders; milk/rumen-fluid infrared spectroscopy proxies	Individual intake, diet composition, methane-yield proxies	Mitigation (nutrient-use efficiency, additive dose optimisation)	[14,26]
Decision-support systems/AI	Cloud dashboards; machine-learning alert algorithms	Integrated multi-sensor outputs; predictive alerts	Mitigation and Adaptation (translating data into management action)	[9,10,22–24]

Note: citations combining review-level sources with single-primary-study reports (e.g., refs. [9,24]) should be read as review-plus-example pairs rather than as convergent independent evidence; readers seeking primary data should consult the specific study-level citations used in Sections 5–7.

Digital Twin (DT) Extensions of PLF

An emerging extension of the PLF framework described above is the Digital Twin (DT): a continuously updated virtual replica of an animal, barn or farm that assimilates environmental and sensor data to simulate physiological trajectories and predict performance deviations before they are clinically or productively apparent [27]. A DT architecture is typically organised into three linked components: an Environmental Twin, which ingests climate data (including reanalysis products) to forecast thermal indices and cumulative heat load; an Animal Twin, which integrates physiological and behavioural sensor streams (respiration rate, activity, feed intake, milk yield) to estimate individual heat-stress and welfare risk; and a Barn Twin, which simulates housing-level conditions such as ventilation performance, airflow and cooling-system efficiency [28]. This concept is introduced here as a conceptual extension of the PLF architecture shown in Figure 2. As summarised in Figure 3, the mitigation pathway proceeds through methane monitoring, precision feeding, genomic selection, and manure management, while the adaptation pathway proceeds through heat-stress detection, behavioural and welfare monitoring, and smart environ-

mental control; both pathways draw on the same underlying sensor and decision-support architecture shown in Figure 2. These three components are illustrated in Figure 4. Two later sections build directly on it: Section 6.3 applies DT-style reasoning to a specific regional case study that couples farm-level sensor data with climate reanalysis products, and Section 9 discusses the broader future potential of DT architectures for climate-smart livestock management. Current DT implementations for livestock remain at a comparatively early technology readiness level, and their practical deployment faces non-trivial challenges around real-time synchronisation between sensor layers and simulation modules, the cybersecurity of networked farm IoT infrastructure, and unresolved questions of who owns and controls farm- and animal-level data feeding the model. Relative to a conventional decision-support system, which mainly issues reactive alerts from current sensor readings, a DT's distinguishing contribution is forward-looking simulation—projecting how an animal, barn, or region is likely to respond to forecast conditions before that response is observed.

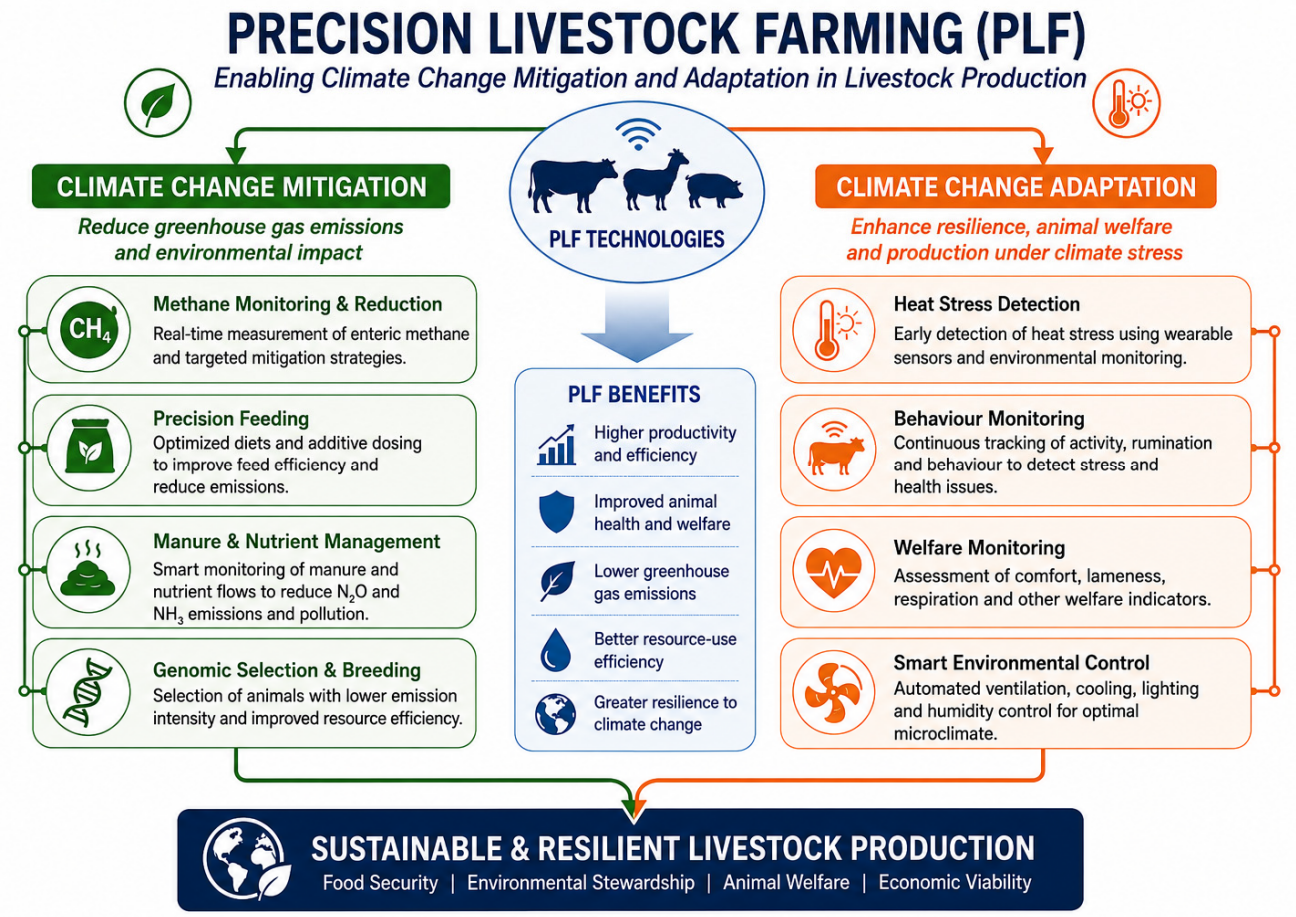


Figure 3. Climate change mitigation and adaptation pathways enabled by precision livestock farming (PLF). On the mitigation pathway, PLF contributes to reducing greenhouse gas emissions through methane monitoring, precision feeding, genomic selection, and improved manure management; on the adaptation pathway, PLF enhances animal resilience through early heat-stress detection, behavioural and welfare monitoring, and smart environmental control.

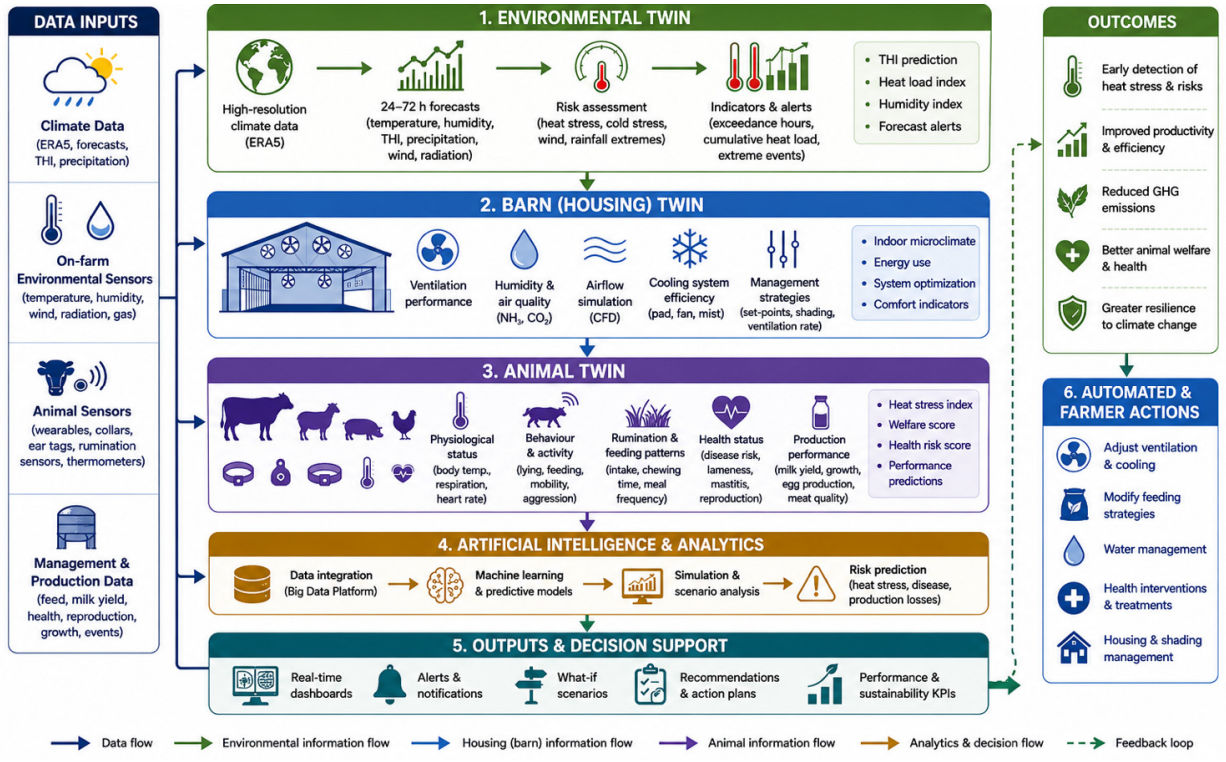


Figure 4. Digital Twin framework for climate-resilient livestock farming, integrating an Environmental Twin (climate forecasts and thermal-stress prediction), a Barn Twin (simulated ventilation, cooling, humidity and air quality), and an Animal Twin (physiological and behavioural sensor data), with AI-based analytics generating risk assessments and management recommendations. The framework is organised into six numbered stages, drawing on four categories of data inputs shown on the left (climate data, on-farm environmental sensors, animal sensors, and management/production data): (1) Environmental Twin; (2) Barn (Housing) Twin; (3) Animal Twin; (4) Artificial Intelligence and Analytics, integrating and modelling data across the three twins; (5) Outputs and Decision Support, generating dashboards, alerts, scenarios, and recommendations; and (6) Automated and Farmer Actions, translating outputs into ventilation, feeding, water, health, and housing management responses, which feed into the outcomes shown on the right. Coloured arrows (bottom legend) indicate the data and information flow associated with each layer (data, environmental, housing, animal, and analytics/decision flows) and the feedback loop returning outcomes to the data-input stage. See Section 4 for the underlying conceptual definition.

5. PLF Applications for Climate Change Mitigation

5.1. Enteric Methane Monitoring and Reduction

Direct measurement of enteric methane under farm conditions has historically relied on respiration chambers, which are accurate but impractical for large-scale or routine use. PLF has expanded the toolbox of proxy and semi-continuous measurement methods, including automated feed-station 'sniffers', the GreenFeed system [25], and hand-held laser methane detectors that estimate methane output non-invasively during short measurement bouts [15]. Because measurement precision with laser detectors is influenced mainly by measurement duration rather than distance or angle to the animal, these devices are increasingly practical for on-farm phenotyping across commercial herds [15]. Milk mid-infrared spectroscopy has also been explored as a low-cost, indirect proxy for individual methane output that can be layered onto routine milk recording [10]. Although enteric methane remains the most intensively studied GHG in livestock systems, a comprehensive mitigation strategy must also address CO_2 and N_2O emissions arising from energy consumption, fossil-fuel use, feed production and manure management; PLF technologies support this

broader goal by informing decisions on resource allocation and energy efficiency across the whole farm, not solely on enteric methane output.

The methane-monitoring methods described above are not equally applicable across species. Respiration chambers, GreenFeed stations and hand-held laser detectors have been developed and validated primarily in dairy and beef cattle, reflecting both the larger per-animal methane output and the greater commercial incentive to measure it in this species group. Milk mid-infrared spectroscopy is, by definition, restricted to lactating dairy animals (cattle and dairy sheep/goats) with existing milk-recording infrastructure. Comparable individual-level methane measurement in pigs and poultry remains far less developed, since enteric methane is a minor component of their overall emissions profile; PLF's climate contribution in these species is therefore concentrated instead in manure-related emissions and housing energy use, discussed in Sections 5.3 and 6.2, respectively.

The practical applicability of methane-monitoring technologies should be assessed cautiously. Commercial, farm-level adoption of CH_4-measurement systems remains largely confined to research or pilot-project settings, and all currently available methodologies carry important limitations, including high acquisition and maintenance costs, infrastructure and calibration requirements, and difficulty obtaining measurements that are representative of an animal's full daily emission pattern, since many systems sample only during specific periods or activities [29]. Significant technological and economic progress therefore remains necessary before large-scale commercial implementation becomes feasible.

These measurement tools support mitigation in two complementary ways. First, they allow methane-reducing feed additives—such as 3-nitrooxypropanol (3-NOP), essential oils, and polyunsaturated fatty acids—to be dosed and evaluated with individual precision rather than at the herd level; meta-analyses of such additives report enteric methane reductions in the order of 10–25%, depending on additive type, dose and basal diet [14,30]. Second, continuous individual-level methane data create the phenotypic foundation for genetic selection: heritability estimates for methane-related traits in dairy cattle populations have been reported to range from approximately 0.10 to 0.39, indicating meaningful scope for breeding programmes to reduce methane emission intensity over successive generations [17]. Beyond feed-mixed dosing, PLF-enabled precision delivery of methane-mitigating compounds through drinking water is emerging as a practical alternative for pasture-based and extensive systems where individual feed-bunk dosing is impractical: an essential-oil blend delivered via drinking water has been shown to reduce enteric methane production in cattle [31], and a stabilised bromoform-based Investigational Veterinary Product delivered via drinking water reduced methane production by 37%, methane yield by 26%, and methane intensity by 36% while increasing feed conversion efficiency by 15% in beef steers, with no adverse effects on liveweight gain or health [32]. The same delivery strategy has also been extended to a different compound and species: 3-nitrooxypropanol administered via drinking water reduced enteric methane emissions in sheep by 36–41%, comparable to or exceeding the reductions achieved with feed-mixed dosing of the same compound [33]. Because beef cattle account for a substantial share of the global cattle population, it is worth noting that bromoform-containing compounds have also been evaluated specifically in beef systems beyond the single-study IVP example above: a recent meta-analysis pooling 14 studies and 39 treatment comparisons in beef and dairy cattle fed bromoform-containing seaweed and synthetic bromoform-based additives confirmed consistent, dose-dependent reductions in enteric methane production, yield and intensity, while also identifying a dose-dependent reduction in dry-matter intake that warrants attention in on-farm implementation [34].

5.2. Precision Feeding and Resource-Use Efficiency

Precision feeding systems adjust the amount and composition of feed delivered to individual animals or small groups based on real-time data on intake, growth stage, production level and physiological status, rather than applying a single ration across a heterogeneous group. By reducing over- or under-feeding, these systems lower feed waste and nutrient excretion per unit of product, indirectly reducing both the carbon and nitrogen footprint of production [10]. In beef and dairy systems, matching energy and fermentable carbohydrate supply to individual requirements has also been associated with reductions in enteric methane output per unit of product, although the magnitude of this effect under commercial field conditions still requires further validation across a wider range of herds and management systems [10].

This same logic extends to small ruminants, where routine digital records already collected for management purposes can be repurposed for emission-intensity tracking without additional sensor investment. In a preliminary field application reported to date only in conference-proceedings form and not yet peer-reviewed [35], individual digital milk-yield and bulk-tank milk-quality records from a dairy goat herd, collected at three points across the lactation season, were used to derive herd-level enteric methane emission-intensity indices, expressed per litre of raw milk and, separately, per kilogram of fat- and protein-corrected milk (FPCM). Relative to the seasonal production peak, emission intensity was reported as 18% higher (per kg FPCM) to 48% higher (per litre of raw milk) in early and late lactation, when milk yield was lower despite comparable or higher milk solids content; the difference between the two figures reflects the choice of denominator rather than two independent findings. If confirmed by peer-reviewed follow-up, this would illustrate how existing digitalisation and herd-management data could be turned into a practical, farm-level mitigation and training tool for small ruminant systems without requiring new precision hardware [35].

Proposed as a practical route to reducing this mismatch, improving feed efficiency and lowering nutrient excretion per unit of product [36]. In broiler breeders specifically, individual precision feeding stations that identify birds via RFID and dispense feed according to individual body-weight targets have been shown to improve flock uniformity relative to conventional group feeding, a production outcome closely linked to feed-conversion efficiency and, indirectly, emission intensity [37]. More broadly, RFID-linked feeding/drinking monitoring, computer-vision-based weight and behaviour estimation, and acoustic feed-intake monitoring are increasingly combined with environmental sensors in broiler houses to support real-time feed-management decisions, although most of these tools remain at an early stage of commercial validation [38].

5.3. Manure and Nutrient Management

Sensor-based monitoring of manure storage conditions, together with automated separation and treatment technologies, can improve nutrient recovery and reduce methane and ammonia losses during storage and land application [16,39]. Integrating manure-management data with feeding and housing information within a single farm-management platform allows nutrient flows to be tracked from feed intake through excretion to field application, supporting more targeted, whole-farm mitigation strategies rather than addressing each emission source in isolation [16].

Direct field measurements of manure-related methane and nitrous oxide emissions across different livestock production systems in sub-Saharan Africa illustrate that baseline emission rates vary substantially with manure management practice and system intensity, underlining the value of context-specific monitoring rather than the uniform application of default emission factors [40].

Biodigesters have become a practical, commercially deployed technology in many tropical livestock production systems, particularly in swine and feedlot cattle operations, and illustrate how manure management can be integrated with PLF data platforms rather than treated as a separate workstream. In addition to reducing methane emissions from stored manure, anaerobic co-digestion generates biogas that can be used for electricity or heat production and yields a nutrient-rich effluent suitable for fertigation, while solid manure fractions are widely reused as organic fertiliser, contributing to nutrient recycling and reducing dependence on synthetic fertilisers [41]. Sensor-based monitoring of digester performance and feedstock composition can further improve the efficiency and reliability of these systems within a whole-farm management platform.

5.4. Genomic Integration and Breeding for Efficiency

PLF-derived phenotypes are increasingly combined with genomic information to accelerate genetic progress for traits relevant to both efficiency and climate resilience, including feed efficiency, methane yield, and thermotolerance. In dairy cattle, genomic predictions derived from controlled heat-stress trials have been shown to distinguish heat-tolerant from heat-susceptible cohorts, providing a route towards breeding herds that are simultaneously more resilient to warming and more efficient per unit of product [42,43]. Because breeding decisions have a cumulative, permanent effect on herd genetics, integrating PLF phenotyping with genomic selection represents one of the more durable mitigation pathways available to the sector, complementing shorter-term nutritional and management interventions. It should be emphasised that many of the biological mechanisms linking genotype to environmental adaptation, feed efficiency, methane emission and resilience remain only partially understood, and genomic predictions should be interpreted with corresponding caution. Beyond conventional genomic selection, emerging disciplines—including nutrigenomics, metagenomics and rumen microbial community characterisation, transcriptomics, metabolomics and, potentially, epigenetics—are increasingly being integrated to better understand host–microbiome interactions and the biological basis of productivity, efficiency, adaptation and environmental sustainability, and are likely to complement PLF-derived phenotyping in future breeding programmes [44].

6. PLF Applications for Climate Change Adaptation

6.1. Heat Stress Detection and Behavioural Monitoring

Traditional heat-stress assessment relies on environmental indices, most commonly the temperature–humidity index (THI), combined with periodic observation of panting or reduced feed intake. These approaches provide a herd-level picture but fail to capture individual variability or the earliest stages of thermal strain [7]. PLF wearable sensors address this gap by continuously tracking behavioural proxies—lying time, rumination, feeding and drinking time, and general activity—that shift measurably before productivity losses become apparent. In lactating dairy cows exposed to heat waves (THI $\geq$ 72), noseband-sensor systems have recorded significant reductions in drinking time and chewing rate alongside increased general activity, illustrating how behavioural sensors can flag thermal stress in near real time [7]. Ear-tag accelerometer data have similarly been used to identify individual 'heat-sensitive' cows—animals whose milk yield drops disproportionately during heat waves independent of other health events—enabling more targeted cooling or nutritional intervention for the most vulnerable animals within a herd [13].

Beyond behaviour, wearable and implantable temperature sensors (ear-base loggers, rumen boluses) and non-contact infrared thermography provide direct or proxy measures of core or surface body temperature, which can be combined with activity data in machine-learning models to generate individualised heat-stress alerts ahead of visible

clinical signs [18]. This shift from herd-level environmental indices toward individualised, behaviour- and physiology-based detection is one of the most consistently reported benefits of PLF for climate adaptation across species.

As an illustrative case example of how this multi-level monitoring logic performs under real production conditions rather than in controlled trials, a recent field study on a single commercial farrow-to-finish pig farm in central Greece is summarised briefly below; its findings should be read as a detailed demonstration from one Mediterranean system rather than as representative of the wider heat-stress-in-pigs literature (see also Section 8). Continuous Bluetooth Low Energy (BLE) neck-skin temperature sensors applied to lactating sows tracked a statistically significant seasonal rise in skin temperature that peaked in July, strongly correlated with daily outdoor THI (Pearson r = 0.60, $p < 0.001$) [45]. In the same herd, welfare-impairment scores, oxidative-stress markers and production indices (TBARS, total antioxidant capacity, average daily gain, post-weaning mortality; full values given in Table 3) all worsened in parallel with rising THI, and histopathological examination of animals that died during the hot season revealed lesions consistent with systemic vascular injury and endothelial dysfunction [45]. By combining environmental, physiological, oxidative-stress, welfare, histopathological and production data within a single commercial system, this study provides one of the more complete field demonstrations that continuous, low-cost skin-temperature sensing can flag thermoregulatory strain in pigs before it is apparent from routine performance records alone [45].

Comparable reproductive vulnerability to heat has been documented in extensively managed small ruminants: rising ambient temperatures have been associated with reduced lambing rates and lower lamb birth weights in the Australian sheep flock, reinforcing the case for extending individualised thermal and reproductive monitoring beyond cattle and pigs [46].

6.2. Smart Environmental Control of Housing Systems

In confined systems, environmental sensors for temperature, humidity, ventilation rate and harmful gas concentration (NH_3, CO_2) allow automated climate-control systems to adjust ventilation, misting or cooling in response to real-time conditions rather than fixed schedules [10]. In poultry and pig housing, validated energy-consumption models coupled with sensor feedback have demonstrated the potential to optimise ventilation and cooling strategies while reducing energy use per unit of output by approximately 5–10% [10]. Facility design choices, such as green roofing and adjustable stocking density, further interact with sensor-based climate control to influence thermal comfort, welfare and sensor reliability, underscoring that PLF adaptation strategies work best when integrated with, rather than substituted for, sound building design [10]. In poultry specifically, sensor-based environmental control is increasingly discussed alongside non-PLF adaptation measures such as nutraceutical dietary interventions (e.g., probiotics and ascorbic acid supplementation), which have been reported to reduce heat-stress impacts in broilers independently of housing modifications, illustrating that PLF-based climate control and nutritional strategies are best viewed as complementary rather than substitutable [47,48].

6.3. Extensive and Pastoral Systems

Extensive livestock enterprises face particular constraints for climate adaptation: large operational scale, low-input management, and limited infrastructure make regular data collection logistically difficult [14]. Nonetheless, a growing set of technologies—GPS-enabled ‘smart tags’, walk-over-weigh platforms, virtual fencing, remote-sensing of pasture biomass, and drone-based mustering—extend precision monitoring into rangeland systems without requiring the fixed infrastructure typical of intensive housing [14,49]. In lower-resource

settings, low-cost Internet of Things (IoT) sensors have been used to track temperature, humidity and harmful gas concentrations in poultry housing under tropical conditions, illustrating that scalable, affordable PLF solutions can extend climate-adaptation benefits beyond high-input commercial systems [4].

Unmanned aerial vehicles (UAVs) are increasingly used to complement ground-based sensors in extensive and rangeland systems. Fixed-wing and multirotor drones equipped with RGB, thermal and multispectral cameras have been used to estimate pasture biomass and forage quality, detect localised vegetation or water stress, and support rotational-grazing decisions over areas too large for routine ground survey [50]. Beyond vegetation monitoring, UAV-based thermal imaging and animal-detection algorithms have also been applied directly to herd counting, spatial distribution mapping and the identification of animals showing heat-stress-related behaviour in open rangeland, offering a scalable complement to individual wearable sensors where fitting devices to every animal is impractical [51]. GPS-enabled smart tags, virtual fencing and walk-over-weigh platforms of the kind described above are not restricted to small ruminants: comparable systems are already used commercially in extensive beef cattle operations to manage grazing distribution, track individual location and body condition, and reduce land degradation, as summarised for beef cattle in Table 2. Taken together with the expansion of satellite-based connectivity noted in the Introduction, UAV-based remote sensing and IoT/satellite data transmission are expected to jointly extend PLF-style monitoring into rangeland and smallholder contexts that lack fixed broadband or cellular infrastructure [8,50,51].

A complementary strategy for extending adaptation planning beyond the individual farm is to combine coarse-resolution climate reanalysis products with local, farm-level thermal measurements. In a spatially explicit assessment across the Thessaly region of Greece (14,036 km^2), six years (2020–2025) of hourly air temperature and dew point fields from the ERA5-Land reanalysis ($0.1^\circ \times 0.1^\circ$ spatial resolution) were used to map maximum temperature and THI across ten livestock units (sheep and goats, dairy cattle, and pigs) spanning lowland and mountainous locations. Maximum daily temperatures in the central and southeastern lowland plain regularly exceeded 38–40 °C and locally surpassed 45 °C in August, compared with temperatures 6–10 °C lower at higher-elevation sites only tens of kilometres away, while nighttime temperatures above 25 °C in the lowlands limited overnight thermoregulatory recovery [28]. At the level of individual livestock units, severe heat stress (THI > 82) accounted for approximately 19–21% of all hours between May and September at several lowland sites, with a further 5–10% of hours in the high category (THI 79–82), confirming that thermal exposure in this region is a sustained, cumulative seasonal burden rather than a series of isolated heatwave events [28]. This regional-local framework illustrates how reanalysis datasets can be paired with farm-level PLF and environmental sensing both to benchmark current heat-stress risk across a region and to project how that risk may evolve under future climate scenarios; the same study proposes operationalising this within the three-component DT architecture introduced in Section 4 (Environmental, Animal and Barn Twins) as a route toward detecting subclinical heat stress before productivity losses occur [28].

7. Species-Specific Considerations

The relative maturity and focus of PLF applications differ substantially across livestock species, reflecting differences in production system, unit value per animal, and the historical availability of sensor technology. Table 2 summarises representative PLF applications for dairy and beef cattle, small ruminants, pigs and poultry, together with their principal contribution to climate change mitigation or adaptation. For small ruminants specifically, a recently published dedicated review of IoT and decision-support technologies for dairy

sheep offers a considerably more detailed technological and methodological synthesis than is possible within the multi-species scope adopted here and is a useful complementary resource for readers focused on this species group [52]. Dairy and beef cattle receive proportionally more attention here because they are the species for which the largest body of published PLF-climate evidence currently exists, not because the review treats other species as secondary; Table 2 and Figure 5 present dairy and beef cattle, small ruminants, pigs and poultry as four parallel, equally structured categories, and the species-specific gaps in the evidence base for non-cattle systems are discussed explicitly in Section 8.

Table 2. Species-specific applications of precision livestock farming relevant to climate change mitigation and adaptation.

Species/System	Representative PLF Tools	Mitigation Contribution	Adaptation Contribution
Dairy cattle	Wearable collars/ear tags; rumen boluses; automated milking and feeding systems; milk MIR spectroscopy	Individual methane phenotyping for breeding; precision feeding to reduce nutrient excretion [14,16,18]	Early behavioural detection of heat stress; automated cooling triggers; fertility/health monitoring under thermal load [7,13]
Beef cattle (intensive)	GreenFeed/sniffer stations; growth-monitoring cameras; automated feed-intake systems	Feed-efficiency-linked reduction in methane intensity per kg gain [10,15]	Behavioural and thermal monitoring in feedlots during heat events [10]
Beef cattle (extensive/rangeland)	GPS smart tags; walk-over-weigh platforms; virtual fencing; remote pasture sensing; drones	Improved grazing distribution and reduced land degradation, indirectly limiting emission intensity [14,49]	Early identification of nutritional and thermal stress across large, low-input areas [14]
Small ruminants (sheep/goats)	Activity and rumination sensors; housing microclimate sensors; camera-based behaviour monitoring; digital milk-yield/quality records	emission-intensity tracking, supporting lower emission intensity per unit of product [27,39] (preliminary)	and reproductive performance; improved housing design [46,53]
Pigs	Camera/microphone-based welfare monitoring; RFID; environmental (gas/climate) sensors; BLE skin-temperature sensors	Manure-linked methane/ammonia modelling to guide management system choice [24,39,40,54]	Automated ventilation and cooling; early detection of heat-related behavioural and physiological change [24,45,54]
Poultry (layers/broilers)	Climate and air-quality sensors; camera-based flock behaviour analysis; automated ventilation control	Energy-consumption optimisation in housing (approx. 5–10% reduction) [10]	Real-time thermal-comfort management; stocking-density-informed welfare monitoring; nutraceutical/dietary heat-stress mitigation (probiotics, ascorbic acid) [10,47,48,54]

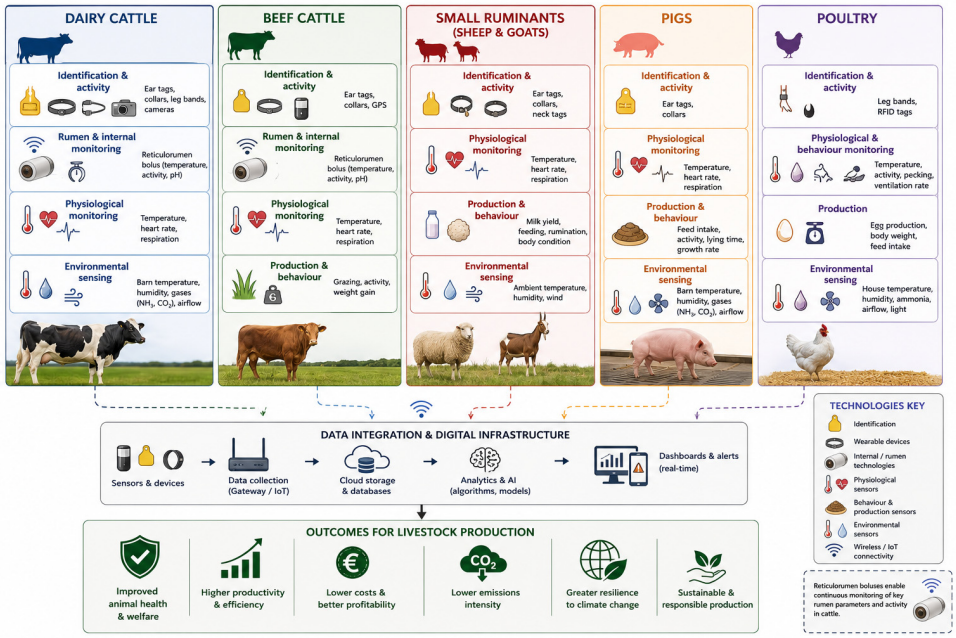


Figure 5. Species-specific applications of precision livestock farming (PLF) technologies in dairy cattle, small ruminants, pigs, and poultry, summarising representative monitoring technologies, environmental sensing, nutritional management, health/welfare surveillance, and data-integration approaches used in each species group; corresponds to the detail given in Table 2.

Table 3. Quantitative effects of precision livestock farming (PLF) and precision-nutrition interventions on climate-relevant metrics reported in the reviewed literature. The first six rows underlie the ranges plotted in Figure 6; the final four rows report additional field-study findings discussed in the text.

Species/System	Intervention	Reported Metric	Effect Size	Level of Evidence	Refs.
Dairy cattle	Precision-dosed methane-reducing feed additives (PUFA, 3-NOP, essential oils, monensin)	Enteric methane yield/intensity	Reduction of approx. 10–25%, additive-dependent	Meta-analysis (systematic review)	[14,30]
Beef cattle	Bromoform-containing seaweed and synthetic bromoform-based additives (pooled across studies)	Enteric CH4 production (g/d); CH4 yield (g/kg DMI); CH4 intensity	Consistent, dose-dependent reductions across studies; concurrent dose-dependent reduction in DMI also identified	Meta-analysis (pooled, 14 studies, 39 comparisons)	[34]
Dairy cattle	3-Nitrooxypropanol (3-NOP) specifically, individually dosed at study-optimised levels (single-study estimate, exceeding the additive-class range shown in the row above, reflecting a study-optimised dose)	Enteric CH_4 production (g/day); CH_4 yield (g/kg DMI)	Reduction of approx. 32.5% (production); 29.3% (yield)	Single study (modelling-based estimate)	[55]
Dairy cattle	Sensor-derived phenotyping for genetic evaluation	Heritability (h2) of methane-related traits	h2 approx. 0.10–0.39	Review (synthesised heritability estimates)	[17]
Dairy cattle	Noseband/activity sensors under heat stress (THI $\geq$ 72)	Drinking time; chews per minute; general activity	−51.2% drinking time; −12.9% chewing rate; +17.0% activity	Field study	[7]
Poultry/pigs	Smart, sensor-driven housing climate control	Housing energy consumption per unit of output	Reduction of approx. 5–10%	Review	[10]
Dairy cattle	IMU-based collar accelerometry	Behavioural classification accuracy (activity/rumination)	Approx. 92–95% classification accuracy	Systematic review	[18]
Pigs (lactating sows)	Continuous BLE neck-skin temperature monitoring, Mediterranean summer	Neck skin surface temperature vs. daily outdoor THI	Peak monthly mean +1.05 °C (June to July); Pearson r = 0.60 ($p < 0.001$)	Single-farm field study	[45]
Pigs (multi-category)	Seasonal heat stress (severe THI, June–August)	Total antioxidant capacity (TAC); lipid peroxidation (TBARS)	TAC reduced approx. 22–36% at seasonal nadir; TBARS up to 2.7-fold higher (July vs. October)	Single-farm field study	[45]
Pigs (farrow-to-finish)	Seasonal heat stress, farm-level records	Average daily gain (ADG); post-weaning mortality	ADG-21% (May to July); post-weaning mortality more than tripled (Oct to July)	Single-farm field study	[45]
Dairy goats	Digital milk-yield and milk-quality records repurposed for emission tracking (preliminary, not yet peer-reviewed)	Emission intensity per litre of milk/per kg FPCM	18–48% higher outside peak lactation vs. seasonal peak	Conference abstract	[35]
Mixed ruminants and pigs (regional)	ERA5-Land reanalysis-derived THI, 10 farms, 6 warm seasons	Hours per warm season (May–Sept) in severe THI category (>82)	Approx. 19–21% of hours at lowland units; 6–10 °C cooler at upland units	Multi-site field/reanalysis study	[28]

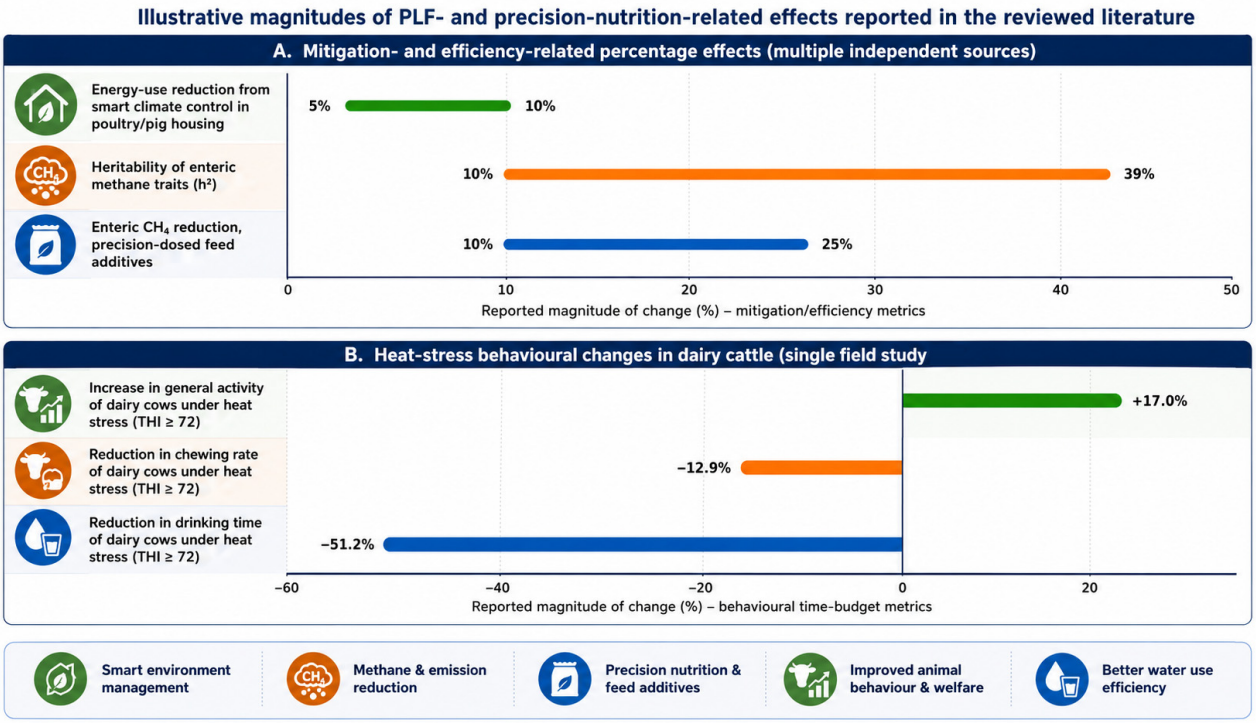


Figure 6. Illustrative magnitudes of PLF- and precision-nutrition-related effects reported in the reviewed literature, split into two panels to avoid implying comparability across unrelated metric types. Panel A shows percentage-based mitigation and efficiency effects drawn from multiple independent sources (enteric methane reduction from precision-dosed feed additives, heritability of methane-related traits, and energy savings from smart housing climate control). Panel B shows behavioural time-budget changes in dairy cows under heat stress (temperature-humidity index, THI $\geq$ 72) reported in a single field study. Values are drawn from the studies cited in brackets; this is not a pooled or meta-analytic estimate, and values should not be compared across panels or interpreted as a single aggregate effect size. Data sources: enteric CH_4 reduction, precision-dosed additives [14]; heritability of methane traits [17]; housing energy-use reduction [10]; dairy cow drinking time and activity under heat stress [7]. Full effect sizes and units are listed in Table 3.

8. Challenges and Limitations

Despite the accumulating evidence base, several barriers continue to limit the widespread adoption of PLF as a climate strategy. High upfront investment and ongoing costs for sensors, connectivity and software subscriptions remain a significant obstacle, particularly for small and medium-sized farms and for producers in extensive or low-resource systems [24,54]. This is compounded by the demographic and structural profile of European livestock farming itself: a continent-wide survey of the pig and poultry sectors found that 58% of European farm managers are aged 55 or older (33% of whom are over 65), and that small, mainly family-run holdings accounted for 94.8% of all EU farms in 2020, a combination that the survey authors argue makes rapid, capital-intensive technology adoption structurally difficult regardless of the underlying welfare or environmental case for it [54]. The same survey found that a lack of clear, quantifiable return on investment, combined with limited technical support and training, contributes to farmer hesitancy in adopting new technologies even when the underlying benefits are recognised [54]. Interoperability between proprietary sensor platforms and data formats also remains limited, hindering the integration of multiple data streams into a single decision-support system [24]. Cross-sector standards such as the ISO/IEC 30141 IoT reference architecture and open agricultural data-exchange frameworks (e.g., FIWARE) have been proposed to address this barrier, although their adoption within livestock-specific PLF platforms remains limited [52]. Notably, few

of the studies reviewed here report detailed cost–benefit analyses, return-on-investment estimates or payback periods for specific PLF technologies; quantifying these economic parameters across farm sizes and production systems remains an important gap for future research aiming to support adoption decisions. A similarly limited availability of standardised, quantitative cost–benefit and total-cost-of-ownership analyses has recently been highlighted specifically for small-ruminant PLF systems, indicating that this is a cross-species rather than climate-specific evidence gap [52]. These barriers, together with corresponding enabling strategies identified in the reviewed literature, are summarised in Table 4.

From a technical standpoint, sensor reliability under field conditions—battery life, robustness to dirt, moisture and mechanical damage, and the need for frequent recalibration—continues to constrain performance relative to controlled research settings [10,18]. Many published validation studies are conducted on a limited number of farms, breeds or climatic conditions, so that thresholds and algorithms developed in one context do not always transfer reliably to others [13]. Even well-designed commercial-farm studies illustrate this constraint candidly: the authors of one recent multi-domain field study on heat stress in pigs (used as an illustrative case example in Section 6.1) explicitly and transparently flagged their single-farm design and the small number of monthly time-points available for correlating environmental and biological data as restricting statistical power and generalisability, notwithstanding the biological coherence of the associations observed [45]. Finally, extensive and pastoral systems, which are often the most climate-vulnerable, remain comparatively underserved by commercially available PLF solutions designed primarily for intensive, housed production [14]. Continuous, individual-level monitoring also raises ethical considerations that are only beginning to receive systematic attention in the PLF literature, including who owns farm- and animal-level data, whether such data could be used for purposes beyond animal welfare (e.g., insurance assessment or supply-chain conditionality), and the need for clear consent and data-governance arrangements between farmers, technology providers and downstream data users [56].

A further limitation applies to this review itself rather than to PLF adoption in the field. As noted in the Introduction, several of the most recent and quantitatively detailed primary studies drawn upon here—particularly those underpinning the heat-stress case example in Section 6.1, the small-ruminant emission-intensity example in Section 5.2, and the regional DT framework discussed in Sections 4, 6.3 and 9—originate from a single, overlapping research group working in one Mediterranean country (refs. [11,28,35,45]). While these studies are recent, methodologically transparent, and directly relevant, this concentration means the review's more granular quantitative content is not drawn from as geographically or institutionally diverse an evidence base as would be ideal; findings framed as illustrative Mediterranean case examples should not be over-generalised to other climates or production systems without independent confirmation. In addition, one of these sources [35] is currently available only as a conference-proceedings abstract and has not yet undergone full peer review; the corresponding figures in Section 5.2 and Table 3 should be treated as preliminary until a full peer-reviewed publication becomes available.

Table 4. Principal barriers to precision livestock farming (PLF) adoption for climate-smart livestock production, and potential enabling strategies identified in the reviewed literature.

Barrier Category	Description	Potential Enabling Strategies	Refs.
Economic/investment	High upfront cost of sensors, connectivity infrastructure and software subscriptions; unclear or slow return on investment. A continent-wide EU survey found 94.8% of farms are small, mainly family-run holdings with limited capital for technology investment	Shared/cooperative equipment models; targeted subsidies or climate-finance mechanisms; simplified low-cost sensor packages for smallholders	[4,24,54]
Technical reliability	Limited battery life, sensitivity to dirt/moisture, need for frequent recalibration, and reduced accuracy outside controlled research conditions	Ruggedised, low-power sensor design; standardised field-validation protocols across farms, breeds and climates	[10,13,18]
Data interoperability	Proprietary data formats and platforms that do not communicate with one another, hindering integration of multi-sensor data streams	Open data standards; interoperable application programming interfaces (APIs); independent third-party validation	[24]
Knowledge/training	Insufficient technical support, training and extension services; farmer distrust or unfamiliarity with new technologies. The same EU survey found 58% of farm managers are aged $\geq$ 55 (33% of these >65), a demographic profile associated with slower technology uptake	Farmer-centred co-design; demonstration farms; collaboration between farmers, scientists and engineers	[54]
System-type applicability	Commercial PLF tools designed primarily for intensive, housed systems; limited infrastructure and connectivity in extensive, pastoral or low-resource settings	Scalable, low-cost IoT and satellite/remote-sensing solutions adapted to rangeland and smallholder contexts	[4,14]

9. Future Perspectives

Several directions appear likely to shape the next generation of PLF applications for climate change mitigation and adaptation. First, multimodal data fusion—combining wearable, environmental, and imaging data within unified machine-learning frameworks—is expected to improve the accuracy and lead time of both heat-stress and methane-related predictions relative to single-sensor approaches [10,24]. Second, closer integration between PLF phenotyping and genomic selection programmes is likely to accelerate genetic gains in thermotolerance and methane efficiency, converting short-term monitoring data into durable, heritable improvements at the population level [16,42]. Third, continued cost reduction and standardisation of low-power IoT sensors should improve accessibility for smallholder and extensive systems, which currently bear a disproportionate share of climate risk with the least technological support [4,14]. Fourth, pairing farm-level PLF data with coarser climate reanalysis products (e.g., ERA5-Land) within the DT architecture introduced in Section 4 offers a practical route to scaling heat-stress risk assessment from individual farms to whole regions and to translating current monitoring data into forward-looking, climate-projection-based planning tools [28]. Finally, greater transparency and interoperability standards between commercial platforms, alongside independent, multi-farm validation studies conducted across a wider range of countries and institutions than the largely Mediterranean evidence base reviewed here, and that jointly capture physiological, oxidative-stress, welfare, histopathological and production-level outcomes—as recently demonstrated for pigs [45]—will be needed to build the evidence base and farmer trust required for PLF to move from a promising research tool to a mainstream component of

climate-smart livestock management [24,54]. Related to this, edge-computing architectures that process sensor data locally on-farm, together with federated-learning approaches that allow predictive models to be trained across multiple farms without centralising raw data, may help address the interoperability and data-governance barriers discussed in Section 8 while reducing connectivity requirements for lower-resource settings. Embedding welfare considerations directly into the technology-design process from the outset—a 'welfare-by-design' approach recently articulated for small-ruminant PLF systems—together with greater participatory involvement of farmers in the design process, may further help ensure that future PLF tools are both ethically sound and more readily adopted [52]. Figure 7 illustrates how several of these strands—multimodal sensor fusion, machine-learning-based risk prediction, and iterative model refinement—can be integrated within a single AI-driven decision-support workflow.

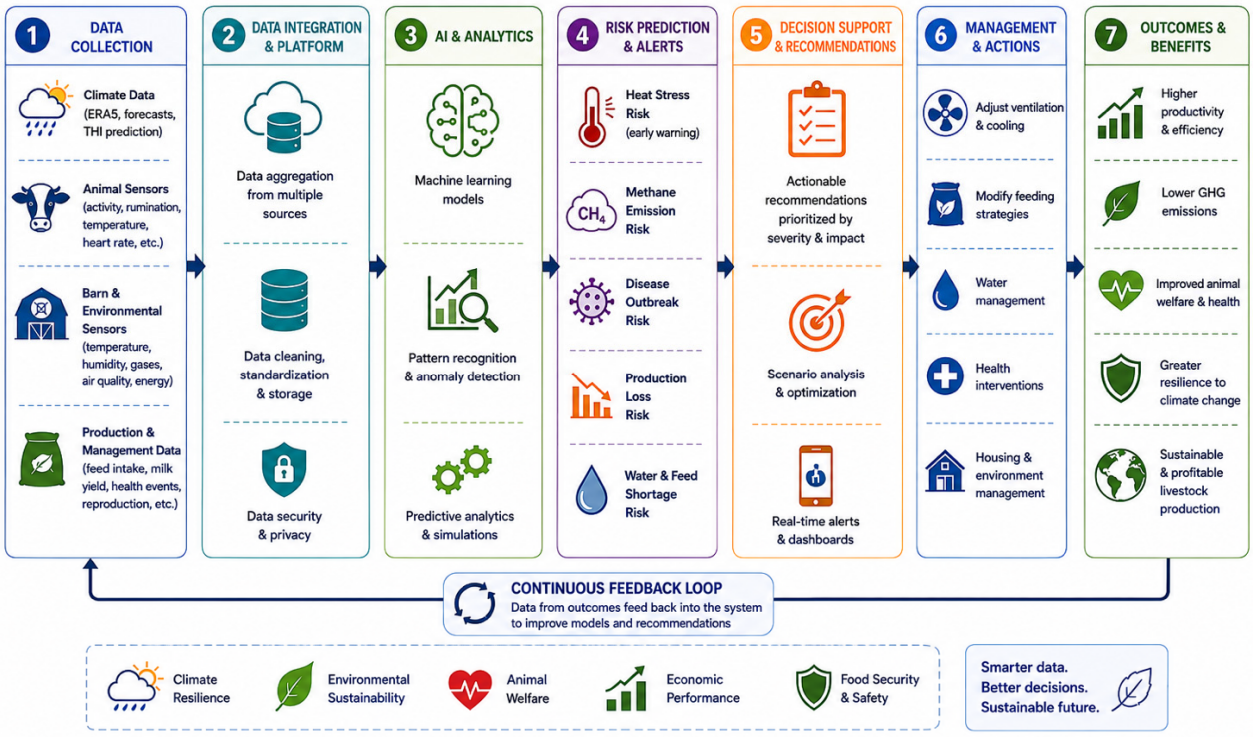


Figure 7. AI-driven decision-support workflow integrating climate data, PLF sensor streams, production records and environmental monitoring through data collection, integration, machine-learning analytics, and risk prediction (heat stress, methane emissions, disease, production loss), generating prioritised management recommendations with a continuous feedback loop for model refinement. The workflow is organised into seven numbered stages: (1) Data Collection; (2) Data Integration and Platform; (3) AI and Analytics; (4) Risk Prediction and Alerts; (5) Decision Support and Recommendations; (6) Management and Actions; and (7) Outcomes and Benefits, shown left to right with arrows indicating the sequential data and decision flow between stages. The dashed arrow at the base is the continuous feedback loop, returning outcome data to stage 1 to refine future models. The five icons beneath the workflow (climate resilience, environmental sustainability, animal welfare, economic performance, and food security and safety) summarise the overarching benefit domains the workflow is designed to support.

10. Conclusions

Livestock production and climate change are connected through a genuinely bidirectional relationship: the sector contributes materially to global GHG emissions while farm animals are simultaneously exposed to escalating climatic risk. Precision livestock farming offers a coherent set of tools to address both sides of this relationship, using continuous,

individualised sensor data to lower emission intensity through precision feeding, methane phenotyping and genomic integration, while simultaneously strengthening animal resilience through early detection of heat stress and smarter environmental control of housing systems. The evidence reviewed here indicates that these benefits are measurable, but not yet uniformly accessible: adoption remains concentrated in intensive, well-resourced systems, and meaningful gaps persist in cost, interoperability, and applicability to extensive and smallholder production. Realising the full climate potential of PLF will require continued technological refinement alongside deliberate efforts to extend affordable, validated solutions to the full diversity of livestock systems that will need to adapt to, and help mitigate, a changing climate. In short, PLF's contribution to climate-smart livestock production should be judged jointly on its mitigation performance, its adaptation performance, and its accessibility across production systems and species—the same three axes used to structure this review.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/sci8090247/s1, Table S1. Summary of primary research articles and reviews cited in this manuscript, listing author(s), publication year, country/region of the study (where applicable), and the livestock species addressed. Sources marked "Multi-species/General" address more than one species group or are not species-specific (e.g., methodological, bibliometric, or cross-cutting reviews). Table S2. Approximate number of sources reviewed per livestock species group (a source addressing multiple species is counted once in each applicable row; general/methodological sources are counted separately).

Author Contributions: Conceptualization, V.G.P. and L.F.; methodology, V.G.P., A.P., I.V., Z.T. and G.I.P.; software, L.F.; validation, L.F., I.K., G.M. and G.I.P.; formal analysis, L.F., V.G.P., Z.T., I.K. and G.I.P.; investigation, L.F., G.I.P., I.K., G.M., Z.T. and V.G.P.; writing—original draft preparation, V.G.P., L.F., I.K., G.M. and G.I.P.; writing—review and editing, A.P., I.V. and V.G.P.; supervision, V.G.P., A.P. and I.V. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by "SUB1.1. Clusters of Research Excellence (CREs)" (O.P.S. code TA 5180519), is included in Subproject 1 of the Action "Promoting Quality, Innovation, and Extroversion in Universities" (Strategy for Excellence in Universities & Innovation—ID 16289) of the National Recovery and Resilience Plan "Greece 2.0." with the title "Study on the impact of heat stress on livestock: Adaptation and Mitigation/AdaMit-Livestock HS" and the under grant number 8289 of the Research Committee of the University of Thessaly.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: During the preparation of this manuscript/study, the authors used ChatGPT (OpenAI, GPT-4o, May 2024 version) for the purpose of creating the graphical abstract and Figures 1–7. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DMI	Dry matter intake
DSS	Decision-support system
DT	Digital Twin
FAO	Food and Agriculture Organization of the United Nations

FPCM	Fat- and protein-corrected milk
GHG	greenhouse gas
IMU	Inertial measurement unit
IoT	Internet of Things
PLF	Precision livestock farming
PUFA	Polyunsaturated fatty acid
RFID	Radio-frequency identification
TAC	Total antioxidant capacity
TBARS	Thiobarbituric Acid Reactive Substances
THI	temperature–humidity index
GPS	Global Positioning System
BLE	Bluetooth Low Energy
ADG	Average daily gain

References

1. United Nations, Department of Economic and Social Affairs, Population Division. *World Population Prospects 2022: Summary of Results*; UN DESA/POP/2022/TR/NO. 3; United Nations: New York, NY, USA, 2022.
2. Steinfeld, H.; Gerber, P.; Wassenaar, T.; Castel, V.; Rosales, M.; de Haan, C. *Livestock's Long Shadow: Environmental Issues and Options*; Food and Agriculture Organization of the United Nations: Rome, Italy, 2006.
3. Gerber, P.J.; Steinfeld, H.; Henderson, B.; Mottet, A.; Opio, C.; Dijkman, J.; Falcucci, A.; Tempio, G. *Tackling Climate Change Through Livestock: A Global Assessment of Emissions and Mitigation Opportunities*; Food and Agriculture Organization of the United Nations: Rome, Italy, 2013.
4. FAO. Livestock Solutions for Climate Change. Available online: https://www.fao.org/family-farming/detail/en/c/1634679/ (accessed on 12 July 2026).
5. FAO. *Pathways Towards Lower Emissions–A Global Assessment of the Greenhouse Gas Emissions and Mitigation Options from Livestock Agrifood Systems*; FAO: Rome, Italy, 2023. [CrossRef]
6. IPCC. Agriculture, Forestry and Other Land Uses (AFOLU). In *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Shukla, P.R., Skea, J., Slade, R., Al Khourdajie, A., van Diemen, R., McCollum, D., Pathak, M., Some, S., Vyas, P., Fradera, R., et al., Eds.; Cambridge University Press: Cambridge, UK, 2022; Chapter 7.
7. Berckmans, D. Precision livestock farming technologies for welfare management in intensive livestock systems. *Rev. Sci. Tech.* **2014**, *33*, 189–196. [CrossRef] [PubMed]
8. Bakir, M.E.; Perea, A.R.; Funk, M.; Rahman, S.; Spetter, M.J.; Macon, L.; Cox, A.; Estell, R.E.; Cao, H.; Cibils, A.F.; et al. A scalable, end-to-end IoT and remote sensing platform for precision rangeland and livestock management. *Comput. Electron. Agric.* **2026**, *247*, 111615. [CrossRef]
9. Marino, R.; Petrera, F.; Abeni, F. Scientific Productions on Precision Livestock Farming: An Overview of the Evolution and Current State of Research Based on a Bibliometric Analysis. *Animals* **2023**, *13*, 2280. [CrossRef]
10. Jiang, B.; Tang, W.; Cui, L.; Deng, X. Precision Livestock Farming Research: A Global Scientometric Review. *Animals* **2023**, *13*, 2096. [CrossRef] [PubMed]
11. Papakonstantinou, G.I.; Voulgarakis, N.; Terzidou, G.; Fotos, L.; Giamouri, E.; Papatsiros, V.G. Precision Livestock Farming Technology: Applications and Challenges of Animal Welfare and Climate Change. *Agriculture* **2024**, *14*, 620. [CrossRef]
12. Green, B.N.; Johnson, C.D.; Adams, A. Writing narrative literature reviews for peer-reviewed journals: Secrets of the trade. *J. Chiropr. Med.* **2006**, *5*, 101–117. [CrossRef] [PubMed]
13. McNicol, L.C.; Bowen, J.M.; Ferguson, H.J.; Dewhurst, R.J. Adoption of precision livestock farming technologies has the potential to mitigate greenhouse gas emissions from beef production. *Front. Sustain. Food Syst.* **2024**, *8*, 1414858. [CrossRef]
14. Dalmonte, T.; Barbieri, N.; Giacomozzi, S.; Palmonari, A.; Indio, V.; Vecchio, Y.; Guluzade, G.; Abdullayev, I.; Formigoni, A.; Serraino, A.; et al. Use of feed additives to reduce enteric methane emissions in dairy cattle: Meta-analysis of data retrieved through a systematic review. *Front. Anim. Sci.* **2025**, *6*, 1754069. [CrossRef]
15. Boré, R.; Bruder, T.; El Jabri, M.; March, M.; Hargreaves, P.R.; Rouillé, B.; Dewhurst, R.J.; Chagunda, M.G.G. Measurement Duration but Not Distance, Angle, and Neighbour-Proximity Affects Precision in Enteric Methane Emissions when Using the Laser Methane Detector Technique in Lactating Dairy Cows. *Animals* **2022**, *12*, 1295. [CrossRef] [PubMed]
16. Ghavi Hossein-Zadeh, N. Advancing climate-resilient livestock systems: Next-generation emission mitigation strategies and integrated technological innovations. *Vet. Anim. Sci.* **2026**, *31*, 100588. [CrossRef] [PubMed]

17. Brito, L.F.; Heringstad, B.; Klaas, I.C.; Schodl, K.; Cabrera, V.E.; Stygar, A.; Iwersen, M.; Haskell, M.J.; Stock, K.F.; Gengler, N.; et al. Invited review: Using data from sensors and other precision farming technologies to enhance the sustainability of dairy cattle breeding programs. *J. Dairy Sci.* **2025**, *108*, 10447–10474. [CrossRef] [PubMed]
18. Lamanna, M.; Bovo, M.; Cavallini, D. Wearable Collar Technologies for Dairy Cows: A Systematized Review of the Current Applications and Future Innovations in Precision Livestock Farming. *Animals* **2025**, *15*, 458. [CrossRef] [PubMed]
19. Neethirajan, S. Recent advances in wearable sensors for animal health management. *Sens. Bio-Sens. Res.* **2017**, *12*, 15–29. [CrossRef]
20. Gan, H. Computer Vision for Cattle Health and Welfare Monitoring: A Comprehensive Review of Methods, Applications, and Interdisciplinary Integration in Smart Agriculture. *Sensors* **2026**, *26*, 4271. [CrossRef] [PubMed]
21. Knight, C.H. Review: Sensor techniques in ruminants: More than fitness trackers. *Animal* **2020**, *14*, s187–s195. [CrossRef] [PubMed]
22. Halachmi, I.; Guarino, M.; Bewley, J.; Pastell, M. Smart Animal Agriculture: Application of Real-Time Sensors to Improve Animal Well-Being and Production. *Annu. Rev. Anim. Biosci.* **2019**, *7*, 403–425. [CrossRef]
23. Tedeschi, L.O.; Greenwood, P.L.; Halachmi, I. Advancements in sensor technology and decision support intelligent tools to assist smart livestock farming. *J. Anim. Sci.* **2021**, *99*, skab038. [CrossRef] [PubMed]
24. Bordignon, F.; Provolo, G.; Riva, E.; Caria, M.; Todde, G.; Sara, G.; Cesarini, F.; Grossi, G.; Vitali, A.; Lacetera, N.; et al. Smart technologies to improve the management and resilience to climate change of livestock housing: A systematic and critical review. *Ital. J. Anim. Sci.* **2025**, *24*, 376–392. [CrossRef]
25. McGinn, S.M.; Coulombe, J.-F.; Beauchemin, K.A. Technical note: Validation of the GreenFeed system for measuring enteric gas emissions from cattle. *J. Anim. Sci.* **2021**, *99*, skab046. [CrossRef] [PubMed]
26. Williams, T.; Wilson, C.; Wynn, P.; Costa, D. Opportunities for precision livestock management in the face of climate change: A focus on extensive systems. *Anim. Front.* **2021**, *11*, 63–70. [CrossRef] [PubMed]
27. Arulmozhi, E.; Deb, N.C.; Tamrakar, N.; Kang, D.-Y.; Kang, M.-Y.; Kook, J.; Basak, J.K.; Kim, H.-T. From Reality to Virtuality: Revolutionizing Livestock Farming Through Digital Twins. *Agriculture* **2024**, *14*, 2231. [CrossRef]
28. Papatsiros, V.G.; Chourdakis, E.; Tsegas, G.; Fotos, L.; Papakonstantinou, G.I.; Michailidou, A.V.; Gougoulis, D.; Dimoveli, K.; Stampinas, E.-G.; Meletis, E.; et al. Spatial Assessment of Livestock Heat Stress in Thessaly Region of Greece Using ERA5-Land Reanalysis and Temperature-Humidity Index. *Vet. Sci.* **2026**, *13*, 434. [CrossRef] [PubMed]
29. Tedeschi, L.O.; Abdalla, A.L.; Álvarez, C.; Anuga, S.W.; Arango, J.; Beauchemin, K.A.; Becquet, P.; Berndt, A.; Burns, R.; De Camillis, C.; et al. Quantification of methane emitted by ruminants: A review of methods. *J. Anim. Sci.* **2022**, *100*, skac197. [CrossRef] [PubMed]
30. Macdonald, A.; Shephard, R.; Hepworth, G.; Eckard, R. Understanding heterogeneity in methane emissions from confinement-fed dairy and beef cattle supplemented with Bovaer®: A meta-analysis. *Front. Anim. Sci.* **2025**, *6*, 1689264. [CrossRef]
31. Batley, R.J.; Romanzini, E.P.; da Silva, K.D.; de Souza, W.L.; Quigley, S.P.; Harper, K.J.; Trotter, M.G.; Bernardes, P.A.; Naiker, M.; Costa, D.F.A. The essential oil blend Agolin Ruminant L reduces methane production in vitro and in vivo when included in the drinking water of cattle. *J. Anim. Sci.* **2024**, *102*, skae315. [CrossRef] [PubMed]
32. de Souza, W.L.; Quigley, S.P.; Bates, A.L.; Batley, R.J.; Castro, M.A.O.; Gasparina, J.M.; Gillies, O.; Guerreiro, P.; Alvarez-Hess, P.S.; Auldist, M.J.; et al. A bromoform-based Investigational Veterinary Product reduced methane emissions and increased feed conversion efficiency of yearling steers when delivered via drinking water. *Anim. Feed Sci. Technol.* **2026**, *341*, 116823. [CrossRef]
33. Rivelli, I.; Hueso, R.; Müller, I.; Hoermansperger, J.; Gaytán-Pérez, I.; Kinderman, M.; Yáñez-Ruiz, D.R. Efficacy of 3-NOP applied in drinking water on enteric methane reduction in sheep. *Anim. Feed Sci. Technol.* **2025**, *327*, 116400. [CrossRef]
34. Kebreab, E.; Pressman, E.M.; Ramirez-Agudelo, J.-F.; Bannink, A.; van Gastelen, S.; Dijkstra, J. A meta-analysis of effects of seaweed and other bromoform-containing feed ingredients on methane production, yield, and intensity in cattle. *J. Dairy Sci.* **2025**, *108*, 11071–11093. [CrossRef] [PubMed]
35. Kaimakamis, I.; Fotos, L.; Papatsiros, V. Excellence Farms as Live Labs for Climate-Smart Skills in Dairy Goats: Integrating Digital Milk-Yield Data into Training Pathways. In Proceedings of the EAAP-ASAS Conference on Livestock Farming and the Environment: Emissions and Solutions, Book of Abstracts No. 40, Angra do Heroísmo, Terceira Island, Azores, Portugal, 19–21 April 2026; p. 35.
36. Moss, A.F.; Chrystal, P.V.; Cadogan, D.J.; Wilkinson, S.J.; Crowley, T.M.; Choct, M. Precision feeding and precision nutrition: A paradigm shift in broiler feed formulation? *Anim. Biosci.* **2021**, *34*, 354–362. [CrossRef] [PubMed]
37. Zuidhof, M.J.; Fedorak, M.V.; Ouellette, C.A.; Wenger, I.I. Precision feeding: Innovative management of broiler breeder feed intake and flock uniformity. *Poult. Sci.* **2017**, *96*, 2254–2263. [CrossRef] [PubMed]
38. Brassó, L.D.; Komlósi, I.; Várszegi, Z. Modern Technologies for Improving Broiler Production and Welfare: A Review. *Animals* **2025**, *15*, 493. [CrossRef] [PubMed]
39. Yan, X.; Ying, Y.; Li, K.; Zhang, Q.; Wang, K. A review of mitigation technologies and management strategies for greenhouse gas and air pollutant emissions in livestock production. *J. Environ. Manag.* **2024**, *352*, 120028. [CrossRef] [PubMed]

40. Ngwabie, N.M.; Kwe, J.N.; Mitin, S.Y.; Ngong, N.F. Direct measurement of greenhouse gas emission rates from manure management in different livestock production systems in Cameroon. *Greenh. Gases Sci. Technol.* **2025**, *15*, 102–110. [CrossRef]
41. Kadam, R. A Review on the Anaerobic Co-Digestion of Livestock Manures in the Context of Sustainable Waste Management. *Energies* **2024**, *17*, 546. [CrossRef]
42. Garner, J.B.; Douglas, M.L.; Williams, S.R.O.; Wales, W.J.; Marett, L.C.; Nguyen, T.T.T.; Reich, C.M.; Hayes, B.J. Genomic Selection Improves Heat Tolerance in Dairy Cattle. *Sci. Rep.* **2016**, *6*, 34114. [CrossRef] [PubMed]
43. Negri, R.; Daltro, D.S.; Kluska, S.; Otto, P.I.; Machado, M.A.; do Carmo Panetto, J.C.; Martins, M.F.; de Oliveira, H.R.; Cobuci, J.A.; da Silva, M.V.G.B. Genomic-enhanced breeding values for heat stress tolerance in Girolando cattle in Brazil. *Livest. Sci.* **2023**, *278*, 105360. [CrossRef]
44. Abdelrahman, M.; Wang, W.; Shaukat, A.; Kulyar, M.F.-A.; Lv, H.; Abulaiti, A.; Yao, Z.; Ahmad, M.J.; Liang, A.; Yang, L. Nutritional Modulation, Gut, and Omics Crosstalk in Ruminants. *Animals* **2022**, *12*, 997. [CrossRef] [PubMed]
45. Papatsiros, V.G.; Papakonstantinou, G.I.; Meletis, E.; Gougoulis, D.; Dimoveli, K.; Stampinas, E.-G.; Eliopoulos, C.; Fotos, L.; Polychronidou, N.; Arapoglou, D.; et al. Multilevel Effects of Heat Stress on Welfare, Physiology, Oxidative Status, and Productivity in a Commercial Farrow-to-Finish Pig Farm. *Agriculture* **2026**, *16*, 1498. [CrossRef]
46. Van Wettere, W.H.E.J.; Culley, S.; Swinbourne, A.M.F.; Leu, S.T.; Lee, S.J.; Weaver, A.C.; Kelly, J.M.; Walker, S.J.; Kleemann, D.O.; Thomas, D.S.; et al. Heat stress from current and predicted increases in temperature impairs lambing rates and birth weights in the Australian sheep flock. *Nat. Food* **2024**, *5*, 206–210. [CrossRef] [PubMed]
47. Oke, O.E.; Uyanga, V.A.; Oretomiloye, F.; Abioja, M.O. Editorial: Climate-Smart Livestock Production: Strategies for Enhanced Sustainability and Resilience. *Front. Vet. Sci.* **2025**, *12*, 1638289. [CrossRef] [PubMed]
48. Mangan, M.; Siwek, M. Strategies to combat heat stress in poultry production—A review. *J. Anim. Physiol. Anim. Nutr.* **2024**, *108*, 576–595. [CrossRef] [PubMed]
49. Golińska, B. Virtual Fencing Technology for Cattle Management in the Pasture Feeding System—A Review. *Agriculture* **2023**, *13*, 91. [CrossRef]
50. Bastos, K.M.; Barcelos, J.P.; Orioli, G.F.; Nascimento, S.T. Use of Drones for Trough Reading, Animal Counting, and Production Monitoring in Feedlot Systems. *AgriEngineering* **2024**, *6*, 4460–4475. [CrossRef]
51. Santos, W.M.d.; Martins, L.D.C.d.S.; Bezerra, A.C.; Souza, L.S.B.d.; Jardim, A.M.d.R.F.; Silva, M.V.d.; Souza, C.A.A.d.; Silva, T.G.F.d. Use of Unmanned Aerial Vehicles for Monitoring Pastures and Forages in Agricultural Sciences: A Systematic Review. *Drones* **2024**, *8*, 585. [CrossRef]
52. Mura, M.C.; Trimasse, O.; Carcangiu, V.; Luridiana, S. Precision Livestock Farming for Dairy Sheep: A Literature Review of IoT and Decision-Support Systems for Enhanced Management and Welfare. *AgriEngineering* **2026**, *8*, 58. [CrossRef]
53. Ciliberti, M.G.; Albenzio, M.; Sevi, A. From Sensors to Sustainability: Integrating Welfare, Management, and Climate Resilience in Small Ruminant Farm Systems. *Animals* **2025**, *15*, 3240. [CrossRef] [PubMed]
54. Kopler, I.; Marchaim, U.; Tikász, I.E.; Opaliński, S.; Kokin, E.; Mallinger, K.; Neubauer, T.; Gunnarsson, S.; Soerensen, C.; Phillips, C.J.C.; et al. Farmers' Perspectives of the Benefits and Risks in Precision Livestock Farming in the EU Pig and Poultry Sectors. *Animals* **2023**, *13*, 2868. [CrossRef] [PubMed]
55. Feng, X.; Kebreab, E. Net reductions in greenhouse gas emissions from feed additive use in California dairy cattle. *PLoS ONE* **2020**, *15*, e0234289. [CrossRef] [PubMed]
56. Neethirajan, S. The Significance and Ethics of Digital Livestock Farming. *AgriEngineering* **2023**, *5*, 488–505. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.