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# The Application of Remote Sensing Technology to Disease Surveillance and Animal Health

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Submitted in fulfilment of the requirements for the degree of Doctor of Philosophy (PhD)




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## Abstract

This thesis represents an interdisciplinary, mixed methods study which explores how remotely sensed data could contribute to the development of integrated early warning systems for production animal disease. In so doing, it examines the technical, methodological, and institutional considerations that could shape the assimilation of novel data into existing animal health surveillance frameworks. The introductory chapter lays the foundation of this endeavour with an extensive literature review of novel technologies and current animal health surveillance frameworks in Scotland, the rest of the UK, and beyond. Chapter 2 explores existing research regarding disease detection in livestock using infra-red thermography. Inconsistencies in parameter reporting among different studies are revealed together with a paucity of current research on the principal metric of 'emissivity'. Chapter 3 is concerned with the "journey" of animal disease data in the UK and, by way of a stakeholder consultation approach, identifies key frictions that emerge when considering integration of potential novel data from new technologies. Chapter 4 is a case study of one necessary component in the development of a novel integrated animal health system where drone-derived thermal imagery is analysed using machine learning to gauge its ability to detect livestock. This novel technology is found to show promise and recommendations are proposed for future study refinements in order to increase accuracy. The final discussion chapter synthesises findings across these three research fields to examine their broader implications for the integration of remote sensing technologies into veterinary surveillance frameworks.

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## Publications and Conference Presentations

McManus, Rosemary, Boden, Lisa, Weir, William , Viora, Lorenzo , Barker, Robert, Kim, Yunhyong , McBride, Pauline and Yang, Shufan (2022) 'Thermography for disease detection in livestock: a scoping review'. Frontiers in Veterinary Science, 9, 965622. (doi: 10.3389/fvets.2022.965622)

McManus, Rosemary, Boden, Lisa, Weir, William , Viora, Lorenzo , Barker, Robert, Kim, Yunhyong , McBride, Pauline and Yang, Shufan (2022). 'Thermography for Disease Detection in Livestock' [Poster Presentation] In: European College of Veterinary Public Health Annual Scientific Conference 2022, Athens, Greece, 28-30 September 2022.

McManus, Rosemary, Weir, William , Viora, Lorenzo , Barker, Robert, Kim, Yunhyong , McBride, Pauline , Yang, Shufan and Boden, Lisa (2022) 'Investigating Gaps For Novel Animal Health Surveillance Data Within Scotland'. [Oral Presentation] European Commission for control of foot-and-mouth disease (EUFMD) Open Session (OS22), Marseille, France, 26-28 October 2022.

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## Author's Declaration

"I declare that except where explicit reference is made to the contribution of others, this thesis is solely the result of my own work and does not include work presented for another degree at the University of Glasgow or any other institution."

Rosemary Furlong

February 2026

# List of Abbreviations

| | |
|---|---|
| AWS | Amazon Web Services |
| AAT | American Academy of Thermology |
| APHA | Animal and Plant Health Agency |
| AI | Artificial Intelligence |
| BPNN | Back Propagate Neural Net |
| BVLOS | Beyond Visual Line of Sight |
| BTv | Bluetongue |
| BRD | Bovine Respiratory Disease |
| BSE | Bovine Spongiform Encephalopathy |
| BVD | Bovine Viral Diarrhoea |
| CMT | California Mastitis Test |
| CTS | Cattle Tracing System |
| CVO | Chief Veterinary Officer |
| CAA | Civil Aviation Authority |
| CAP | Civil Aviation Publication |
| COCO | Common Objects in Context |
| CNN | Convolutional Neural Network |
| CPH | County Parish Holdings |
| DPIA | Data Protection Impact Assessment |
| Defra | Department for Environment, Food and Rural Affairs |
| DfT | Department for Transport |
| EWS | Early Warning System |
| EID | Electronic Identification |

| | |
|---|---|
| EPR | Electronic Patient Record |
| EPIC | Epidemiology, Population Health and Infectious Disease Control, Scotland's Centre of Expertise on Animal Disease Outbreaks |
| EC | European Commission |
| EEA | European Economic Area |
| ENISA | European Union Agency for Cybersecurity |
| FN | False Negative |
| FP | False Positive |
| FOV | Field-of-View |
| FAIR | Findable, Accessible, Interoperable and Reusable |
| FAO | Food and Agriculture Organisation of the United Nations |
| FMD | Foot and Mouth Disease |
| FLIR | Forward Looking Infra-Red (Brand Name) |
| GDPR | General Data Protection Regulation |
| HPA | Hypothalamic-Pituitary-Axis |
| ID | Identification |
| IMDRF | International Medical Device Regulators Forum |
| IR | Infra-Red |
| IRT | Infra-Red Thermography |
| iFOV | Instantaneous Field-of-View |
| ISO | International Organisation for Standardisation |
| IoU | Intersection Over Union |
| LLP | Limited Liability Partnership |
| LIS | Livestock Information Service |
| MHRA | Medicines and Healthcare products Regulatory Agency |
| ML | Machine Learning |

| | |
|---|---|
| mAP | Mean Average Precision |
| NPV | Negative Predictive Value |
| NIS | Network and Information Systems |
| NETD | Noise Equivalent Temperature Difference (Thermal Sensitivity) |
| NMS | Non-Maximum Suppression |
| NDVI | Normalised Difference Vegetation Index |
| PI | Persistently Infected |
| PRIMO | Pig Records, Identification and Movement Order |
| PPV | Positive Predictive Value |
| PLEWS | Predictive Livestock Early Warning System |
| PwC | PricewaterhouseCoopers |
| QMS | Quality Meat Scotland |
| RFID | Radio Frequency Identifier |
| RF | Random Forest |
| RTK | Real-Time Kinematics-enabled |
| RGB | Red-Green-Blue |
| ROI | Region of Interest |
| RVF | Rift Valley Fever |
| SRUC | Scotland's Rural College |
| SAOS | Scottish Agricultural Organisation Society |
| ScotEID | Scottish Electronic Identification Livestock Traceability Research |
| IACS | Scottish Integrated Administration and Control System |
| SAVSNET | Small Animal Veterinary Surveillance Network |
| SDLC | Software Development Life Cycle |
| SEGs | Species Expert Groups |

| | |
|---|---|
| SI | Statutory Instrument |
| SVR | Support Vector Regression |
| SEDA | Surveillance Epidemiology and Data Analysis |
| SIU | Surveillance Intelligence Unit |
| TIR | Thermal Infra-Red |
| TN | True Negative |
| TP | True Positive |
| UKSF | United Kingdom Surveillance Forum |
| UAV | Unmanned Aerial Vehicle |
| VI | Veterinary Inspector |
| VLO | Visible Light (Optical) |
| WHO | World Health Organisation |
| WOAH | World Organisation for Animal Health |
| YOLO | You Only Look Once |

# 1 Introduction

## 1.1 Background

The World Organisation for Animal Health (WOAH) defines the aims of animal health surveillance as “demonstrating the absence of infection or infestation, determining the presence or distribution of infection or infestation or detecting as early as possible exotic diseases or emerging diseases” (WOAH, 2022). Surveillance consists of a set of tools for facilitating infection or infestation control, monitoring disease trends, providing data for use in animal and public health risk analysis, substantiating the rationale for sanitary measures and providing assurances to trading partners. Choice of surveillance method depends on objective, available data and outputs required for informed decision-making (WOAH, 2022). Many types of surveillance exist, encompassing elements of early warning surveillance (veterinary scanning surveillance, horizon scanning and monitoring of international disease), risk-based targeted ('active') surveillance and surveillance for determining freedom of disease at country level (UK Surveillance Forum, 2019). Surveillance may be conducted through active or passive systems and may be directed at specific diseases or, in the case of syndromic or event-based surveillance, at broader indicators of health and disease, while monitoring describes ongoing efforts aimed at assessing the overall health and disease status of a given population. Together they aim to assess disease prevalence or incidence and describe changes over time. They can detect potential sources of infection and act as early warning systems for the new introduction or re-emergence of a disease. They are also critical for demonstrating disease freedom for notifiable diseases (those which are reportable to government authorities by law, due to their potential detrimental effects on humans, animals and trade). Definitions of surveillance vary across organisations and authors, particularly regarding the relationship between surveillance and monitoring (UK Surveillance Forum, 2019; WOAH, 2022; Thrusfield, 2004). For the purposes of this thesis, the UK Surveillance Forum definition of surveillance is adopted as the “systematic, continuous or repeated measurement, collection, collation, analysis, interpretation and timely dissemination of animal health and welfare related data from defined populations” (UK Surveillance Forum, 2019). This definition was selected

because it reflects the UK veterinary surveillance and regulatory context within which this research was conducted.

A distinction must be made between syndromic surveillance, diagnostic surveillance, and monitoring or management tools. Syndromic surveillance refers to the collection and analysis of non-specific indicators of health or disease that may provide early warning of emerging disease events prior to formal diagnosis. Diagnostic surveillance is concerned with confirming the presence or absence of specific diseases or pathogens, typically through clinical investigation or laboratory testing. Monitoring or management tools are primarily designed to support ongoing assessment, optimisation, or management of animal health and production, although such tools may also contribute data relevant to surveillance activities. This work focuses primarily on syndromic surveillance, but developed tools could also be used for monitoring and management purposes. Syndromic surveillance (sometimes used synonymously with early warning surveillance) seeks to collect, analyse and interpret the magnitude, distribution and temporal attributes of possible outbreaks, to monitor disease trends and to provide feedback to those charged with investigation and follow-up of outbreaks to enable decision-making on courses of action (Henning, 2004). It has been suggested that syndromic surveillance systems will encourage and enhance collaboration among public health bodies, academic researchers, health-care providers, information-system professionals and industry, but that stakeholders should be made aware of both the limitations and advantages of syndromic surveillance systems (Henning, 2004). A 2017 paper identified real-time data collection on animal health as one of three major gaps in animal health surveillance (Meidenbauer, 2017) and a 2020 report by the Scottish Agriculture and Rural Economy Directorate predicted that the potential of available and emerging technologies was one of three expected future challenges and opportunities within Scotland with respect to delivery of services concerning animal health and welfare (Scottish Government, 2020).

The increasing emphasis on real-time and data-driven surveillance has prompted growing interest in technologies capable of supporting rapid, scalable, and non-invasive animal health data collection. Remote sensing, defined as “the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object,

area, or phenomenon under investigation", has emerged as one such approach (Lillesand & Kiefer, 2015). Remote sensing may be conducted using a range of sensing platforms and approaches, from satellite systems to proximal sensing technologies operating at much smaller spatial scales. This definition encompasses both UAV-mounted and stationary cameras, including those used for non-contact sensing at short distances from animals (proximal sensing). In this thesis, particular focus is placed on UAV-acquired thermal imagery and machine learning approaches for image analysis as tools to support animal health surveillance. This technology was chosen because UAVs offer the ability to rapidly capture high-resolution imagery of individual animals across large or difficult-to-access areas, while thermal imaging enables non-invasive assessment of physiological changes potentially associated with disease. Thermal imagery also produces relatively smaller datasets than some alternative imaging modalities, supporting more rapid processing and near-real-time analysis. Machine learning approaches further facilitate rapid interpretation of image data, increasing the potential scalability of such systems within surveillance contexts.

However, careful consideration must be given to resulting legal, ethical and social impacts of the use of such technologies. The pace of technological evolution currently outstrips that of its governing legal and ethical policies. Thus, there is an urgent need for regulatory frameworks to be modernised to allow new technologies to be exploited to improve animal health.

This introduction provides a background for this thesis by reviewing existing surveillance systems in the first section, identifying and exploring relevant technology in the second section and examining some of the ethical and social questions that an integrated real-time animal health surveillance system would posit in the final section. The thesis is presented as a series of interrelated studies that collectively examine the role of emerging technologies in animal health surveillance. While each chapter addresses a distinct research question, they are unified by a common objective: to evaluate how remotely sensed data, and in particular UAV-derived thermal imagery, can contribute to animal health surveillance systems.

The structure of the thesis follows a logical progression from conceptual and evidential grounding to applied investigation. Chapter 2 synthesises existing

literature to identify current capabilities and limitations of infrared thermography for disease detection in animals. Chapter 3 examines how animal health data are generated, interpreted and utilised within existing surveillance systems, with a particular focus on stakeholder perspectives and data flows. The chapter then explores how novel data might function within the current surveillance system in the event of an outbreak of foot and mouth disease. Chapter 4 then builds on these insights to evaluate the technical feasibility of UAV-based thermal imaging combined with machine learning approaches for livestock detection in the field. Together, these studies provide a multi-layered assessment of the opportunities and constraints associated with integrating remote sensing technologies into animal health surveillance.

Tables 1-1 and 1-2 summarise the principal technical terms used in this chapter. These are explained further, with supporting references, in the relevant sections.

**Table 1-1.** Surveillance and evaluation terms used in Chapter 1.

| Term | Meaning |
|---|---|
| Animal health surveillance | Systematic, continuous or repeated measurement, collection, collation, analysis, interpretation and timely dissemination of animal health and welfare data from defined populations (UK Surveillance Forum, 2019). |
| Syndromic surveillance | Collection and analysis of non-specific indicators of health or disease that may provide early warning before a specific diagnosis is established. |
| Diagnostic surveillance | Surveillance concerned with identifying specific diseases or pathogens through clinical investigation or diagnostic testing. |
| Monitoring and management tools | Tools supporting ongoing assessment and management of animal health or production. Their outputs may also contribute to surveillance. |
| Surveillance pipeline | The linked stages through which data are acquired, processed, analysed, interpreted, and communicated to inform action. |
| Ground-truthing | Obtaining independent reference observations of the animals or conditions being studied, against which sensor measurements or model outputs can be assessed. |
| Validation | Assessing whether a measurement method, model or system performs adequately for its intended purpose. |
| Diagnostic sensitivity | The proportion of animals with the target disease or condition that test positive. |
| Diagnostic specificity | The proportion of animals without the target disease or condition that test negative. |

**Table 1-2.** Sensing and computational terms used in Chapter 1.

| Term | Meaning |
|---|---|
| Remote sensing | Obtaining information about an object, area or phenomenon using a device that is not in direct contact with it. |
| Proximal sensing | Sensing at short distances from the target, including stationary cameras used for non-contact observation of animals. |
| Unmanned aerial vehicle (UAV) | An aircraft operated without an onboard pilot; also referred to as a drone. |
| Infrared thermography | Imaging infrared radiation to represent thermal patterns across a surface. |
| Thermogram | An image produced by a thermal camera that represents the spatial distribution of detected infrared radiation or derived apparent surface temperatures. |
| Emissivity | The efficiency with which a surface emits thermal radiation relative to a blackbody under equivalent conditions. |
| Artificial intelligence (AI) | The broader field concerned with computational systems capable of tasks such as perception, reasoning and learning. |
| Machine learning (ML) | A subfield of AI in which models learn patterns from data to generate predictions, classifications or other outputs. |

## 1.2 Existing Surveillance Systems

The act of disease detection is part of a larger animal health governance system in which there is coordination of and communication between local, national and international stakeholders. In a world of finite resources, which diseases are important to detect, by whom, when, and why? At an international level, the WOAH is responsible for the list of “notifiable” diseases (along with other emerging diseases) which are diseases that have the potential to seriously impact human and animal health. The organisation aims to safeguard world trade by publishing health standards for international trade in animals and animal products. Diseases are classified as notifiable by WOAH when they have the capacity to cause significant impacts to livestock and public health and could adversely affect wildlife conservation. Diseases can be further categorised as endemic or exotic; endemic diseases are those that are consistently present in a country or geographical area while exotic diseases are not known to be

present in a country or defined geographical area. In England and Wales, for instance, bovine tuberculosis (bTB) is considered endemic whereas foot and mouth disease (FMD) is classed as exotic throughout the United Kingdom (UK).

Animal health surveillance is overseen by the UK Surveillance Forum (UKSF), which comprises the Chief Veterinary Officers and policy leads from all four administrations (England, Wales, Scotland and Northern Ireland). At the UK level, the Animal and Plant Health Agency (APHA) is responsible for disease surveillance to identify new and re-emerging threats to animal and public health under the direction of the Department for Environment, Food and Rural Affairs (Defra**),** while surveillance policy and delivery are devolved in Scotland and Northern Ireland. This is achieved through a combination of statutory and scanning surveillance activities. Statutory surveillance is the monitoring and collection of notifiable and reportable disease information while scanning surveillance consists of voluntary submission and collection of information arising from diagnostic investigations, including those initiated by private veterinary surgeons (UK Government, 2025). This surveillance allows the APHA to characterise disease threats, assess risk to animal health and welfare, public health, and international trade, and to communicate with government and industry to foster decision-making on appropriate actions. Disease surveillance is implemented across several animal sectors, including equine, livestock, wildlife, and companion animal surveillance. With regard to livestock, the APHA collects data from diagnostic testing and post-mortem examinations of farm animals and, through its national network, provides advice and support to veterinary surgeons to diagnose, control, and prevent disease. The national network comprises Veterinary Investigation Centres in England and Wales, independent surveillance pathology partners (providing post-mortem examination services under contract), and APHA Lasswade, which provides a specialist poultry service. In Scotland, animal disease surveillance is performed by Scotland's Rural College (SRUC) Veterinary Services under the Scottish Government’s Veterinary Services Programme. However, in the event of the occurrence of a notifiable disease, the operational investigation of affected premises and livestock is led by the APHA. APHA surveillance data are analysed by the Surveillance Intelligence Unit (SIU), which manages veterinary scanning surveillance activities at APHA, with surveillance outputs produced alongside data from SRUC Veterinary Services.

The SIU consists of the Species Expert Groups (SEGs) and the Surveillance Epidemiology and Data Analysis (SEDA) team.

The detection or suspicion of notifiable disease is legally required to be reported to the competent national authorities. When there is a suspicion of a notifiable disease in Scotland, it must be reported to the APHA duty veterinary officer according to the notifiable disease pathway, triggering a visit to the premises by an APHA veterinary inspector (VI). If disease cannot be ruled out, samples will be obtained by the VI and submitted to an appropriate National Reference Laboratory for the suspected disease. An APHA official will serve a legal notice to the livestock keeper outlining restrictions on animal, person and vehicular movements. Verbal notice may be supplied prior to a written notice to the livestock keeper. Local authorities may also be involved in compliance monitoring and enforcement of disease controls as part of the multi-agency response. If, following investigation, a notifiable disease is no longer suspected by the VI, restrictions may be lifted. For certain notifiable diseases, such as avian influenza and FMD, statutory disease control zones are imposed around affected premises, typically including a 3 km protection zone and a wider surveillance zone of at least 10 km, to prevent disease spread.

### 1.3 Information technology enabled animal health surveillance

Modern technology is already applied to many aspects of veterinary surveillance. From wearable devices in precision livestock farming (Neethirajan, 2017) to mapping of vector habitats with drones and satellites (Polo, Labruna and Ferreira, 2015; Carrasco-Escobar *et al.*, 2019) and the use of "Big Data" analytical techniques to inform disease prevalence as carried out by the Small Animal Veterinary Surveillance Network (SAVSNET), the industry is already embracing new technologies, but there are further possibilities that are yet to be developed. SAVSNET, a surveillance system established in the UK to monitor the small animal vet-visiting population, is being used to analyse data concerning disease prevalence, drug use and antimicrobial resistance. Passive surveillance studies concerning zoonotic pathogens like ticks within the UK have been undertaken using this system (Tulloch *et al.*, 2017). These data can then be cross-referenced with the occurrence of tick-borne diseases, such as borreliosis (Lyme disease), in both humans and animals. Other UK initiatives, such as

VetCompass, also use primary-care veterinary data to characterise disease prevalence and risk factors in companion animals.

### 1.4 Future animal health surveillance systems

In a rapidly changing and increasingly automated world, there exists an immense opportunity to harness available technology to optimise both human and animal health. Given that 'animal health surveillance is necessary to protect human and animal health, rural economies and the environment from the consequences of large-scale disease outbreaks' (Boden *et al.*, 2017), it follows that we should develop and integrate technologies that will enhance animal health. Technology is poised to play a pivotal role in future surveillance. Researchers worldwide are endeavouring to develop real-time Early Warning Systems (EWS) for disease outbreaks (Dórea, Sanchez and Revie, 2011; Perez *et al.*, 2011; Thompson *et al.*, 2016). In the US, a centralised animal disease surveillance platform has been proposed which would have the capacity to collect, analyse, and integrate multiple data streams with subsequent communication to end-users (Thompson *et al.*, 2016). The system is not intended to be disease specific and would instead establish baseline animal health information, alerting veterinary services to anomalies potentially indicative of disease outbreaks and to changes in trends of endemic disease (Thompson *et al.*, 2016). There is also ongoing research into weather-driven EWS that can enable prediction of climatic conditions that are drivers for both human and animal disease outbreaks (Morin *et al.*, 2018). As far back as 2011, there have been calls for improved EWS with real-time applications that can directly inform policy-and-response decision-making (Dórea, Sanchez and Revie, 2011; Perez *et al.*, 2011; Dórea and Vial, 2016).

In Scotland, livestock animal health surveillance is implemented using a combination of passive surveillance, abattoir-based recording of disease and active surveillance for specific pathogens or diseases, such as *Trichinella spiralis* and Bovine Viral Diarrhoea. Surveillance is undertaken via multiple pathways and by various actors with relatively little integration between systems (Boden *et al.*, 2017). Participants in a scenario planning workshop run by the Centre of Expertise on Animal Disease Outbreaks (EPIC Scotland), outlined three possible strategic visions for the future of animal health surveillance in Scotland (Boden *et al.*, 2017). All three visions ("Smart Data", "Smart Investments" and "Smart Users") reference technology in some shape or form, including (i) data collection

by remote sensing; (ii) investment in technology and surveillance; and (iii) ways to improve digital literacy and disease expertise for end-users, such as farmers and veterinary staff. However, all aspects of the application of new technologies within the veterinary sphere should be carefully weighed and considered before new large-scale systems are deployed. In a 2018 report commissioned by the World Economic Forum, aspects of how to utilise emerging technologies were discussed and analysed to explore possible outcomes, both beneficial and detrimental (World Economic Forum, 2018). The report detailed artificial intelligence (AI) "game changers" for the earth, speculating on the future possibilities of autonomous systems, smart agriculture, and the more distant possibility of completely autonomous farming and an end-to-end optimised food system. Potential downsides of relying on AI were also discussed, with the authors identifying risks relating to performance, security, control, ethics, economics, and society.

The creation of a real-time animal health monitoring system utilising thermal sensors that identifies illness in livestock would have the potential to vastly improve the ability to respond to both endemic and exotic disease. It is suspected that 75% of emerging disease threats are zoonotic (WHO, FAO and WOAH, 2006) which reinforces the need for interdisciplinary research spanning many fields, including medicine, epidemiology, veterinary medicine and engineering, in order to create viable public health solutions. Bartlow *et al.* (2019) identify "three major challenges in achieving the scientific and technological advances made in weather forecasting and transferring them into disease forecasting": data availability, human behaviour, and funding (Bartlow *et al.*, 2019). Regarding data availability, the authors comment that there is a lack of real-time ground truth data to inform disease forecasting models. They go on to say that to advance disease forecasting ability, billions of sensors around the world collecting and uploading real-time information would be required to feed into forecasting models. An article reviewing advances in wearable sensors for animal health management states the necessity to integrate all available sensors (i.e. image-detection techniques, microfluidics, and serodiagnosis etc.) to create an efficient online system that can monitor animal health status in real time (Neethirajan, 2017). The practical value of such systems depends not only on technical feasibility, but also on appropriate

ground-truthing, validation against relevant disease or health outcomes, and consideration of how outputs would be integrated into existing surveillance workflows.

The development of remote sensing approaches for animal health surveillance can be conceptualised as a pipeline from risk identification through to surveillance action. In a fully implemented system, predictive risk signals, such as climatic or environmental indicators, may first be used to identify locations or populations where disease risk is elevated. These signals may then inform targeted deployment of sensing technologies, such as UAV-mounted sensors. Data acquisition involves the capture of relevant imagery or sensor data, including thermal imagery. Detection and processing then convert raw data into interpretable outputs, for example through machine learning-based animal detection or tracking. Finally, interpretation and action involve assessing whether these outputs provide meaningful syndromic or surveillance-relevant information and determining whether further investigation, intervention, or policy response is required.

This thesis focuses on selected stages of this wider pipeline. It does not evaluate the first stage, predictive risk signal generation, although this stage provides the wider rationale for targeted deployment of sensing technologies. The thesis addresses targeted deployment conceptually by considering UAV-mounted sensing as a potential means of collecting animal-level data in relevant locations. It addresses data acquisition through the review of infrared thermography in Chapter 2 and the collection of UAV-acquired thermal imagery in Chapter 4. It addresses detection and processing directly in Chapter 4 through machine learning-based livestock detection. It addresses interpretation and action at a systems level in Chapter 3, which examines how novel data outputs might be integrated into existing surveillance workflows and decision-making structures, and in Chapter 5, which synthesises the implications for governance, validation, implementation, and human oversight. The thesis therefore does not attempt to deliver a complete operational surveillance system, but instead evaluates key technical, methodological, and institutional components required for such a system to be developed.

## 1.5 Relevant technology

Remotely sensed imagery could be highly valuable in veterinary epidemiology, particularly for risk forecasting and early warning, where disease surveillance, epidemiological analysis, and case reporting are key activities (Martin *et al.*, 2007). For instance, Rift Valley Fever (RVF) is associated with elevated rainfall over areas of Africa endemic for the disease. Using satellite measurements of global and regional elevated sea surface temperatures, elevated rainfall, and satellite derived-normalised difference vegetation index data, researchers correctly predicted areas where outbreaks of RVF in animals and humans were expected (Anyamba *et al.*, 2010). Another example is the Predictive Livestock Early Warning System (PLEWS) which is supplied with remotely-sensed imagery to evaluate the possibility of drought occurrence in Kenya. Drought affects both human populations and their livestock and can result in conflict, displacement, severe food insecurity, increased poverty and the deaths of hundreds of animals due to lack of forage and water.

Other sensing approaches offer complementary information for animal health surveillance. Multispectral imaging records information in several selected spectral bands, whereas hyperspectral imaging records many narrow, contiguous bands, providing more detailed spectral information. These approaches can support environmental characterisation and identification of potential disease-vector habitats, contributing to the risk-identification stage of the surveillance pipeline (Polo, Labruna and Ferreira, 2015; Carrasco-Escobar et al., 2019). Thermal imaging instead captures emitted infrared radiation, providing information about surface-temperature patterns and thermal contrast. The suitability of these approaches therefore depends on the information required and the stage of the surveillance pipeline being addressed.

Wearable and on-animal sensors can provide repeated measurements of individual animals, including behavioural and physiological indicators relevant to health monitoring (Neethirajan, 2017). Unlike UAV-mounted cameras, these systems require devices to be fitted to individual animals, but can support monitoring between aerial surveys and link observations to the same animal over time. They are therefore relevant to the wider surveillance system, although they fall outside the UAV-based experimental scope of this project.

The project was established to explore UAV-based sensing for animal health surveillance, with hyperspectral imaging initially envisaged. However, the availability, payload requirements and cost of suitable hyperspectral equipment constrained its feasibility within the project. Thermal imaging was taken forward as a practicable approach with potential relevance to animal health assessment, informed by the existing thermography literature. The experimental work subsequently focused on animal detection using thermal contrast, as explained in Chapter 4. Other spectral approaches and wearable systems are consequently considered as complementary technologies rather than evaluated experimentally in this thesis.

### 1.5.1 Unmanned aerial vehicles

Much of remote sensing to date has been carried out using satellites, but in recent years there has been an increase in the use of unmanned aerial vehicles (UAVs or drones) by both commercial and recreational pilots (House of Commons Science and Technology Committee, 2019). There is considerable potential for UAV use in this context as a tool to safeguard public health, sustain livestock production and trade in both developed and developing nations when the capture of real-time data is necessary. They enable access into areas which are difficult to reach, creating safer operational conditions by removing the need to place people in potentially dangerous situations, such as rescue operations and building inspections. Thus, UAVs have the potential to provide us with up-to-date information within a very short space of time, for instance, in an outbreak situation.

UAVs were originally developed for military purposes but are now being used extensively by civilians for both leisure and commercial reasons (House of Commons Science and Technology Committee, 2019) and hence, their use in scientific research projects for data collection has been increasing.

In the field of epidemiology, research groups are using remotely sensed imagery to visualise wildlife and their habitats (Barasona *et al.*, 2014; Hodgson *et al.*, 2016) or to estimate vector habitats (Polo, Labruna and Ferreira, 2015; Carrasco-Escobar *et al.*, 2019). Drones have also been identified as potential vehicles for control of zoonotic diseases, delivering anthelminthics to wild carnivores in inaccessible areas in order to reduce incidence of echinococcosis in humans (Yu *et al.*, 2017; Yu, Liu and Xiao, 2018). Drones offer some advantages over

satellites since they are less likely to be hindered by clouds, they can fly below high cloud cover and flight plans can be altered more readily if adverse weather conditions occur. They are relatively inexpensive and have the ability to collect detailed spatial information in real time, providing better image resolution than satellites due to proximity to the earth (Fornace *et al.*, 2014; Bansod *et al.*, 2017; Dlamini *et al.*, 2019). Fornace *et al.* (2014) examined their potential in mapping infectious diseases and found they can provide data that is critical in understanding the links between the environment and disease transmission. However, the authors went on to say that they would augment, rather than replace, existing remote sensing methods, such as satellite, due to the time and resources required for large-scale geographical data collection. The authors opined that UAVs do not possess the spectral resolution of most satellite data, but that this would likely change in the future, as technology and sensors evolve. Recognised disadvantages of drone use are the limited battery life and, consequentially, the short flight times. Moreover, multiple cameras are required for data collection, the extra weight further reduces flight time.

### 1.5.2 Thermal imaging systems

Thermography is the science concerned with infrared (IR) imaging. IR sensors detect radiation in the infrared range of the electromagnetic spectrum and produce images called thermograms. Imaging systems work by capturing ranges of wavelengths through sensors. The amount and amplitude of the range, as well as quality and quantity of sensors, vary in different systems. While the visible light range (0.38μm to 0.7μm) can be captured by 'common' cameras, capturing ultra-violet (0.01 μm – 0.38 μm) and infra-red (0.7 μm – 15 μm) wavelengths require special sensors. The amount of radiation emitted by an object increases with temperature, allowing variations in temperature to be detected with this technology.

Thermal cameras typically detect radiation within the long-wave infrared (LWIR) range of approximately 7–14 μm, which corresponds to thermal emission from objects at typical environmental and biological temperatures. Data from sensors can be translated into representative images of the emission intensity. A thermal camera consists of several core components: an infrared-transmitting optical system, a detector, signal processing electronics, and a display or digital output. The lens focuses incoming infrared radiation onto the detector. In many field-

deployable and UAV-mounted thermal cameras, the detector is an uncooled microbolometer array, in which each pixel absorbs infrared radiation and undergoes a change in electrical resistance proportional to the incident radiation. This detector response is converted into an electrical signal and processed to generate a thermogram, in which pixel values represent apparent surface temperature patterns. This system is outlined graphically in Figure 1-1. Cooled thermal cameras may instead use cryogenically cooled photon detectors, such as indium antimonide or mercury cadmium telluride detectors, which offer higher sensitivity but are typically more expensive and less practical for routine field deployment. The accuracy of the resulting thermogram depends not only on the camera components, but also on factors such as emissivity (the efficiency with which a surface emits infrared radiation), distance from the target, ambient temperature, humidity, wind, solar radiation, and the angle of observation.

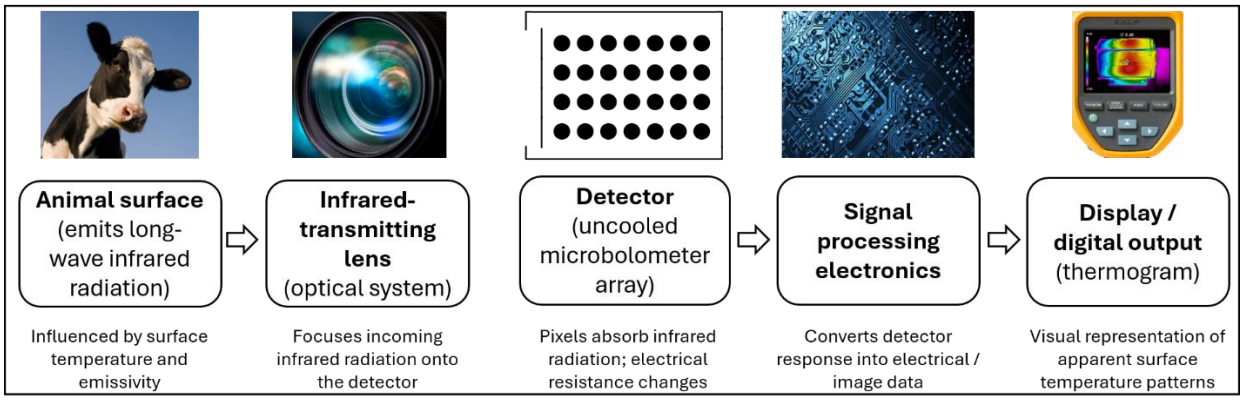



**Figure 1-1.** Simplified schematic of thermal image formation in an uncooled thermal camera. Long-wave infrared radiation emitted from the animal surface is focused by the infrared-transmitting optical system onto a detector, commonly an uncooled microbolometer array in field-deployable systems. The detector response is converted by signal processing electronics into a thermogram representing apparent surface temperature patterns. Schematic images are stock images sourced from Microsoft 365 via PowerPoint.

Current uses of thermal systems within the veterinary and medical sphere are within food production, surgery and cancer diagnosis. The use of IR imagery (correlating IR intensity with temperature) has been in development for the detection of diseases affecting the hoof (Nikkhah *et al.*, 2005; Rainwater-Lovett *et al.*, 2009; Alsaaod *et al.*, 2014) and udder (Berry *et al.*, 2003; Polat *et al.*,

2010; Pezeshki *et al.*, 2011; Sathiyabarathi *et al.*, 2018) in cattle. There have also been several studies investigating orbital temperature for correlation with fever using IR sensors in cattle (Schaefer *et al.*, 2004, 2007, 2012) to ascertain its feasibility and accuracy for disease detection, thereby potentially reducing the need for use of a *per rectum* thermometer.

### 1.5.3 Artificial intelligence: machine learning for image processing

Artificial intelligence (AI) is a broad field concerned with the development of computational systems capable of perceiving, reasoning, learning, and acting. Machine learning (ML) is a subfield of AI concerned with methods that improve performance based on experience (Russell and Norvig, 2021). In an applied context, this commonly involves algorithms learning patterns from data to generate predictions, classifications, or other outputs without being explicitly programmed for each decision. In this thesis, ML is the term used specifically for the image analysis approaches applied in Chapter 4, while AI is used when referring to the wider system-level context in which such approaches may be deployed, including automation, decision support, interpretability, governance, and human oversight.

A mathematical model is built on sample data which is used to "train" the ML system which can then extract forecasts or inferences without being explicitly programmed to do so. Such models may be predictive (predicting outcomes), descriptive (describing real-world events and the relationships between factors responsible for them) or both, and can perform tasks in real-time. Researchers have been using ML algorithms since 1988. However, with the enhanced performance of cameras in the past decades, its use has expanded for image processing. In livestock agriculture, it has many applications, such as analysing facial expressions in sheep to detect pain (McLennan and Mahmoud, 2019) and for on-farm recognition of pigs (Hansen *et al.*, 2018; Wang, Liu and Xiao, 2018). Moreover, Valletta *et al.* describe the use of ML applied in animal behaviour analysis (Valletta *et al.*, 2017). The use of this technology clearly has great potential to increase animal welfare for production animals.

An example of ML being used as an on-farm early warning system for mastitis detection in cattle is the EU-funded AGRICAM project (Agricam AB, n.d.). The system is a patented thermal imaging system called "CaDDi Mastitis" (Cattle Disease Diagnostics). It measures and analyses the temperature of the udder of

individual cows as they come in for milking via two thermal cameras positioned on either side of the animal that can detect heat changes in the udder prior to clinical signs of mastitis developing. The system 'learns' what is normal for each individual cow over time, using the cow's Radio Frequency Identifier (RFID) ear tag as an identifier. When heat changes are detected which are considered abnormal for a particular cow, the system automatically alerts staff to the possibility of mastitis.

While ML plays a pivotal role in translating complex datasets into scientific knowledge, there is a central dilemma concerning its use: if we cannot extract understanding from the decision process of a ML, we have little information on the possible inherent failures from its training or underlying structure. This is typically observed in problems due to overtraining (Amari *et al.*, 1997). Moreover, algorithms mine for patterns in data that are best at predicting an outcome and these patterns can sometimes differ from important subjective aspects easily perceived by humans (Valletta *et al.*, 2017). That said, they offer a tangible method to improve animal disease surveillance which has been limited by the lack of information systems enabling real-time data capture, sharing, analysis, and related decision- and policy-making (Perez *et al.*, 2011).

### 1.6 Social, ethical and legal implications

Evolving technologies raise novel social and legal dilemmas, requiring policy responses to guarantee the harmonic and productive use of technology. Surveillance, in particular, raises important questions concerning law, policy and data. There are likely to be many challenges associated with implementing UAV-based surveillance systems: the cost of operation and hardware, government legislation and industry regulation, safety, security and the complex data processing required (Bansod *et al.*, 2017). UAVs appear to be one of the most promising types of novel technology for surveillance. However, the drone industry is becoming highly regulated with many legal changes in the UK in the last few years, essentially catching up with the increased usage in both commercial and recreational fields (Haylen, 2019). The Drone Code, which is derived from CAP 2320 (Civil Aviation Publication 2320), was introduced by the Civil Aviation Authority to assist drone users in operating safely and in compliance with UK aviation law (Civil Aviation Authority, 2022). The CAA is an independent statutory body responsible for regulating civil aircraft including

UAVs. Drone policy and legislation are primarily the responsibility of the UK Government, through the Department for Transport (DfT). The DfT have conducted two consultations since 2016 covering various aspects of drone policy. Several proposals, including new operating restrictions and a registration scheme, were introduced in November 2019 (Haylen, 2019). Drones made the headlines following the disruption caused in December 2018 when Gatwick Airport was shut down after several reported drone sightings (Haylen, 2019). The disruption affected 140,000 passengers and 1,000 flights and cost Gatwick airport an estimated £1.4 million, with even higher costs being incurred by airlines. Safety is another concern. A near miss incident between two aircraft in the sky is termed an 'airprox' and this can be reported by either pilot involved or by an air traffic control witness. These incidents are reported to the UK Airprox Board which then issues a report to mitigate for future occurrences. In 2018, 319 airprox were assessed by the board, of which 125 were identified as drones by the reporting pilot (UK Airprox Board, 2019). Perceived benefits of increasing UAV use include the disruption of industries and stimulation of economic growth. A May 2016 report from PwC (PricewaterhouseCoopers) revealed that commercial drone usage could lead to disruption in $127 billion of traditional industries, while global spending on the production of drones for both commercial and military use is projected to reach $93 billion in the next ten years (PwC, 2016). A subsequent report from PwC revealed that the economic and social benefits of UAVs in the UK by 2030 may represent up to £16 billion in net cost savings and an addition of £42 billion to the Gross Domestic Product, with over 600,000 jobs in the drone sector (PwC, 2018). The report predicts that there will be in excess of 76,000 drones flying over the UK, with this number split across several different industries.

According to the results of a public survey undertaken in the UK in 2018, public understanding of AI is “broad” but not “deep” (Bristows LLP, 2018). Written evidence submitted to the House of Lords Select Committee emphasises “the importance of public trust to the successful propagation of AI systems across society” and highlights the need for clarity around accountability, responsibility, and access to remedies when AI systems fail (UK Parliament, 2017). It is notable that many AI inventions perceived as being “new” have much earlier origins. For example, artificial neural networks were first conceptualised in the 1940s, re-

emerged in the 1980s and now represent one of the most important paradigms within artificial intelligence (Przegalinska, 2019). Media coverage of emerging technologies is often very polarised, shaping public sentiments towards one of two extremes, the positive or the negative (Stöcker *et al.*, 2017). Where societal resentments exist, Stocker *et al.* (2017) argue that they can be neutralised by campaigns directed towards public education, awareness and information. To reduce public uncertainty and mistrust, there is an increasing need for explainable artificial intelligence so that both the general public and end-users can understand what the technology is being used for, what it can do, and why it is being utilised (World Economic Forum, 2018). Privacy concerns are also high among citizens (Bansod *et al.*, 2017; Stöcker *et al.*, 2017). There is a need for the AI industry to be more transparent about how products and services work, and to illustrate both the benefits to the individual and to society as a whole (Bristows LLP, 2018).

### 1.7 Data considerations

Animal health surveillance systems generate large volumes of data, making decisions about how those data are managed from the point of collection onwards critically important. Data type, accuracy and potential bias inherent in some datasets must all be considered. It is possible that stakeholders may be unwilling to share or supply data due to worries over perceived economic losses. The cost of data collection should not be overlooked, as the 'value of data needs to be judged in the context of the cost of collecting them' (Thrusfield, 2004). Consequences of inadequate surveillance can be devastating but surveillance resources are not infinite. Traditionally, investment is made in surveillance that yields statistically valid inferences concerning disease prevalence in target animal populations in a cost-effective manner. Conducting analyses that accurately reflect the state of animal health is largely dependent on data quality, with animal and premises identification being key data elements for both surveillance and response (FAO, 2011). Quality and representativeness of data is best assured by quality controls at the point of data collection and surveillance data should be reviewed for accuracy, validating, cleaning, and editing prior to certification and aggregation at regional or national level for analysis (FAO, 2011).

The surveillance pipeline outlined in Section 1.4 requires reference information against which measurements and analytical outputs can be assessed. Ground-truthing involves obtaining observations that establish what is occurring in the setting being studied, independently of the sensor or model output under evaluation. Depending on the stage of the pipeline, this might involve direct observations of animals, reference temperature measurements, or veterinary examinations supported by appropriate diagnostic tests. These observations provide a basis for evaluating remotely sensed data, although their own uncertainty and limitations must also be recognised.

Validation uses this reference information to assess whether a measurement method, model or system performs adequately for its intended purpose. For disease detection, sensitivity describes the proportion of affected animals correctly identified, while specificity describes the proportion of unaffected animals correctly identified as negative. Evaluation should reflect the intended operating conditions and, where models are developed, use data separate from those used for model development. Each stage of the surveillance pipeline requires evaluation appropriate to its function. Successful validation of an individual stage does not establish the effectiveness of the complete system. The progression from data acquisition through interpretation to action must also be assessed against the surveillance objective.

Practical deployment also requires arrangements for moving from an analytical output to an appropriate response. These include how data will be transferred, stored and linked to animal or premises records. Responsibilities must also be established for reviewing alerts and communicating findings to the farmer, veterinarian or surveillance organisation responsible for follow-up. Connectivity, processing resources, costs and staff time must be considered alongside measurement and model performance. Integration with existing recording systems and working practices is therefore necessary if novel sensing technologies are to contribute usable information to surveillance. These organisational and technical considerations are explored further in Chapters 3 and 5.

Surveillance systems generate diverse data that may have value beyond their original purpose, making it important to consider how such data are managed over time. Concepts from data curation literature emphasise the active and

ongoing management of data across their lifecycle in order to maintain relevance, quality, and usability (Freitas and Curry, 2016). Effective management approaches support data discovery and analysis by addressing issues of data quality, documentation, and usability, thereby enabling data to be re-used over time (Freitas and Curry, 2016).

More broadly, research has highlighted the importance of understanding how data are generated, transformed, and linked throughout their development, and of documenting these processes to support future interpretation and re-use (Howard *et al.*, 2010). Attention to provenance, structure, and context can enhance the long-term value of data by supporting findability, interpretability, verification, and reuse. Lifecycle-based perspectives on data management similarly stress the need to consider data needs at different stages, ensuring that data remain reliable, usable, and fit for purpose over time, and that the value of investment in data collection is maximised (Higgins, 2008).

### 1.8 Scientific aims

The overarching aim of this thesis is to evaluate how UAV-acquired thermal imagery, as a form of remotely sensed data, can contribute to the development of an integrated early warning system for animal disease, and to examine the technical, methodological, and institutional considerations that shape its integration into existing animal health surveillance frameworks.

This aim is addressed through a series of complementary chapters. Chapter 2 explores existing research concerning disease detection in animals using thermography. This is a published scoping review (McManus *et al.*, 2022). Chapter 3 is concerned with the "journey" of animal disease data in the UK and identifies key questions that emerge when considering integration of potential novel data from new technologies. Chapter 4 is a case study of one facet of developing a novel integrated animal health system. Remotely sensed, UAV-derived thermal data is utilised, with captured imagery analysed using ML techniques to detect livestock from the air. Chapter 5 synthesises findings across these three research studies to examine their broader implications for the integration of remote sensing technologies within veterinary surveillance systems.

# 2 Thermography for Disease Detection: A Scoping Review

## 2.1 Introduction

In relation to the surveillance technology pipeline outlined in Chapter 1, this chapter contains a published scoping review on the use of infrared thermography for disease detection in livestock. The review is primarily concerned with thermographic measurements of animal surface temperature and their relationship to disease status, including both absolute temperature estimates and relative temperature differences. These surface measurements are distinguished from core body temperature, which thermography does not measure directly. Within the broader thesis, this evidence base is used to identify both the potential and the limitations of thermographic approaches for animal health surveillance. Although most studies reviewed here did not use UAV-mounted sensors, the methodological issues identified are relevant to UAV-based thermal imaging because airborne acquisition increases the importance of factors such as distance, viewing angle, environmental conditions, image resolution, and validation. The identified limitations inform the later use of UAV-acquired thermal imagery in Chapter 4, where relative temperature differences between animals and their surrounding environment are used for livestock detection rather than direct diagnosis of disease. The published article can be found at https://doi.org/10.3389/fvets.2022.965622. It is reproduced here under a creative commons license (CC-BY 4.0 license).

Tables 2-1 and 2-2 summarise key terminology used in this chapter. Detailed descriptions of the parameters extracted from the reviewed studies are provided in Section 2.2.4.

**Table 2-1.** Review and thermographic measurement terms used in Chapter 2.

| Term | Meaning |
|---|---|
| Scoping review | A review that maps the breadth and nature of existing research, methodological variation and knowledge gaps. |
| Infrared thermography (IRT) | Imaging infrared radiation to obtain information about surface-temperature patterns. |
| Thermogram | An image representing detected infrared radiation or derived apparent surface temperatures. |
| Infrared thermometry | Measurement of temperature using an infrared thermometer without producing a thermal image. |
| Surface temperature | Temperature of the animal's external surface, influenced by physiological processes and environmental conditions. |
| Core body temperature | Temperature within the body, assessed using an appropriate reference measurement; not measured directly by IRT. |
| Absolute temperature measurement | A numerical estimate of temperature, rather than a difference between measurements. |
| Relative temperature measurement | Assessment of temperature differences between anatomical sites, animals or time points. |
| Region of interest (ROI) | The selected anatomical area or image region from which thermal information is extracted. |
| Radiometric JPEG (RJPG) | A thermal image file containing embedded radiometric data that allow surface-temperature estimates to be extracted from individual pixels using compatible software. The file format alone does not ensure measurement accuracy. |
| Correlation coefficient (r) | Describes the strength and direction of a linear relationship between two variables. Values range from −1 to +1; values closer to either extreme indicate a stronger linear relationship, while 0 indicates no linear correlation. |

**Table 2-2.** Thermal principles and calibration terminology used in Chapter 2.

| Term | Meaning |
|---|---|
| Blackbody | An ideal absorber and emitter of radiation, with an emissivity of 1. |
| Emissivity (ε) | The ratio of radiation emitted by a surface to that emitted by a blackbody at the same temperature, wavelength and viewing conditions. |
| Conduction | Heat transfer through direct contact. |
| Convection | Heat transfer between the animal's surface and surrounding air. |
| Radiation | Energy transfer through electromagnetic emissions. |
| Evaporation | Heat loss associated with moisture evaporating from the skin or respiratory tract. |
| Calibration | Establishing the relationship between the camera's response and known reference temperatures. |

### 2.1.1 Early detection of animal disease

Early disease detection is critical to avert health and socio-economic impacts for livestock and agricultural sectors. Animal diseases can be categorised into 'production', 'endemic' and 'exotic' classes, important concepts in terms of animal welfare, health and economics. This review explores thermal imaging as a methodology to improve early warning systems, to facilitate better identification and/or discrimination of diseased versus non-diseased animals, timely collection of data and rapid analysis and communication. Early detection is a crucial factor in animal and zoonotic disease preparedness and control. Swift and decisive action in response to disease incursion and spread is necessary to protect animal and human health, farmer livelihoods and the wider economy. Mandatory infectious disease reporting to national authorities and endemic disease surveillance play critical roles in the prevention and control of disease. When an infectious disease outbreak occurs in livestock, there can be significant negative impacts on trade and the economy in the affected country. For example, the 2001 foot and mouth disease (FMD) outbreak in the UK cost an estimated £3.1 billion to the agriculture and food sectors and the UK Bovine Spongiform Encephalopathy (BSE) crisis is estimated to have cost the country £3.7 billion (Beck, Asenova and Dickson, 2005). Wider social impacts have also been documented, such as loss of public confidence in animal products (Evans,

2006), adverse mental health in agricultural workers (Peck *et al.*, 2002) and food insecurity (Dehove *et al.*, 2012).

### 2.1.2 Infra-red thermography

There has been a great deal of research into infra-red thermography (IRT) as a potential tool to aid the early detection of important animal diseases. Infra-red Thermography uses infrared (IR) imaging to collect temperature-related data. Infra-red sensors detect radiation in the long-IR range of the electromagnetic spectrum and produce images of that radiation, called thermograms. The amount of radiation emitted by an object increases with temperature, allowing variations in temperature to be detected. The principal components and operation of a thermal camera are described in Section 1.5.2 and illustrated in Figure 1-1. Animal surface temperature reflects both heat generated within the body and heat exchange with the surrounding environment. Heat is transferred by conduction through direct contact, convection between the body surface and surrounding air, and radiation through electromagnetic emissions. Evaporation of moisture from the skin and respiratory tract also removes heat. Together, these processes influence the relationship between core body temperature, surface temperature and environmental conditions (Li et al., 2021). Infrared thermography detects radiation from the animal's surface to estimate its temperature; it does not directly measure core body temperature. Changes in surface temperature must therefore be interpreted in the context of environmental conditions as well as the animal's physiological state.

An elevated core body temperature and/or an increase in temperature regionally on an animal are key indicators for many infectious diseases and inflammatory processes. Core temperatures are usually taken per rectum, but this method is time-costly and labour-intensive, especially in extensively managed herds. If temperature measurement were carried out remotely and in an automated manner, this would likely (a) reduce the time to detect disease, (b) reduce overall farmer costs and (c) improve overall animal husbandry and welfare by enabling more rapid treatment. Reliable, non-invasive, automated, remote sensing systems utilising IR technology would enable easier monitoring of early indicators of animal health aberrations. Such systems would have clear utility in veterinary bio-surveillance and biosecurity programs but would need to be reliable, accurate, cost-effective and user-friendly to be implemented and

attract user uptake. Repeated calls to augment early warning systems for disease surveillance with real-time applications that can be integrated into animal health policy and disease control pathways have been made (Perez *et al.*, 2011; Dórea *et al.*, 2019). Hence, accurate IRT used as a non-invasive temperature measurement tool for livestock has the potential to be a cost- and time-saving technique that would propel both the animal health sector and the precision livestock industry into the future.

### 2.1.3 Accuracy, methods and reporting standards

Harrap *et al.* (2018) published a systematic review of thermographic methods employed in biological research. The review described the ideal requirements for accurate thermographic measurements: (i) a well-focused image of the target; (ii) an emissivity measurement of the object being imaged; (iii) a reflected temperature measurement of the target; (iv) an environmental temperature measurement; (v) a relative humidity measurement and (vi) a distance measurement between the camera and the target, noting that omission of parameters can drastically impair accuracy. Reliable interpretation of thermographic findings depends on both the accuracy of temperature measurements and the completeness of methodological reporting. These related but distinct requirements are considered separately below.

#### 2.1.3.1 Measurement accuracy

Emissivity is a measure of the efficiency of a surface to emit thermal energy relative to a perfect “blackbody” source. It represents the ratio of the energy radiated from a material's surface to that radiated from a perfect emitter (a blackbody) at the same temperature and wavelength and under the same viewing conditions. A blackbody is a body or surface that absorbs all radiant energy at all wavelengths and has an emissivity value of 1. Many technical aspects are critical in the field of IRT.

Partial errors result from uncertainties in the parameters used to estimate the real temperature: emissivity, reflected temperature, transmittance, ambient temperature, camera response and calibrator (blackbody) temperature accuracy. It is therefore imperative that, whenever possible, these parameters are controlled. Emissivity, ambient and reflected temperature, and relative humidity are usually determined by the user and manually input into the thermal camera to be included in internal IR calculations. Typically, ±2°C or ±2%

uncertainty of the reading is quoted as the accuracy of thermal cameras. This refers to how close the camera is to providing the true temperature value. The estimation is obtained using the 'Root-Sum-of-Squares' uncertainty analysis technique. The total measurement error (ΔT) is estimated from partial errors for each parameter involved (ΔTi), following the equation below:

$$\Delta T = \sqrt{\Delta T_1^2 + \Delta T_2^2 + \cdots + \Delta T_n^2}$$

This prescribes how total measurement error is calculated based on individual parameter errors. Understanding the impact each of the individual parameters has on the uncertainty is, therefore, crucial in establishing the reliability of temperature measurement and thus the true efficacy of IRT. To date, no paper has highlighted all possible parameters which should be considered in attempts to reduce partial errors.

#### 2.1.3.2 Reporting standards

Incomplete information being presented on thermographic parameters was attributed to one of two scenarios: that the IR camera was used correctly with appropriate parameter adjustment, but that details were omitted in the published methodology, or, that the camera was used incorrectly and consequently, parameters were not adjusted or reported (Harrap *et al.*, 2018). Measurement accuracy and completeness of reporting are therefore related but distinct. Missing methodological information prevents readers from assessing how measurements were obtained, but does not by itself establish that those measurements were inaccurate. Complete reporting is necessary to assess study quality, reproduce methods and compare findings across studies.

### 2.1.4 Existing guidelines

The American Academy of Thermology (AAT)[1] created guidelines to aid the performance of veterinary thermography. Several areas where IRT is appropriate are outlined with the following being most applicable to disease detection: (i) as a diagnostic aid where changes in the thermal patterns of scanned regions of interest suggest a regional or systemic diagnosis whereby anatomic imaging

[1]American Academy of Thermology. Guidelines for Veterinary Thermography (2022). https://aathermology.org/wp-content/uploads/2018/04/Guidelines-for-Veterinary-Thermography-2022.pdf [Accessed June 6, 2022].

modalities can then be used to characterise the nature of the problem; and (ii) as a method to enhance the clinical assessment of the veterinary patient. Boundaries within which IRT should be undertaken are offered and these have been considered in the discussion of individual parameters in this section. The guidelines state that IRT is highly sensitive to environmental conditions and therefore an understanding of these is imperative. IRT is contraindicated if certain environmental parameters, such as sunlight, ambient temperature and the presence of draughts, cannot be controlled. Further contraindications for use include the absence of relevant expertise (infrared radiation physics), the inability to evaluate bilaterally symmetrical images and the involvement of an uncooperative patient. These guidelines represent the current basis for standardisation of thermographic methods in animals.

### 2.1.5 Aims of review

The aim of this scoping review was to map and critically assess the methodological parameters and reporting practices used in infrared thermography studies for disease detection in mammalian livestock, identifying limitations and informing recommendations for future research.

To address this aim, the review had three objectives: to (i) investigate knowledge gaps in the field, with a focus on livestock emissivity values; (ii) critically examine the parameters necessary to optimise IRT for disease detection in livestock and make recommendations for minimum operating and reporting standards of experimental parameters; and (iii) discuss the current direction of experimental research in this field and predict future trends. The review focuses on the use of IRT for disease detection in livestock, with emphasis on studies reporting thermographic assessment of individual animals or specific anatomical sites rather than evaluations of complete herd-level surveillance systems. Within the wider thesis, this review establishes the evidence base and methodological constraints relevant to the use of thermographic data in future animal health surveillance applications.

## 2.2 Methods

This section outlines the search criteria, the eligibility criteria, the review process, and the parameters extracted from each study included in the review. A scoping review methodology was selected because the aim was to map the breadth and nature of existing literature on infrared thermography for disease

detection in animals, rather than to answer a narrowly defined intervention or diagnostic accuracy question. The field includes heterogeneous species, diseases, anatomical sites, imaging protocols, outcome measures, and reporting standards, making formal meta-analysis or systematic assessment of a single effect estimate inappropriate. A scoping approach was therefore considered suitable for identifying the range of applications, summarising methodological variation, and highlighting knowledge gaps relevant to future research and surveillance applications.

### 2.2.1 Search criteria

A literature search was carried out using *Web of Science* (Clarivate Analytics), covering papers published between 1864 and 2021 using all databases comprising the Web of Science Core Collection, CABI: CAB Abstracts, BIOSIS Citation Index, BIOSIS Previews, Current Contents Connect, MEDLINE, Derwent Innovations Index, Russian Science Citation Index, Zoological Record, SciELO Citation Index, Data Citation Index, KCI-Korean Journal Database. A weekly Web of Science search alert was established on 2 February 2021 to identify newly available studies during the review, with eligible studies added as results became available. The final search and cut-off for including studies identified through these alerts was 22 September 2021.

The search of a wide range of dates and databases was undertaken to include any foundational articles concerning IRT methods and their use in agricultural settings. Web of Science was used as the primary search platform because it provided access to multiple databases covering veterinary, biomedical, agricultural, biological, and interdisciplinary literature relevant to infrared thermography and livestock disease detection.

The following search query was employed, using English as the search language: [TS = (cow* OR cattle OR calf OR calves OR bovine OR bovid* OR horse OR equid* OR ruminant* OR goat* OR sheep OR pig* OR deer OR pony OR ponies) AND TS=(fever OR disease OR mastitis OR lame*) AND TS=("infrared thermography" OR "infra-red thermography" OR irt OR "thermal imaging") ], where 'TS' denotes 'Topic' and '*' denotes all derivations of a word. Multiple words concerning livestock were included to ensure the search captured all derivations or words in common use to describe cattle, horses, sheep, goats and pigs. Additional literature was sourced through screening reference lists of included articles and

supplementary searches in Google Scholar and Scopus. These sources were used to broaden coverage and identify potentially relevant studies not retrieved through the structured Web of Science search. Their use complemented the main search in a field spanning veterinary science, agriculture and imaging technology, where terminology and indexing varied across disciplines.

The structured Web of Science search formed the reproducible core of the search strategy. The supplementary search approach is summarised in Appendix 1 (Table A1-1). However, no contemporaneous log of the supplementary searches is available. The search combinations presented in the appendix are illustrative rather than verified records of the exact searches performed. Exact supplementary search dates, query sequences and numbers of results screened cannot be reconstructed, limiting the reproducibility of this component. A further limitation of the search strategy is that livestock search terms were not evenly distributed across species. Cattle-related terms were more numerous than those used for some other species, reflecting the terminology identified during search development and the relative prominence of cattle-focused thermography literature. This may have increased sensitivity for cattle studies compared with studies in other livestock species.

### 2.2.2 Eligibility criteria

Articles were deemed eligible for inclusion in the review if they were a primary research article or communication, published in a peer-reviewed journal or as a conference paper with sufficient methodological detail, reporting thermographic studies in livestock and containing relevant imagery or data. Inclusion criteria are outlined in Table 2-3.

Eligible studies collected thermographic data as images or video. Infrared thermometry studies using a thermometer that displayed a temperature reading without producing a visual thermogram were excluded. The review focused on mammalian livestock, including agricultural and food-producing mammals; companion animals, wild animals and birds, including poultry, were excluded. The restriction to mammals maintained a focused scope, as differences between avian and mammalian physiology were considered to warrant a separate review of avian thermography. Studies concerned with physiological processes other than disease detection, such as stress, heat responses, fear and reproduction, were excluded.

Conference papers were eligible where sufficient methodological detail was provided to assess the study; peer review was not required for these publications. Isolated conference abstracts without a methods section were excluded. Only publications in English were included, and publications retracted by the publishing body at the time of the final search were excluded.

### 2.2.3 Review process

Search results were examined in chronological order and publications were cross-referenced against inclusion criteria (Table 2-3). This process meant that only research papers that reported work utilising IRT for disease detection in livestock were retained in the study. Data on IRT methodology and use, and reporting of relevant parameters were extracted manually, described and assessed against the inclusion criteria. After completion of the full review process, search results were examined for a second time to ensure accuracy and consistency.

**Table 2-3.** Inclusion and exclusion criteria applied in the scoping review of infrared thermography for disease detection in mammalian livestock.

| | **Inclusion criteria** | **Exclusion criteria/notes** |
|---|---|---|
| **Topic** | Infra-red thermography studies with data collected as images or video. | Infra-red thermometry studies were excluded. These are studies which utilise an IR thermometer to digitally display a temperature, but do not display a visual thermogram. |
| **Sector** | Mammalian livestock, including agricultural animals or food-producing animals. | Companion animals, wild animals and birds were excluded. |
| **Purpose** | Disease detection in livestock. | Studies concerned with other physiological processes such as stress, heat, fear and reproduction were excluded. |
| **Type** | Primary research articles or communications published in peer-reviewed journals, and conference papers containing sufficient methodological detail to assess the study. Peer review was not required for conference papers. | Isolated abstracts from conferences not containing a methods section were excluded. |
| Rigor | Publications not retracted by the publishing body at the time of the last search. | Publications retracted by the publishing body at the time of the last search were excluded. |
| Language | Published in English. | Non-English publications were excluded. |

### 2.2.4 Parameters and definitions

Parameters were classified according to the following categories: 'camera', 'animal' and 'environmental' parameters. Descriptions of these parameters are included in Tables 2-4, 2-5 and 2-6.

#### 2.2.4.1 Camera parameters

Parameters and definitions pertaining to the thermal camera used in each publication were extracted and are outlined in Table 2-4. Missing parameters were classified as 'not recorded' if they were not reported in the paper.

**Table 2-4.** Camera-related parameters extracted from studies included in the scoping review of infrared thermography for disease detection in mammalian livestock, with descriptions of the information recorded.

| Datapoint | Description |
|---|---|
| Camera make and model | The manufacturer and model of the thermal camera(s) used in the publication |
| Spectral range | The range of wavelengths that the thermal camera can measure in μm |
| Calibration | Whether calibration of the thermal camera was performed or not |
| Calibration method | The method of calibration provided in the manuscript; denoted as 'n/a' if this does not apply |
| Temperature range | The span of temperatures between the minimum and maximum temperatures that the camera can measure in degrees Celsius (°C) |
| Video or image | Whether video or static image data was collected |
| Video frame rate | The video frame rate of the thermal camera; denoted as 'n/a' if the paper used still imagery |
| Resolution | The image resolution of the thermal camera in pixels per inch |
| Field-of-view | The maximum area of a sample that a camera can image |
| Instantaneous field-of-view | The measure of the spatial resolution of a remote sensing imaging system; defined as the angle subtended by a single detector element on the axis of the optical system |
| Lens | Details of the lens of the thermal camera |
| Thermal Sensitivity (Noise Equivalent Temperature Difference) | A measure of how well a thermal imaging detector can distinguish between very small differences in thermal radiation in the image, expressed in millikelvin (mK) |
| Focus | Details of the focus of the thermal camera |
| Focal length | The focal length of the lens |
| Spot size | The area each pixel covers on the target |
| Drift | Thermal inaccuracies caused by camera components |
| Stability | Thermal inaccuracies over time |
| Accuracy | The supplied accuracy of the thermal camera |
| Fixed/handheld | An indication of whether the camera was fixed in position or was handheld by an operator |

#### 2.2.4.2 Environmental parameters

Parameters and definitions pertaining to the environment in each publication were extracted from each paper and are outlined in Table 2-5. Missing parameters were classified as 'not recorded' if they were not reported in the paper.

**Table 2-5.** Environmental parameters extracted from studies included in the scoping review of infrared thermography for disease detection in mammalian livestock, with descriptions of the information recorded.

| Datapoint | Description |
|---|---|
| Ambient temperature considered | An indication of whether ambient temperature was considered |
| Ambient temperature recorded | The ambient temperature that was recorded |
| Relative humidity considered | An indication of whether relative humidity was considered |
| Relative humidity recorded | The relative humidity that was recorded |
| Reflected temperature considered | An indication of whether reflected temperature was considered |
| Sheltered from direct sunlight | An indication of whether the research was carried out in a sheltered environment or in direct sunlight |
| Angle considered | An indication of whether angle to the area of interest was considered |
| Angle recorded | The angle to the area of interest that was recorded in the manuscript |
| Distance | An indication of whether distance from the area of interest was considered |
| Distance recorded | The distance from the area of interest that was recorded |
| Wind considered | An indication of whether wind speed was considered |
| Rain considered | An indication of whether presence of rain was considered |

#### 2.2.4.3 Animal-related parameters

Parameters and definitions pertaining to the animals used in each publication were extracted from each paper and are outlined in Table 2-6. Missing parameters were classified as 'not recorded' if they were not reported in the paper.

**Table 2-6.** Animal-related parameters extracted from studies included in the scoping review of infrared thermography for disease detection in mammalian livestock, with descriptions of the information recorded.

| Datapoint | Description |
|---|---|
| Species | The species of the animal(s) of interest |
| Emissivity (ε) | The ε value used. Emissivity refers to the efficiency with which a surface emits infrared radiation. Values range from 0 to 1 |
| Emissivity (ε) value source | The source cited for the ε value (i.e., independently measured or citation of another publication) |
| Region of Interest | The body region of interest of the animal for thermal imaging |
| Stress | An indication of whether the manuscript noted any stress effects on the research animals |
| Coat or skin colour | An indication of whether the manuscript noted the coat or skin colour of the research animals; denoted as 'not recorded' if this was not provided |
| Coat length | An indication of whether the manuscript noted the length of the coat/hair of the research animals; denoted as 'not recorded' if this was not provided |
| Age | The age of the animal(s) of interest |

## 2.3 Results

### 2.3.1 Literature search

The literature search identified published articles that utilised IRT in the livestock sector and extracted the methodology for thermography in each manuscript to assimilate the range of parameters used. The *Web of Science* search yielded a total of 634 results and extended literature searching and citation chasing yielded another 75 articles. After 12 duplicates were removed, a total of 697 records remained. Further screening of titles and abstracts resulted in the exclusion of 311. The full texts of the remaining 386 articles were assessed and a further 279 articles were excluded. As a result, 107 articles were included in the final review (Figure 2-1). The aims, species, measurement approaches, key findings and identified gaps of the included studies are summarised in Appendix 4 (Table A4-1).

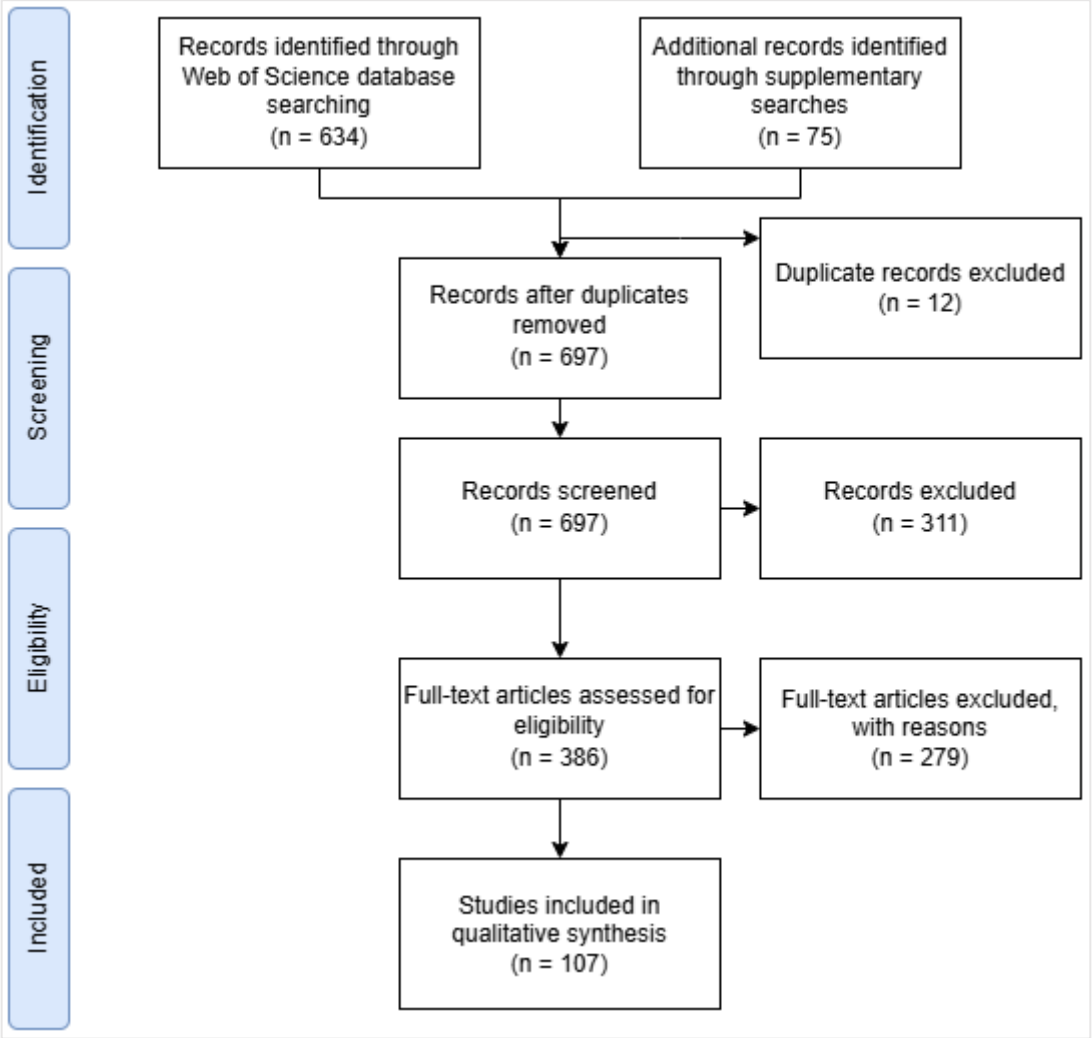



**Figure 2-1.** Literature identification and selection process for the scoping review of infrared thermography for disease detection in mammalian livestock, showing the numbers of records identified, screened, excluded and included.

### 2.3.2 Parameter reporting and opportunities to minimise partial errors

This section outlines the variation in parameter reporting over time together with a breakdown of the animal, camera and environmental parameters reported. These results highlighted the lack of measured values for emissivity in livestock.

### 2.3.3 Variation in parameter reporting over time

Figure 2-2 shows the number of parameters reported by each publication included in the review, plotted by publication year. Parameter reporting ranged from 2 to 23 out of a possible maximum of 39 with a mean of 14, a median of 14 and a mode of 13.

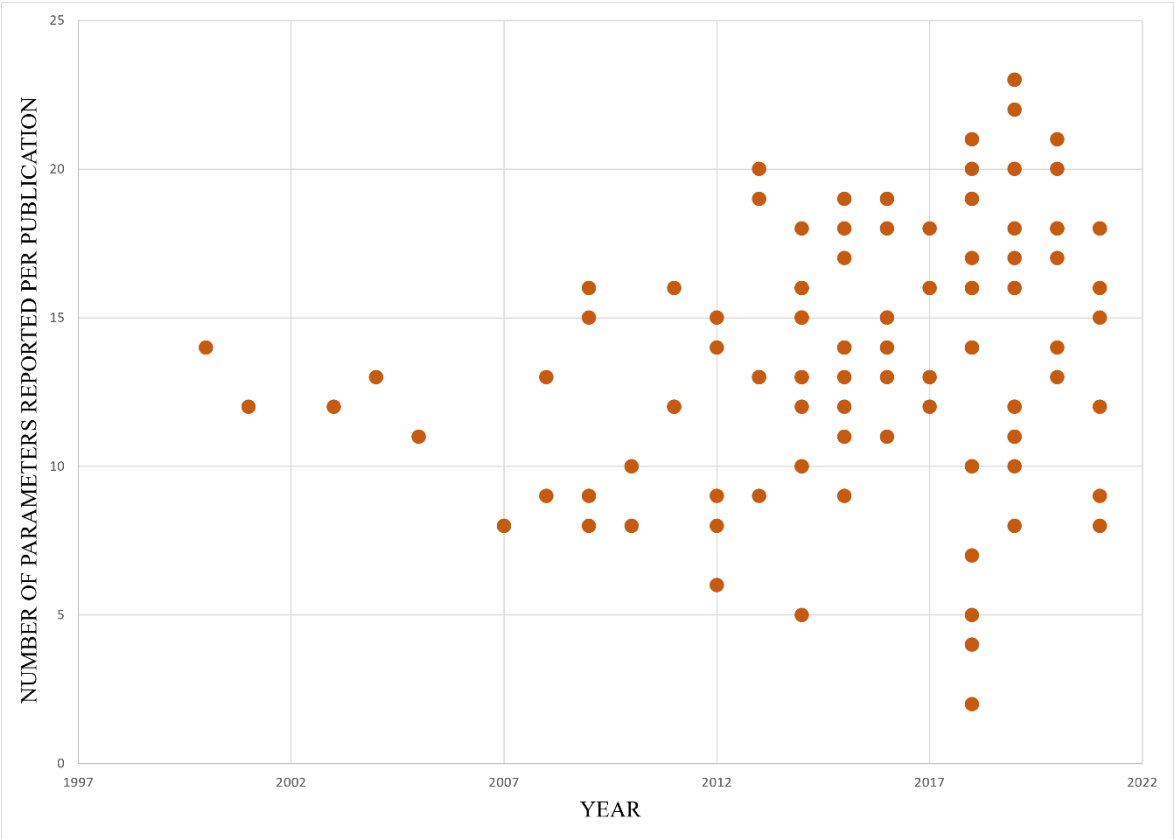



**Figure 2-2.** Number of parameters reported per publication in the scoping review of infrared thermography for disease detection in mammalian livestock, plotted by publication year. Each point represents one of the 107 included publications, assessed against 39 parameters covering camera, environmental and animal-related characteristics. Publications with the same year and parameter count overlap.

### 2.3.4 Animal-related parameters

Animal-related parameters included: emissivity, emissivity value source, coat/skin colour and length, stress, species and the region of interest (ROI) on the animal. Across the review publications, this corresponded to 856 instances where parameters could have been reported (8 parameters × 107 papers). Animal-related parameters were reported in 357 of the possible 856 instances (41.71%) across the review, compared with 43.61% for environment-related parameters and 22.92% for camera-related parameters. Figure 2-3 summarises the reporting of animal-related parameters.

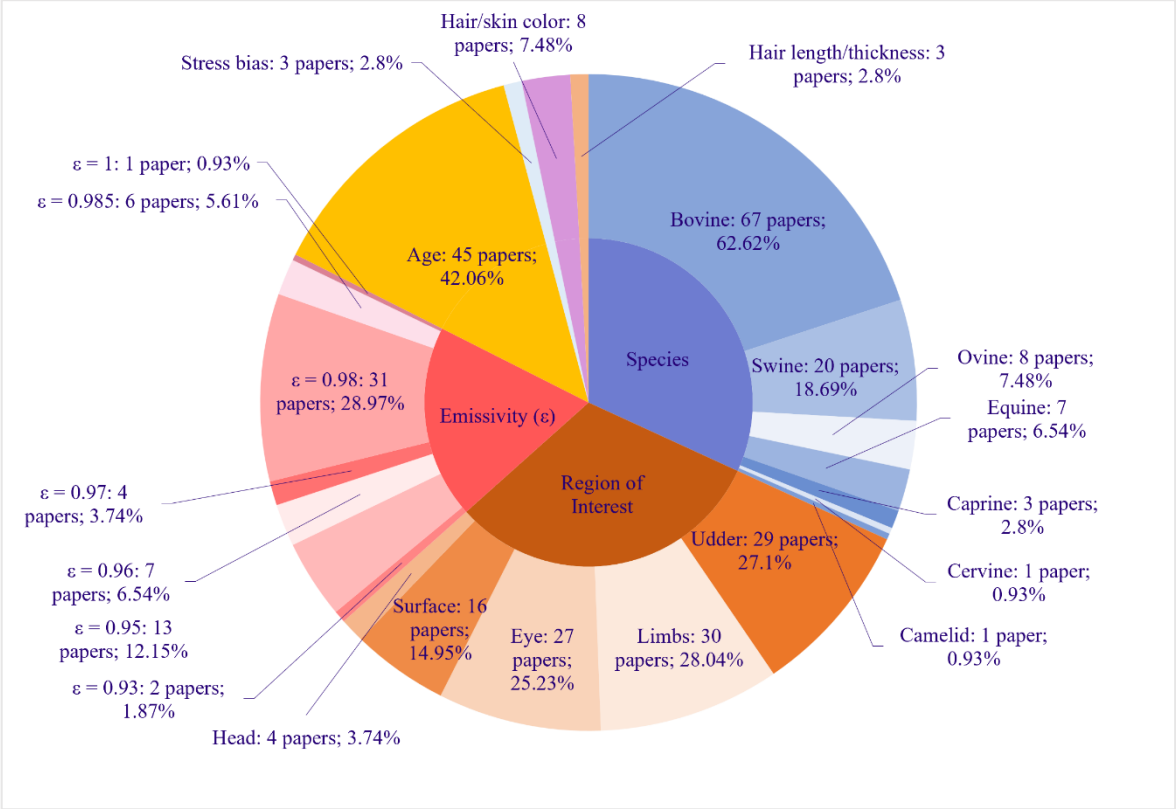



**Figure 2-3.** Animal-related parameter reporting in the 107 publications included in the scoping review of infrared thermography for disease detection in mammalian livestock. The inner sectors identify parameter categories, with outer subdivisions showing species, anatomical regions of interest and emissivity values (ε). Labels indicate the numbers and percentages of publications reporting each item. A publication may contribute to multiple parameter categories.

#### 2.3.4.1 Emissivity

As defined in Section 2.1.3, emissivity is the efficiency with which a surface emits infrared radiation relative to an ideal black body, a theoretical object that absorbs all incident radiation and emits the maximum possible thermal radiation at a given temperature. Emissivity values were reported in 64 studies (59.81%) (Nikkhah *et al.*, 2005; Hovinen *et al.*, 2008; Dunbar *et al.*, 2009; Krogbeumker *et al.*, 2009; Gloster *et al.*, 2011; Pezeshki *et al.*, 2011; Alsaaod and Büscher, 2012; Poikalainen *et al.*, 2012; Hoffmann *et al.*, 2013; Kammersgaard, Malmkvist and Pedersen, 2013; Martins *et al.*, 2013; Pérez de Diego *et al.*, 2013; Schmidt *et al.*, 2013; Alsaaod *et al.*, 2014a, 2015; Caldara *et al.*, 2014; Castro-Costa *et al.*, 2014; Menzel *et al.*, 2014, 2015; Metzner *et al.*, 2014a; Oikonomou *et al.*, 2014; Islam *et al.*, 2015; Montanholi *et al.*, 2015; Talukder, Gabai and Celi, 2015;

Wilhelm, Wilhelm and Fürll, 2015; Digiovani *et al.*, 2016; Hoffmann, Schmidt and Ammon, 2016; Jiao *et al.*, 2016; Orman and Endres, 2016; Pampariene *et al.*, 2016; Rodríguez *et al.*, 2016; Sathiyabarathi *et al.*, 2016; Golzarian *et al.*, 2017; Petry *et al.*, 2017; Stewart *et al.*, 2017; Bobić *et al.*, 2018; Byrne *et al.*, 2018, 2019; Cook *et al.*, 2018; de Moura *et al.*, 2018; Gianesella *et al.*, 2018; Lu *et al.*, 2018; Sathiyabarathi, Jeyakumar, Manimaran, Pushpadass, Kumaresan, *et al.*, 2018; Sathiyabarathi, Jeyakumar, Manimaran, Pushpadass, Sivaram, *et al.*, 2018; Shecaira *et al.*, 2018; Zaninelli *et al.*, 2018; Giro *et al.*, 2019; G. L. Lowe *et al.*, 2019; G. Lowe *et al.*, 2019; Macmillan, Colazo and Cook, 2019; M. Jorquera-Chavez *et al.*, 2019; Scoley, Gordon and Morrison, 2019; Tangorra *et al.*, 2019; Watz *et al.*, 2019; Bell *et al.*, 2020a; dos Santos Sousa *et al.*, 2020; Fabbri *et al.*, 2020; Jia *et al.*, 2020; Jorquera-Chavez *et al.*, 2020; Teixeira, Boyle and Enríquez-Hidalgo, 2020; Anagnostopoulos *et al.*, 2021; Bleul, Hässig and Kluser, 2021; Machado *et al.*, 2021a; Stumpf *et al.*, 2021) with 43 studies Barth, 2000; Loughmiller *et al.*, 2001; Berry *et al.*, 2003; Schaefer *et al.*, 2004, 2007, 2012; Ciutacu, Miclaus and Tanase, 2007; Colak *et al.*, 2008; Friendship, Poljak and McIntosh, 2009; Rainwater-Lovett *et al.*, 2009; Holzer, Rijkenhuizen and Simhofer, 2010; Polat *et al.*, 2010; Westin and Rydberg, 2010; Johnson *et al.*, 2011; Çetinkaya and Demirutku, 2012; Stokes *et al.*, 2012; Soroko *et al.*, 2013; Ajuda, Vieira and Stilwell, 2014; Alejandro *et al.*, 2014; Amezcua *et al.*, 2014; Church *et al.*, 2014a; Cook *et al.*, 2014; Fraser *et al.*, 2014; McCoard *et al.*, 2014; Samara, Ayadi and Aljumaah, 2014; Bortolami *et al.*, 2015; Karakuş *et al.*, 2015; Michelotto, Rocha and Michelotto, 2016; Byrne *et al.*, 2017; Arican *et al.*, 2018; Harris-Bridge *et al.*, 2018; Kleinhenz *et al.*, 2019; Murphy *et al.*, 2018; Schaefer, Genho, *et al.*, 2018; Schaefer, Von Gaza, *et al.*, 2018; Yang *et al.*, 2018; Deak *et al.*, 2019; Jaddoa *et al.*, 2019; Juozaitiene *et al.*, 2019; Reppert *et al.*, 2020; Cadaret *et al.*, 2021; Velasco-Bolaños *et al.*, 2021; Warner *et al.*, 2021) not stating the emissivity value used. Figure 2-4 shows the range of emissivity values used for each species in the review, ranging from 0.93 to 1.0. Of the 64 studies that stated emissivity, just 21 provided a source for the value used (Hovinen *et al.*, 2008; Hoffmann *et al.*, 2013; Kammersgaard, Malmkvist and Pedersen, 2013; Pérez de Diego *et al.*, 2013; Alsaaod *et al.*, 2014b; Castro-Costa *et al.*, 2014; Menzel *et al.*, 2014, 2015; Hoffmann, Schmidt and Ammon, 2016; Jiao *et al.*, 2016; Rodríguez *et al.*, 2016; Petry *et al.*, 2017; Zaninelli *et al.*, 2018; Giro *et al.*, 2019; G. Lowe *et al.*, 2019; Maria Jorquera-Chavez *et al.*,

2019; Tangorra *et al.*, 2019; Jia *et al.*, 2020; Teixeira, Boyle and Enríquez-Hidalgo, 2020; Machado *et al.*, 2021b; Stumpf *et al.*, 2021). Sources for these emissivity values were not immediately clear from the publication and this is explained below. These 21 studies cited 24 references (Steketee, 1973; Wolfe and Zissis, 1978; Girardin *et al.*, 1999; Jones and Plassmann, 2002; Schuster and Kolobrodov, 2004; Diakides and Bronzino, 2007; Hovinen *et al.*, 2008; Montanholi *et al.*, 2008, 2009; Litwa, 2010; Gloster *et al.*, 2011; Lahiri *et al.*, 2012; Bernard *et al.*, 2013; Hoffmann *et al.*, 2013; Weschenfelder *et al.*, 2013; Castro-Costa *et al.*, 2014; Redaelli *et al.*, 2014; Soerensen *et al.*, 2014; Talukder *et al.*, 2014; McManus *et al.*, 2016; Zhang *et al.*, 2016; Stewart *et al.*, 2017; G. Lowe *et al.*, 2019; Souza-Junior *et al.*, 2019) with some studies citing more than one reference and some references being cited multiple times. Three studies (Castro-Costa *et al.*, 2014; Rodríguez *et al.*, 2016; Stumpf *et al.*, 2021) reference the IR camera user manual (offering the emissivity for living tissues of between 0.95 and 0.98)[2, 3, 4], and three of the references were books (Wolfe and Zissis, 1978; Schuster and Kolobrodov, 2004; Diakides and Bronzino, 2007). Some of these source studies were included in the 107 publications identified in this review (Hovinen *et al.*, 2008; Hoffmann *et al.*, 2013; Castro-Costa *et al.*, 2014; Soerensen *et al.*, 2014; Zhang *et al.*, 2016; Stewart *et al.*, 2017; G. L. Lowe *et al.*, 2019; G. Lowe *et al.*, 2019). However, most of these papers were found to fall outside the scope of the review as they were not concerned with the application of IRT to livestock disease.

The range of emissivity values (0.93-1.0) used within each species illustrates a lack of consensus (Figure 2-4). Measured values for emissivity in bovine, ovine, cervine and equine species are absent (Figure 2-5). Soerensen et al. (Soerensen *et al.*, 2014) and Zhang et al. (Zhang *et al.*, 2016) evaluated skin emissivity of pigs, obtaining similar results (Soerensen *et al.*, 2014; Zhang *et al.*, 2016). Soerensen et al. found that ear base, udder, and shoulder (with hair) were 0.978±0.006, 0.975±0.006 and 0.946±0.006, respectively, and also discovered that skin with blood perfusion had higher emissivity than without and that

[2]Teledyne FLIR LLC. FLIR Txxx Series User Manual. https://support.flir.com/DocDownload/Assets/dl/1558792.pdf [Accessed June 6, 2022].

[3]Teledyne FLIR LLC. FLIR ix User Manual. https://support.flir.com/DocDownload/Assets/dl/t559733-en-us_a4.pdf [Accessed June 6, 2022].

[4]Infrared Integrated Systems Ltd. (Irisys). IRI 4010 User Manual. https://www.manualslib.com/manual/1012541/Irisys-Iri-4010.html [Accessed June 6, 2022].

clipping the hairs of the shoulder tended to increase emissivity (Soerensen *et al.*, 2014). Room temperature was found to have an insignificant effect on the calculated emissivity value (Soerensen *et al.*, 2014). Zhang et al. found that surface emissivity varied from 0.945 to 0.978, with the highest value (0.978) being obtained from the ear base and shoulder (Zhang *et al.*, 2016). Experiments used to determine emissivity in both studies were based on data collected from sedated and dead animals, and this is likely to have impacted the results due to the influence of sedation on peripheral blood perfusion.

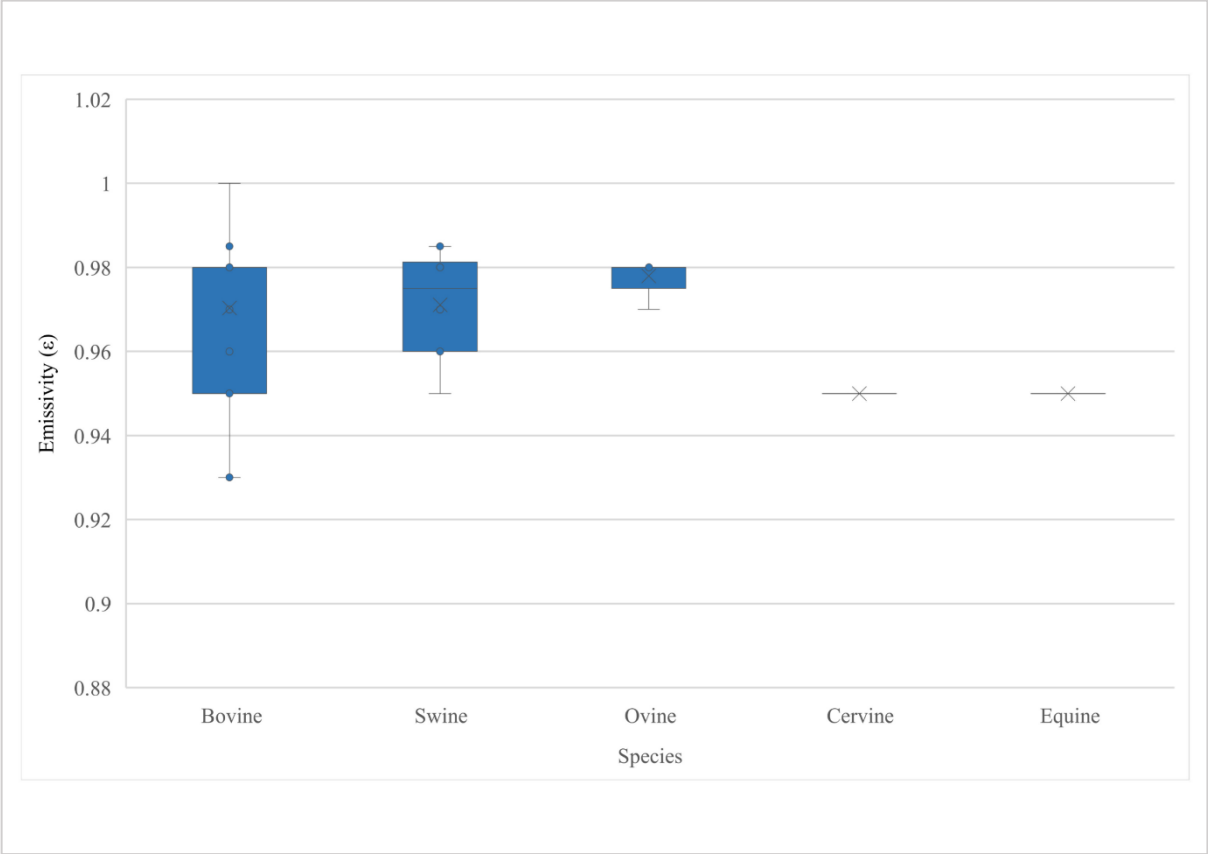



**Figure 2-4.** Distribution of emissivity values (ε) used in the reviewed infrared thermography studies, grouped by animal species. These values represent the emissivity settings reported by the studies, rather than necessarily being independently measured values for those animals.

#### 2.3.4.2 Knowledge gap: emissivity

Camera emissivity settings play a key role in IR temperature estimation because they influence how detected infrared radiation is converted into apparent surface temperature. Emissivity is highly dependent on the target object's surface morphology, roughness, oxidation, spectral wavelength, temperature, and the angle from which it is viewed. Teledyne FLIR's (the largest thermal

imaging systems company in the world) user manual[5] suggests an emissivity measurement method, whereby IR images of the target are taken with and without black insulating electrical tape stuck to the target (which has a known emissivity of 0.97). Emissivity is set to 0.97 when the tape is attached and to 1 when it is not. Further images are then taken without the tape, adjusting the emissivity setting on the camera to match the temperature obtained without the tape to the one obtained with the tape. However, this method is only valid when the surface temperature exceeds the ambient temperature by at least 10°C as may be anticipated in temperate regions. In tropical climes, where animal surface temperatures and ambient temperatures may be within 10°C of each other, this method is unlikely to yield accurate results. While this method is still in current use in human testing (Charlton *et al.*, 2020), the ability to test this method with livestock is dependent on the temperament of the animal and whether it allows this procedure to be carried out.

A network diagram was constructed to elucidate the origins of the emissivity values used in the studies included in this review (Figure 2-5). From this, it can be observed that the majority of independently measured values for emissivity are for human (n=12) (Hardy and Muschenheim, 1934; BuchmÜller, 1961; Gärtner and Göpfert, 1964; Gärtner, Ling and Göpfert, 1964; Mitchell *et al.*, 1967; Mitchell, Wyndham and Hodgson, 1967; Mapstone, 1968; Watmough and Oliver, 1968; Patil and Williams, 1969; Watmough, Fowler and Oliver, 1970; Steketee, 1973; Villaseñor-Mora, Sanchez-Marin and Calixto-Carrera, 2009) rather than livestock tissues with the exception of two measurements in pigs (Soerensen *et al.*, 2014; Zhang *et al.*, 2016). A number of sources (n=13, including manufacturer user's manuals[6, 7, 8]) offer no independently measured or referenced source for the used emissivity value stated (Jacquez *et al.*, 1955; Derksen, Murtha and Monahan, 1957; Litwa, 2010; Pezeshki *et al.*, 2011; Weschenfelder *et al.*, 2013; Redaelli *et al.*, 2014; Talukder *et al.*, 2014; Stewart

[5]Teledyne FLIR LLC. FLIR Ex Series User Manual. https://www.flir.com/globalassets/imported-assets/document/flir-ex-series-user-manual.pdf [Accessed June 6, 2022 ].

[6]Teledyne FLIR LLC. FLIR Txxx Series User Manual. https://support.flir.com/DocDownload/Assets/dl/1558792.pdf [Accessed June 6, 2022].

[7]Teledyne FLIR LLC. FLIR ix User Manual. https://support.flir.com/DocDownload/Assets/dl/t559733-en-us_a4.pdf [Accessed June 6, 2022].

[8]IRISYS. IRI 4010 User Manual. https://www.manualslib.com/manual/1012541/Irisys-Iri-4010.html [Accessed June 6, 2022].

*et al.*, 2017; G. L. Lowe *et al.*, 2019; Souza-Junior *et al.*, 2019) and a number of sources (n=12) did not independently measure emissivity but referenced another source for the value they used (Jones, 1998; Girardin *et al.*, 1999; Jones and Plassmann, 2002; Kastberger and Stachl, 2003; Hovinen *et al.*, 2008; Montanholi *et al.*, 2008, 2009; Lahiri *et al.*, 2012; Bernard *et al.*, 2013; Hoffmann *et al.*, 2013; Castro-Costa *et al.*, 2014; G. Lowe *et al.*, 2019).

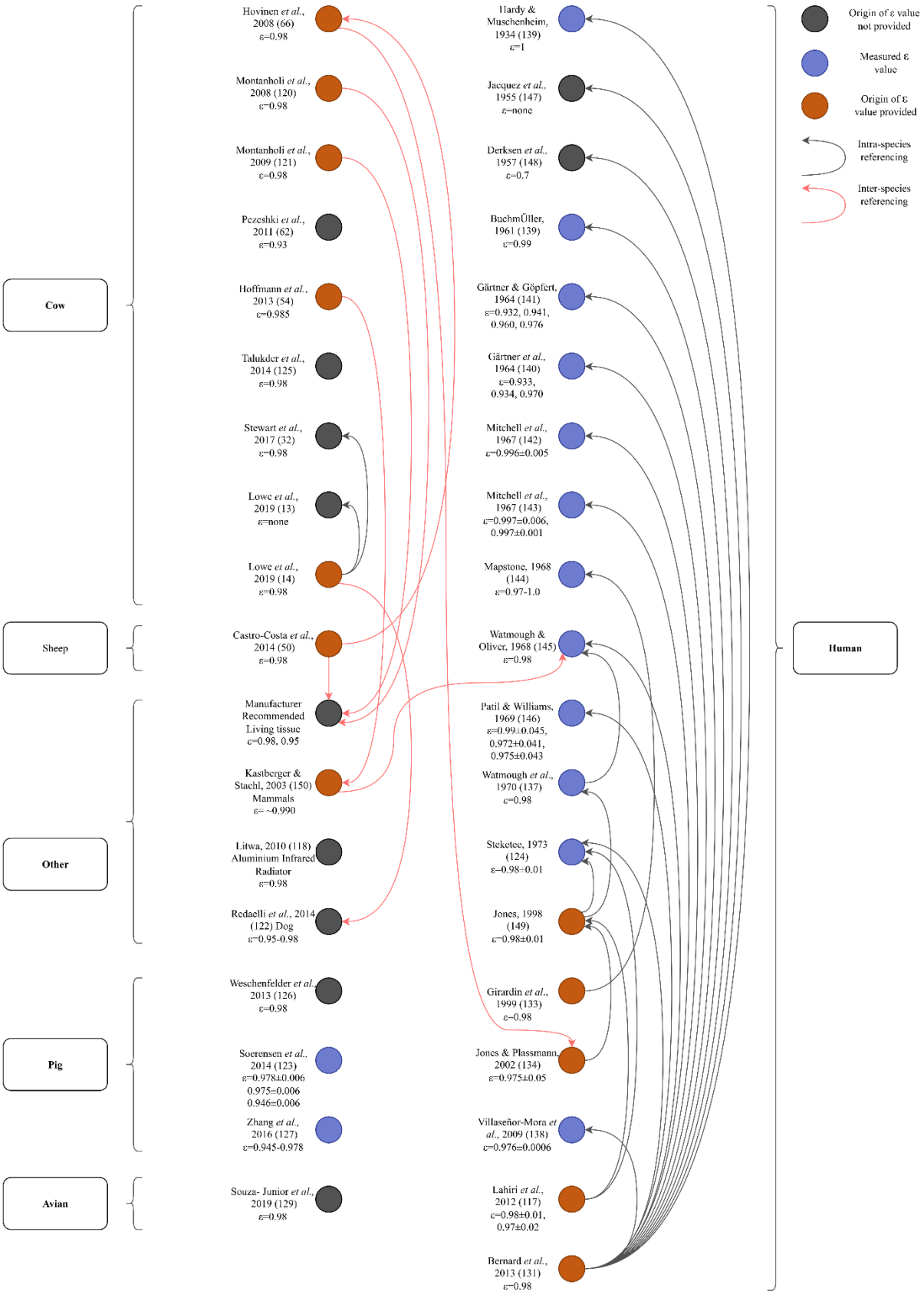



**Figure 2-5.** Diagram tracing the sources of emissivity values (ε) used in studies included in the scoping review of infrared thermography for disease detection in mammalian livestock. Out of 107 papers included in this review, 21 papers provided 27 sources for their emissivity value (20 original research articles, 1

review article, 3 books and 3 references to the camera's manufacturer's manual). These referenced sources and the sources which informed them are mapped out here to ascertain the ε values stated, what species they referred to and whether the values used could be traced to a measured ε value. Arrow direction indicates referencing of older articles. The first author's name, the year of publication and the emissivity value used (if present) are included. For papers that could not be classified based on 'species', the object is stated. For ease of illustration, only the original research articles and the manufacturer's manual that were referenced are included in the diagram. Most independently measured emissivity values identified in this citation network relate to human tissues; the two livestock studies reporting independent measurements both investigated pigs.

Nearly all emissivity research (Figure 2-5) can be traced back to two primary papers (Watmough and Oliver, 1968; Steketee, 1973). Both studies independently measured emissivity, but in human tissues. Watmough and Oliver used an IR camera with a spectral range of 2.0 to 5.4 μm, concluding that the emissivity of human skin was greater than 0.98 (Watmough and Oliver, 1968). However, the researchers did not account for ambient temperature and had they made this correction, they would have concluded that skin emissivity lies between 0.94 and 1.0, within 2.0 to 5.4 μm (Togawa, 1989). Steketee measured skin emissivity using a monochrometer (an optical instrument which measures the light spectrum) and a thermometer (Steketee, 1973). A reference blackbody source formed part of the monochrometer which could be maintained at the same temperature as that of the skin. Skin temperature was measured using a compensated method in which a fine gold ring with a thermocouple was warmed so that its temperature did not change when it touched the skin. The effect of ambient radiation was substituted by adjusting the radiation from another reference source in the monochrometer with which incident radiation was switched in an alternating fashion by chopper blades. The average observed emissivity was 0.98±0.01, within 3 to 14 μm. The experiments were well-designed, the principle being a comparison of the radiation from the skin and that from a blackbody at the same temperature. Because both quantities are close to each other, a small difference in each measurement would cause a considerable error in the difference of the two quantities (Togawa, 1989). Togawa stated that previously reported skin emissivity values were unlikely to

be as reliable as results obtained by a method based on reflectance measurement upon transient stepwise change in the ambient radiation temperature (Togawa, 1989). Togawa's study concluded that within the range of 8 to 14 μm, the emissivities of normal and intact skin of humans from multiple body sites would be about 0.97 on average, and that differences in emissivity for different regions of interest of the body are insignificant (Togawa, 1989). This was improved by Huang and Togawa by applying “least-squares fitting” to 64 IR images instead of only two thermograms as in the previous study but was not appropriate for use in living animals (Huang and Togawa, 1995). Sanchez-Marin *et al.* refined this method based on the calculation of the difference of two IR images, with one image acquired prior to the projection of a $CO_2$ laser beam on the surface of the skin and another after the projection, with the difference between the images being used as the reflectance (Sanchez-Marin, Calixto-Carrera and Villaseñor-Mora, 2009). From this, they were able to estimate emissivity (Sanchez-Marin, Calixto-Carrera and Villaseñor-Mora, 2009).

But is emissivity really that important? In a study evaluating the effect of multiple factors on IR eye temperature in cattle, Church *et al.* (Church *et al.*, 2014b) experimented with changing the emissivity setting on the camera and found that adjusting the value by 0.05 altered the resulting IR temperature by 0.5°C. In a disease surveillance system where the aim is to discriminate between 'positive' (hyperthermic) and 'negative' (normothermic) animals, a difference of 0.1°C may signify the presence or absence of disease. This is the magnitude of difference appreciated by veterinary practitioners when using a rectal thermometer. Emissivity ranged from 0.93 to 1.0 across the studies included in the review, yielding a difference of 0.07 between the top and bottom of the range. As much of the research being conducted is concerned with absolute temperatures and using cut-off points to define a disease, it is critical to use accurate emissivity. Polat *et al.*, did not report an emissivity value, despite IRT cut-off points for diagnosis of sub-clinical mastitis being defined (Polat *et al.*, 2010). This lack of an emissivity value demonstrates an insufficient understanding of critical parameters when utilising IRT in the context of disease surveillance. Table 2-7 illustrates the effect a change in emissivity can have on resulting temperatures using the Stefan-Boltzman constant. From Table 2-7, it can be observed that a change of 0.01 to emissivity (ε) can lead to a systematic

bias of 0.69 to 0.76°C. Dos Santos Sousa *et al.*, defined a cut-off point of 30.0°C to detect laminitis using IRT of the hoof (dos Santos Sousa *et al.*, 2020). This cut-off temperature yielded a sensitivity of 96%, a specificity of 63% and an epidemiological accuracy of 75% when compared with the gold standard of using hoof testers for diagnosis. Emissivity was set at 0.98. As a working guide, in the experiments carried out by dos Santos Sousa et al. (dos Santos Sousa *et al.*, 2020), we find that ε = 0.98±0.01 will imply T = 30.0±0.74°C. Within the range of ε determined in this review (0.93 to 1.0), analyses that employ a hard cut-off temperature point will also be systematically biased, if error of emissivity is not taken into account.

**Table 2-7.** The errors in resulting IR temperature if emissivity is altered for a given temperature of 30.0°C to demonstrate that change of emissivity (ε) = 0.01 can lead to a systematic bias of 0.69 to 0.76°C where E = energy flux (also called the radiant emittance), ε = emissivity, $\sigma$ = Stefan–Boltzmann constant (5.67x10−8 W/ m2 K4). δε denotes the change in emissivity and δT the resulting change in estimated temperature. See Appendix 2 for supporting calculations.

| **Emissivity (ε)** | **E ($W/m^2$)** | **δT coefficient** | **δT (°C), δε=0.01** | **δT (°C), δε=-0.01** | **δT(°C), δε=0.05** |
|---|---|---|---|---|---|
| 1 | 478.9 | -75.8 | -0.76 | 0.76 | -3.79 |
| 0.99 | 474.1 | -74.8 | -0.75 | 0.75 | -3.74 |
| 0.98 | 469.3 | -73.9 | -0.74 | 0.74 | -3.69 |
| 0.97 | 464.5 | -73.0 | -0.73 | 0.73 | -3.65 |
| 0.96 | 459.7 | -72.0 | -0.72 | 0.72 | -3.60 |
| 0.95 | 454.9 | -71.1 | -0.71 | 0.71 | -3.55 |
| 0.94 | 450.1 | -70.1 | -0.70 | 0.70 | -3.51 |
| 0.93 | 445.3 | -69.2 | -0.69 | 0.69 | -3.46 |

What emissivity value is most appropriate for livestock? The AAT recommends using a value of 0.98 (human skin) unless a different emissivity is both known and accepted for the animal and ROI under study. McGowan et al. (McGowan *et al.*, 2018) reported that most mammal emissivities used thus far in research are derived from Hammel (Hammel, 1956). Hammel measured the emissivity of the pelage (hair-covered tissue, pelts cut from dead mammals) of ten species of dead arctic fauna, finding that all furs had emissivity values between 0.98 and 1.00. Hammel used a method described by Hardy (Hardy and Muschenheim, 1934) where a contact probe was used to determine skin temperature, and in order to reduce the effect of ambient air on the contact probe, the room

temperature was raised until it approximated that of the skin. This method has since been proven inadequate for emissivity measurement (Togawa, 1989). McGowan et al. set out to find values for mammals, focusing on pelage and obtained the following values for livestock: Thoroughbred horse: 0.90±0.03, Goat: 0.89±0.02, Friesian cow: 0.79±0.03 and Charolais cow: 0.88±0.03, which are much lower than any values currently in use in IR research in livestock (McGowan *et al.*, 2018). Mean pelage emissivity of sampled specimens was 0.86±0.01 and there was neither a relationship between emissivity and taxonomy, nor between emissivity and hair metrics (McGowan *et al.*, 2018). The authors concluded that single (0.98) or narrow ranges (0.95 to 1.00) of emissivity values are likely inappropriate for obtaining accurate mammal IR surface temperature readings (McGowan *et al.*, 2018). This contradicted the findings of Soerensen et al. (Soerensen *et al.*, 2014) and Zhang et al. (Zhang *et al.*, 2016) who carried out emissivity experiments in pigs using different methods. Soerensen et al. used needle probes attached to a data logger to estimate skin temperature of multiple skin sites with emissivity set to 1 on the IR camera (Soerensen *et al.*, 2014). Images were analysed after collection to estimate emissivities. However, the same study found that skin with blood perfusion had a higher emissivity than without and that removal of hair from the area to be examined increased emissivity, so it remains to be determined which is the most appropriate value for emissivity as these experiments were carried out on non-living tissue with hair (Soerensen *et al.*, 2014). Zhang *et al.* (Zhang *et al.*, 2016) built on earlier human emissivity research (Huang and Togawa, 1995; Otsuka *et al.*, 2002) and estimated surface emissivity in real-time in living animals by changing the surface reflection energy of animals and a reference body and thus altering the ambient radiant energy without confirming the actual temperature of the animal surface. This was a non-invasive approach, unlike Soerensen et al.'s work, so may have more utility in future research. It is also possible that there are differences in emissivity between species, individuals of the same species and regions of interest on the same animal. There is therefore a need to establish usable values for livestock animals.

#### 2.3.4.3 Skin/hair colour and hair thickness

Although few studies recorded coat or hair colour (n=8; 7.48%) or thickness of hair (n=3; 2.80%), both are important drivers of surface temperature. Darker

cows naturally absorb more heat from the sun whereas white cows reflect more heat radiation. Dark coated cows thus have a higher surface temperature on a warm day. The type and colour of coat changes the skin's ability to radiate and absorb heat. A thicker coat will also lead to greater levels of insulation. Anzures-Olvera *et al.* evaluated the impact of coat colour on temperature in cattle, finding that the rectal temperature of black cows was 0.1°C higher than white cows, but that coat colour did not alter body surface temperature readings measured by IRT (Anzures-Olvera *et al.*, 2019). In outdoor field trials, the effect of direct sunlight was strongly dependent on hair colour, having a profound effect on IRT temperature with white areas of cow's heads producing temperatures of ~35°C, while black areas produced temperatures of ~50°C (Church *et al.*, 2014b). Dirt also affects surface temperature measurements, affecting the ability of the surface to radiate energy and to conduct heat. Metzner *et al.* found that surface temperature was markedly lower in the presence of dirt (Metzner *et al.*, 2014b). Udder surface temperatures are affected by the amount of hair present (Barth, 2000), this deviation being most pronounced in German Simmental cattle which have a lot of udder hair (Barth, 2000). Corresponding temperatures were lower than non-haired udders as a result (Barth, 2000). Soerensen *et al.* found that clipping the hairs of the shoulder tended to increase emissivity in pigs (Soerensen *et al.*, 2014) and Giro *et al.* discussed hair length with regard to cattle breed and used a breed with a lower hair density in their study to eliminate the interference of hair with heat elimination from the body and consequent IRT temperature (Giro *et al.*, 2019).

#### 2.3.4.4 Region of interest

Although region of interest (ROI) was reported in nearly all studies (n=106; 99.07%), there is no single ROI which emerges as the most important or useful for health monitoring and disease detection in livestock. The most popular ROIs to be studied included the limbs (n=30; 28.04%) and the udder (n=29, 27.10%) together with the eye (n=27; 25.23%), body surface (n=16; 14.95%) and head (n=4; 3.74%), with many studies investigating multiple ROIs. Studies performing IRT on the udder, limbs and eye were mainly concerned with cattle (n=24, 22.43%; n=21, 19.63% and n=20, 18.69% respectively). In contrast to this, IRT was more commonly used for monitoring body surface temperatures in the context of studies relating to pigs (n=10; 9.35%), the remainder being concerned with cattle

(n=5; 4.67%) and sheep (n=1; 0.93%). Of these papers, 75% were concerned with young animals, namely piglets, calves and lambs, where IRT was applied to thermoregulation capabilities in neonates (Kammersgaard, Malmkvist and Pedersen, 2013; McCoard *et al.*, 2014), vaccine response (Cook *et al.*, 2014) and diseases specific to young animals (Shecaira *et al.*, 2018; G. L. Lowe *et al.*, 2019).

A recent paper documented body surface temperature patterns for Jersey dairy cattle in a thermoneutral environment (Salles *et al.*, 2016). IRT images of the left and right periocular area, right and left eye, caudal left foreleg, cranial left foreleg, right and left flank and forehead were sampled. Of these regions, forehead temperature was shown to have the greatest correlation with rectal temperature (r=0.35). In another study aimed at determining the most reliable body area for measurement of rectal temperature in pregnant and non-pregnant cows, the strongest correlation was found using the thorax (r=0.377) with the udder and the eyeball showing slightly weaker correlations (r=0.357 and r=0.316 respectively) (Deak *et al.*, 2019). Thermogram temperature was also shown to differ between seasons and reproductive phases. Stumpf *et al.* documented a strong correlation between lateral udder and rectal temperatures in cattle (r=0.897) (Stumpf *et al.*, 2021), demonstrating that the udder area has great promise as an indicator of core body temperature. Respiratory rate in calves has also been investigated using IRT; the rate of flank movements as captured by optical imaging was compared with IRT of thermal fluctuations around nostrils (G. Lowe *et al.*, 2019) and, encouragingly, these readings were found to be highly correlated. Given the prevalence and economic importance of pneumonia in young cattle, a role could be envisaged for using IRT for respiratory disease surveillance in this class of stock.

Multiple investigations into using eye measurements as a proxy for rectal temperature have been carried out in animals with induced respiratory and diarrheal disease (Schaefer *et al.*, 2004, 2007, 2012) with more recent work examining correlations between rectal temperature and IRT readings from (i) the eye (maximal value) (r=0.37); (ii) the muzzle (r=0.28); and (iii) the medial canthus of the eye (r=0.27) (Bleul, Hässig and Kluser, 2021). Numerous options for the 'eye' ROI have been previously adopted, thus Shu *et al.* (2022) sought to standardise the ROI for measuring eye temperature. Mean and maximum

temperatures of five orbital ROIs (medial canthus, lateral canthus, eyeball, whole eye and lacrimal sac) were manually captured and the maximum temperature obtained at the lacrimal sac of the left eye was found to provide the highest correlation coefficients with respiration rate (r=0.6) and vaginal temperature (r=0.52). Future research should focus on using maximal readings from this specific locus rather than the entire ocular area.

#### 2.3.4.5 Stress

Stress is one of the main parameters that can influence an animal's temperature, but it was not well-reported in the literature (n=3; 2.80%). The hypothalamic-pituitary-axis (HPA) can lead to stress-induced hyperthermia when stimulated by the sympathetic system when an animal is stressed. In an induced stress study in cows, Stewart *et al.* measured eye temperature and tested serum cortisol to ascertain if increased cortisol (indicating activation of the HPA related to stress) correlated with increased eye temperature (Stewart *et al.*, 2007). It was found that exogenous stimulation of the HPA axis did not increase eye temperature although an increase following catheterization was detected, suggesting there is a cognitive component to stress. It could be hypothesised that an animal may only need to perceive the situation as stressful for eye temperature to increase, meaning habituation to a certain procedure/object could potentially reduce this effect. Gomez *et al.* investigated whether IRT of visible eye white and eye temperature measurements were feasible physiological indicators of acute stress in cows (Gómez *et al.*, 2018). Maximum eye temperature did not differ between stress and control treatments, but the authors found that the IR values differed between breeds. In Brown Swiss cows, maximum eye temperature increased during and after both treatments, whereas in Red Holstein cows, it increased after (but not during) both treatments, which was attributed to differences in eye colouration patterns (Gómez *et al.*, 2018). Stress affects the animal's temperature and so needs to be considered when clinically interpreting the temperature. While this contrasts with other animal-related parameters which account for inaccuracies in the measured temperatures, stress must be considered in advance of future experiments.

### 2.3.5 Camera parameters

Camera specifications including spectral and temperature range, field-of-view, instantaneous field-of-view, resolution, thermal sensitivity and focus are

important when choosing a suitable device for IRT of animals. We collected information regarding reporting of 19 camera parameters. This corresponded to 2033 instances where parameters could have been reported (19 parameters×107 papers). However, only 466 instances of parameters being reported (22.92%) were recorded (Figure 2-6). Despite the importance of camera parameters, they were reported less frequently than animal-related and environmental parameters.

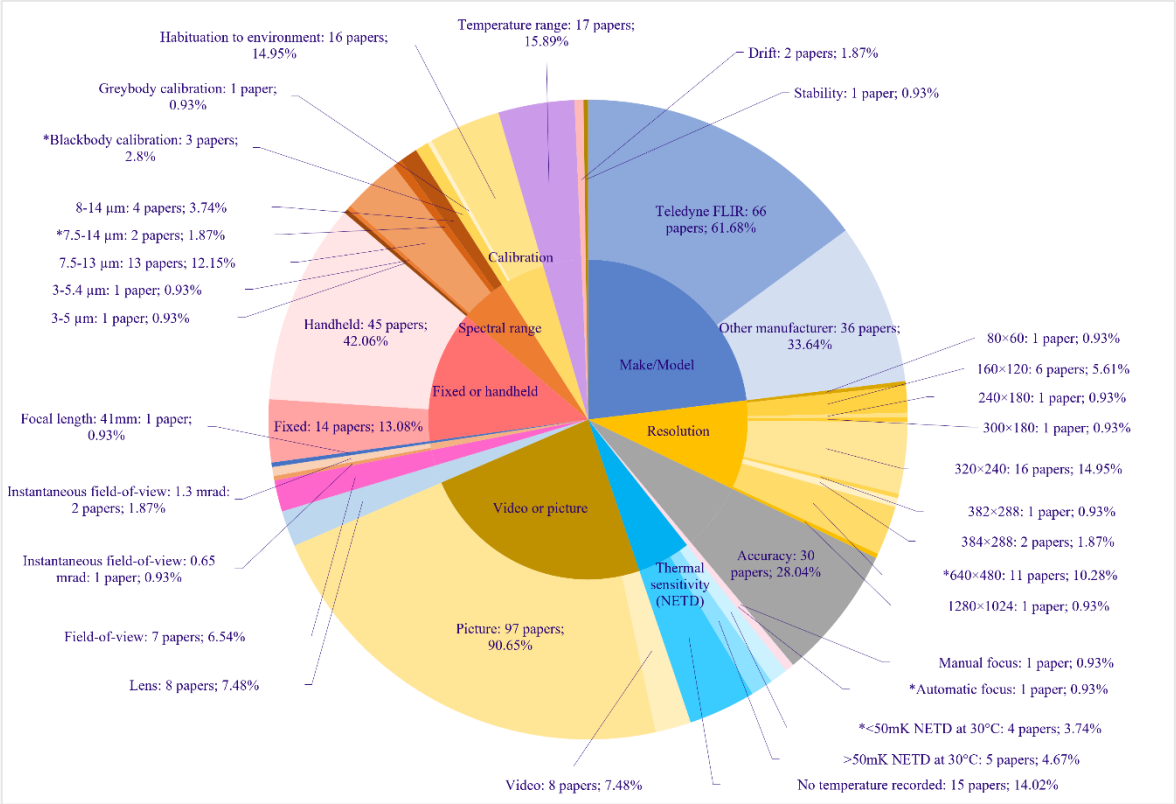



**Figure 2-6.** Reporting of camera-related parameters in the 107 publications included in the scoping review of infrared thermography for disease detection in mammalian livestock. Labels indicate the numbers and percentages of publications reporting each item; a publication may contribute to multiple categories. An asterisk (*) denotes a recommended value or setting. Recommended values for instantaneous field-of-view and spot size are ≤2.6 mRad and 2.1 × 2.0 mm (3 × 3, or 9 pixels) at 40 cm distance from the animal, respectively. Resolution is expressed in pixels. NETD denotes noise equivalent temperature difference; mK denotes millikelvin; and mrad denotes milliradians.

#### 2.3.5.1 Spectral range

Spectral range characterises the part of the electromagnetic spectrum that a thermal camera can detect. It is the range of wavelengths that the sensor in the

camera detects and is measured in micrometres (μm). Apart from gas detection cameras, which operate in the range of 3 to 5 μm, most thermal cameras are longwave, operating between 8 and 14 μm. AAT guidelines recommend a camera detector spectral bandwidth between 8 and 14 μm. Most papers reported the spectral range as 7.5-13 μm (n=13, 12.15%). However, two papers reported spectral ranges outside of AAT guidelines (3 to 5 μm (Loughmiller *et al.*, 2001) and 3 to 5.4 μm (Barth, 2000)). For organic tissue with a temperature of 35°C (308.15 K), the peak of thermal energy intensity peaks at approximately 9.4 μm (Figure 2-7). Cameras covering a more limited wavelength range, for example 3 to 5 μm, detect less emitted radiation at this temperature, potentially increasing uncertainty in the final measurement.

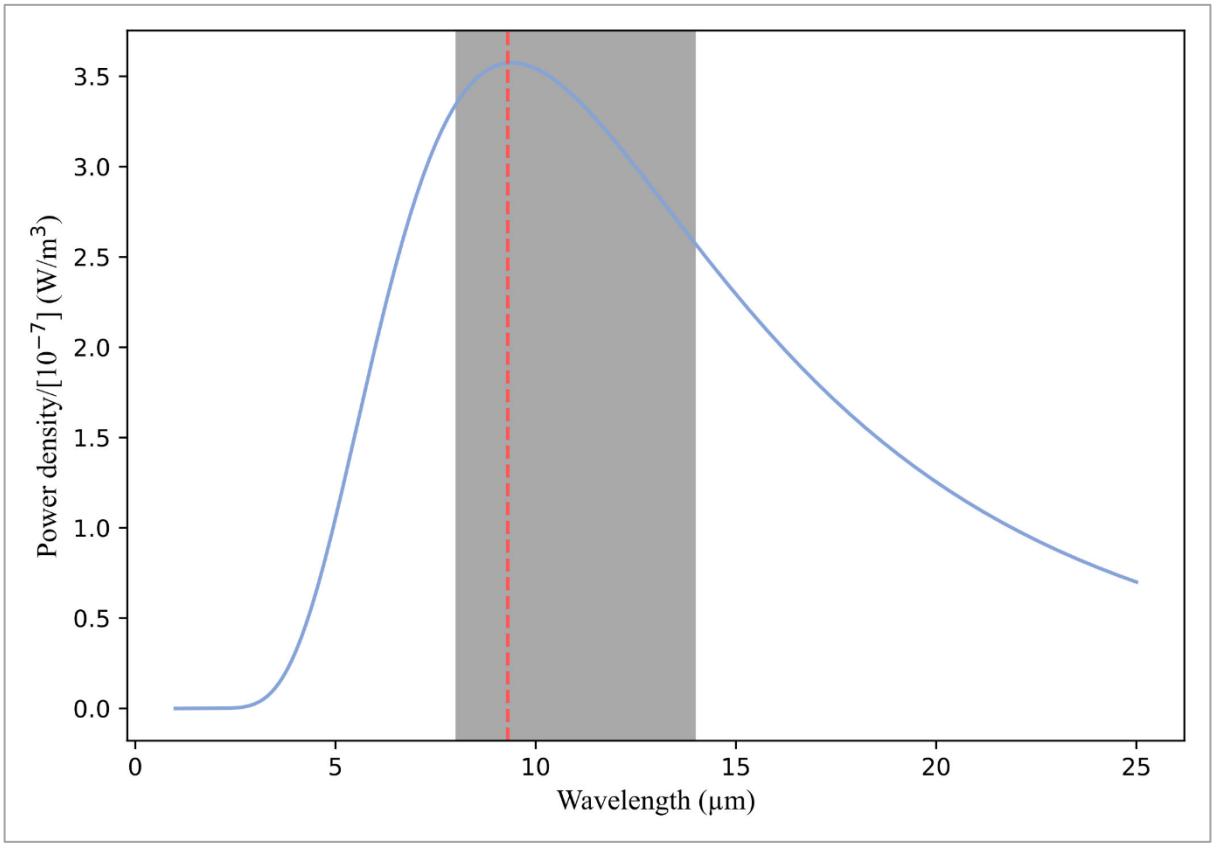



**Figure 2-7.** Graph showing the blackbody emission spectrum for a body at 308.15 K (35°C). The blue curve shows the distribution of emitted radiation with wavelength. The red dashed line marks the emission peak, at approximately 9.4 μm, and the grey shading indicates the 8–14 μm spectral band commonly used by long-wave infrared cameras. Cameras covering a more limited wavelength range, for example 3 to 5 μm, detect less emitted radiation at this temperature, potentially increasing uncertainty in the final measurement.

#### 2.3.5.2 Temperature range

The temperature range is the span of temperatures to which a camera is calibrated and is capable of measuring. Some cameras have multiple ranges to allow for measuring a wider span of temperatures more accurately. However, measuring objects with temperatures at the outer limits of the range leads to loss of image quality. There is an in-camera setting for selecting a narrower range at which the user would like the range to be set. AAT guidelines recommend setting the camera temperature range to cover temperatures within the range of temperatures of the animals to be examined, typically 20 to 45°C. The temperature range was reported in 17 papers (15.89%) and ranged from -40 to 2000°C. As an example, G. Lowe *et al.* (2019) utilised a FLIR 650sc thermal camera, employing these limits. However, the datasheet for the camera states that accuracy is ±1°C or 1% of reading for a limited temperature range for objects between 5 and 120°C at an ambient temperature of between 10 and 35°C, and that this is only valid for temperatures within a range of -40 to 120°C. Thus, thermal measurement accuracy in this case is dependent not only on the temperature of the animal but also on the ambient temperature. If the ambient temperature lies outside of the 10 to 35°C range, thermal measurement accuracy would decrease. Understanding the limitations of the thermal camera being used and ensuring it can measure the temperature in an appropriate range is important to achieve accuracy.

#### 2.3.5.3 Resolution

Resolution determines a camera's ability to generate a high-quality image. The more detector elements (pixels) a thermal camera's detector contains, the higher its resolution and the more detail the image will contain. Pixels are the datapoints for thermal measurement, and these data are used to build an image from the thermal profile. The more datapoints acquired, the higher the resolution and accuracy of the thermal image. Higher resolution IR cameras can detect smaller objects from farther away. Pixel size is responsible for level of detail and is typically measured in μm; a greater number of pixels per unit area will yield superior detail. While resolution was reported accurately in approximately one third of studies (n=40; 37.38%), a few papers used the term 'resolution' in an alternative sense and reported it as a temperature in degrees Celsius (n=8; 7.48%). Some were incorrectly referring to thermal sensitivity

(Barth, 2000; Golzarian *et al.*, 2017) but for the remainder, no corresponding documentation was found to support this error (Berry *et al.*, 2003; Hovinen *et al.*, 2008; Poikalainen *et al.*, 2012; Hoffmann *et al.*, 2013; Digiovani *et al.*, 2016; Hoffmann, Schmidt and Ammon, 2016).While the AAT recommends an absolute detector resolution of greater than 640×480 coupled with a suitable microbolometer and lens, a little over a tenth of papers reported using a camera with this resolution or higher (n=12; 11.21%). High resolution is important, allowing the identification of small thermal details and therefore more accurate temperature measurements, within the same field-of-view.

#### 2.3.5.4 Lens, field-of-view (FOV), instantaneous field-of-view (iFOV), spot size, focal length and focus

The lens influences several parameters including the field-of-view, the instantaneous field-of-view, the spot size and the focus. Lens size (n=8; 7.48%) and field-of-view (n=7; 6.54%) were reported in under 10% of papers (Figure 2-6). The AAT recommends a lens with a field-of-view of 25°. The field-of-view is the extent of a scene (the imaging area the lens can see) that the camera can see at any given moment. For close-up work, a lens with a wide angle is required (≥45°), while for long distance work a telephoto lens is more appropriate (12° or 6°). Some cameras have multiple lenses to allow for different applications. Reported fields-of-view ranged from 15° to 45° (Loughmiller *et al.*, 2001; Dunbar *et al.*, 2009; Samara, Ayadi and Aljumaah, 2014; Harris-Bridge *et al.*, 2018; Shecaira *et al.*, 2018; Giro *et al.*, 2019; Stumpf *et al.*, 2021). Montanholi et al. reported the use of all available lenses with one of the IR cameras they used in their research (a FLIR SC2000 with 12°, 24° and 45° lenses) and applied each lens at different distances and experimental settings (Montanholi *et al.*, 2015). All lenses were used in a 'distance and IR camera comparison' trial, which demonstrated that temperature varied inversely with distance to subject for all lenses, and that the 24° and 45° lenses showed similar decreases of around 1.5 to 2.0°C over an increasing distance of 14.5 m (Montanholi *et al.*, 2015). The 24° lens was used at distances of 100 to 150 cm to take images of specific regions of interest such as the snout, the eye and the ear which is an appropriate use of the lens in this context (Montanholi *et al.*, 2015). The 45° lens was used for close-up work, 80 cm from the animals, which is appropriate. It was also used from 400 cm away to evaluate the pregnancy status of a heifer (Montanholi *et*

*al.*, 2015).While this is not an ideal use of a wide-angle lens, as it was being used for relative temperature measurements to compare flank temperatures, it was appropriate in this context.

A critical parameter that affects how far a thermal camera can see is the focal length of the lens. The focal length of the lens is the distance between the lens and the image sensor when the subject is in focus, usually stated in millimetres. Just one paper reported focal length (0.93%) (dos Santos Sousa *et al.*, 2020). Focal length determines the instantaneous field-of-view (IFOV or spatial resolution) of a thermal camera system. IFOV is the angular field-of-view of a single pixel and represents the smallest angle that can be resolved by the system, provided there is sufficient thermal contrast. The IFOV can then be used to determine the distance at which a target's critical dimension subtends the required number of pixels to achieve detection, recognition or identification. The longer the focal length of the lens, the smaller the IFOV becomes, which translates into more pixels across a target at a fixed range. The IFOV is measured in milliradians (mRad), and the AAT recommends a spatial resolution quality at 8 feet (2.4 m) equivalent to ≤2.6 mRad at 40 cm minimum focus. The few papers which reported IFOV (n=3, 2.80%) adhered to the AAT recommendations (Gianesella *et al.*, 2018; Harris-Bridge *et al.*, 2018; Fabbri *et al.*, 2020).

Knowledge and comprehension of spot size, i.e., how much area each pixel covers on the target, is necessary for accurate interpretation of thermal images. The ratio of the maximum distance at which a camera can accurately resolve and measure a minimum spot size to the spot size itself is called the camera's maximum 'distance to spot size ratio' or simply 'spot size ratio'. The smallest object of interest must be fully delimited by at least a 10×10 pixel grid in order to obtain the closest to absolute temperature accuracy. However, a true measurement (or close to true measurement) may still be possible even if spot size is a single pixel or a 3×3 pixel grid. The AAT recommends a minimum measurable spot size of 2.1×2.0 mm (3×3 or 9 pixels) at 40 cm distance from the animal. Neither spot size nor spot size ratio were reported in any of the articles reviewed. Montanholi *et al.* mention that temperature likely decreased with increased distance for a particular area due to lowered spot size but did not supply any supporting calculations. In a 2021 thermal study concerning human

fever detection and size-of-source effects in IR cameras, Pušnik *et al.* concluded that in order obtain effective images for disease detection, the operator must account for spot size and that the region of interest must contain at least 10×10 pixels of homogeneous temperature of which the area used for temperature should be positioned at least 7 pixels from the edge of the region of interest (Pušnik and Geršak, 2021).

The camera lens should be focused on the object of interest to yield an accurate measurement. Dunbar *et al.* found that eye temperatures of well-focused thermograms indicated a statistically similar temperature to core body temperature (Dunbar *et al.*, 2009), in agreement with Pušnik *et al.* (Pušnik and Geršak, 2021). Cameras may be fixed focus, meaning they are always in focus, manual focus, meaning the operator must adjust the focus on the camera, or automatic focus, meaning the camera will autofocus based on what it can identify for contrast in the scene. In general, entry level cameras have fixed focus, and high-performance cameras have either manual or automatic focus. Focus was reported in two papers, with one using manual focus (Giro *et al.*, 2019) and the other using automatic (Byrne *et al.*, 2017). Precision autofocus is preferred by the AAT, which lends itself to automation and frees up the operator to perform other essential tasks and measurements.

#### 2.3.5.5 Camera calibration, stability, drift and accuracy

Calibrating a thermal camera is the process of correlating what the camera sees, in terms of infrared radiation, with known temperatures, so that it can transform the radiation it detects into an accurate temperature reading. All cameras are initially calibrated to factory specifications, but over time, aging of the electronic components can cause calibration shift and produce inaccurate temperature measurements. It is necessary for cameras to be calibrated annually by the manufacturer to maintain their accuracy. Calibration is performed under controlled conditions with multiple blackbodies which are used as reference temperature sources. The theoretical ideal blackbody has an emissivity of 1.0 and perfectly absorbs and emits all radiation. Blackbodies are arranged in a semi-circle and set to different known temperatures, and then the thermal camera, which is connected to a robotic arm, is pointed at each reference source one by one. The signal value at each temperature is captured by calibration software, and each pair of signal and temperature values are

plotted along a curve, the equation of which is based on a physics model. This data is then loaded into the camera, calibrating it to ensure it meets accuracy specifications. Because of these extensive requirements, cameras need to be calibrated in a laboratory setting. The AAT guidelines recommend that camera temperature offset should be calibrated against the emissivity of a blackbody at 1.0 if needed for the examination being performed.

While calibration of the thermal camera prior to use was reported in 20 papers (18.69%), on closer inspection it was discovered that the actual method described did not conform to this definition. In most of this subset of papers (n=16; 14.95%) camera calibration was interpreted as either allowing the camera to habituate to the testing environment for 10 to 15 minutes, or the operator inputting the recorded relative humidity, ambient temperature and emissivity into the camera prior to use. Of the remaining papers (n=4; 3.74%), one calibrated to a graybody (a body where transmission, absorption, and reflection are all constant with wavelength) prior to use and three were factory calibrated with blackbodies. Ideally, the date of the last laboratory calibration should be reported.

Stability and drift are two main sources of errors in measurement accuracy. Drift was accounted for in two papers (1.87%) and stability was mentioned in one paper (0.93%). Stability is an error that is a function of time, whereas drift is a function of the temperature of the measurement electronics, caused by internal heating of equipment during normal operation or by changes in external ambient temperature. The AAT recommended that thermal drift is strictly controlled by calibration to a known temperature standard if necessary for the study under consideration and advise maintenance of detector uniformity and correction via calibration to a known temperature standard, as outlined above. Other 'field' methods include checking the temperature output by the camera against a known temperature, such as that of ice or boiling water. Kammersgard *et al.* conducted a stability test post data collection (Kammersgaard, Malmkvist and Pedersen, 2013). Using a bucket of icy water as a target, they compared the maximum IR temperature of the water surface (measured using the IR camera) with the surface water temperature (measured using a thermal sensor probe) as a reference temperature. The difference between IR temperature and reference temperature was calculated and it was found on average (over a 90-minute

period) that the maximum IR temperature was just 0.21°C higher than the reference temperature. The authors concluded that this stability test suggested a superior accuracy of the IR camera to that indicated by the manufacturer. Menzel *et al.* applied the 'difference method' (Menzel *et al.*, 2014, 2015), developed by Siewert *et al.* (Siewert *et al.*, 2014) to account for temperature drift. The method uses the principle that "in the case of two electrical analogue signals generated by a sensor and conducted on a printed circuit board which are overlaid with a disturbing signal - caused by electromagnetic coupling into both analogue signal lines - through a difference calculation, a strong limitation of the error is achieved" (Siewert *et al.*, 2014). After showing that the difference ROI method could be used for early detection of elevated body temperature in pigs (>39.5°C), Siewert *et al.* concluded that the difference method is superior to a conventional analysis based on absolute temperature values with error margins in the order of ±2 to ±1.5°C. The method requires that at least two anatomical regions that can be recognised as reproducible are in the IR image, but the authors also state that the results should be interpreted with caution, due to the low sample size of animals used in the study.

Higher-end IR cameras have an internal mechanism to account for drift. A miniature blackbody drops in front of the detector at regular intervals, making a clicking noise when activated. This is called the non-uniformity calibration flag. The camera assumes that this flag has a uniform temperature and corrects for any drift internally. This correction also impacts the temperature measurement and its drift and stability. Ghassemi *et al.* evaluated the drift and stability of two IR cameras according to the methodology issued by the International Organisation for Standardisation (ISO:IEC90601-2-59:2017), which outlines the “particular requirements for the basic safety and essential performance of screening thermographs for human febrile temperature screening” (Ghassemi *et al.*, 2018). They found that neither of the IR cameras satisfied the requirement of both stability and drift being <0.1°C as stated in the international standard without the use of an external temperature reference source within the image (Ghassemi *et al.*, 2018). This finding is likely to impact the possibility of achieving accurate absolute temperatures in the context of livestock disease detection for all IR cameras.

#### 2.3.5.6 Thermal sensitivity

Thermal sensitivity or noise equivalent temperature difference (NETD) describes the smallest temperature difference that can be captured with a thermal camera. It is a measure of how well a thermal imaging detector can distinguish between very small differences in thermal radiation in the image. The lower the number, the better the thermal sensitivity of the IR system. A temperature-controlled blackbody is used to measure the noise equivalent temperature difference of a detector. The blackbody is stabilised before starting the measurement. The noise equivalent temperature difference is then measured at a specific temperature. It is not a single snapshot measurement, but rather a temporal measurement of noise. Noise is defined as random fluctuation in electrical output from a camera's detector. This noise can interfere with the signal one is aiming to capture. The warmer the detector, the more noise will be present. When the noise is equivalent to the smallest measurable temperature difference, the detector has reached the limit of its ability to resolve a useful thermal signal. The more noise present, the higher the NETD value of the detector. In applications where thermography targets have wide temperature differences, a camera with a low NETD is likely unnecessary. However, for more subtle applications, like different ROIs on a living animal, higher sensitivity would be an advantage. NETD is typically expressed in millikelvin, for example: 60 mK at 30°C, and is sometimes referred to as 'thermal contrast'. While NETD was reported in 24 papers (22.43%), inconsistencies in units were noted, with authors using kelvin, mK or °C. The temperature at which NETD was performed was not recorded in 15 papers and two papers attributed the value to resolution instead of NETD. This reduces the numbers of publications reporting accurate NETD parameters to eight (7.48%). The AAT recommends an NETD of <50mK at 30°C. Converting all Celsius temperatures provided to mK and assuming all measurements were performed at 30°C, 12 papers satisfied the AAT requirement (Church *et al.*, 2014b; Metzner *et al.*, 2014b; Hoffmann, Schmidt and Ammon, 2016; Jiao *et al.*, 2016; Byrne *et al.*, 2017, 2018, 2019; Harris-Bridge *et al.*, 2018; Zaninelli *et al.*, 2018; Giro *et al.*, 2019; G. Lowe *et al.*, 2019; Tangorra *et al.*, 2019). NETD was correctly recorded as 0.04 K by Hoffman *et al.* but the temperature at which this was tested (25°C) was not included (Hoffmann, Schmidt and Ammon, 2016). An earlier paper recorded NETD as 0.08 K but this could not be confirmed on the datasheet; supplied NETDs were 40 mK with the

23° lens, 0.3 K with the 6° lens and 0.1 K with the 41° and 72° lenses (Hoffmann *et al.*, 2013).

#### 2.3.5.7 Video imagery

The utilisation of video versus still imagery was reported in nearly all publications (n=105; 98.13%) with the latter dominating (n=97; 90.65%). Video recommendations from the AAT are to incorporate real-time image focus and capture capability and that fast frame rate capability is preferred (50 Hz). The higher the refresh rate, the more frames will be produced each second, and the smoother the rendering but this does not itself ensure that the image is in focus. The refresh rate is measured in Hz, a unit of frequency, denoting the number of times per second one period of an image is cycled. For example, if the refresh rate of a thermal imaging device is 50 Hz, this means that the image refreshes 50 times every second (equivalent to 50 frames/second). Only a minority of studies recorded using video (n=8; 7.48%) (Barth, 2000; Hoffmann *et al.*, 2013; Schmidt *et al.*, 2013; McCoard *et al.*, 2014; Hoffmann, Schmidt and Ammon, 2016; Stewart *et al.*, 2017; G. Lowe *et al.*, 2019; Jaddoa *et al.*, 2019) with just one quarter of those using a frame rate greater than 50 Hz (McCoard *et al.*, 2014; Stewart *et al.*, 2017) due to thermal camera capabilities. The AAT also recommend that for temperature analysis, radiometric video files are used as there is temperature data embedded in each pixel. Use of video rather than still imagery offers the advantage of analysing more than one image per animal, and shows potential as a monitoring system (Hoffmann *et al.*, 2013; G. Lowe *et al.*, 2019), but there is no research as yet into the optimal number of frames per second for IR video capture in livestock. The choice between still imagery and video should reflect the measurement objective and practical constraints. Still imagery provide discrete observations and generally require less storage and processing than extended video recordings at comparable resolution, but may miss brief changes or suitable views of an animal. Video provides repeated observations, allowing selection of frames in which the anatomical region of interest is clearly visible, and enables assessment of changes over time, such as respiratory thermal fluctuations (G. Lowe *et al.*, 2019). These benefits involve greater data-handling and analytical demands, including frame selection and maintaining a consistent region of interest as animals move. Selection criteria should be specified to avoid preferentially retaining frames that support the

expected result, and repeated frames from the same animal should not be treated as independent animals. Video therefore offers additional temporal information, but does not inherently provide more accurate temperature estimates. Its value depends on whether that information justifies the additional acquisition, storage and analysis requirements.

#### 2.3.5.8 Camera choice

Camera make and model was reported in 102 papers (95.33%), with 66 of these being manufactured by FLIR. Whether the camera was fixed or handheld was reported in 59 papers (55.14%) with 14 of these being fixed and 45 being handheld. Bleul *et al.* (Bleul, Hässig and Kluser, 2021) and Jorquera-Chavez *et al.* (Jorquera-Chavez *et al.*, 2020) tested a low cost, small, handheld IR camera (FLIR One) attached to a smart phone to assess its capability for disease detection in animals. Both studies found that the camera had limited efficiency. Bleul *et al.* found it produced large variations in measurements and recommended the use of a higher quality thermal camera for future experiments (Bleul, Hässig and Kluser, 2021). Jorquera-Chavez *et al.* noted in their study that because respiratory rate was analysed from non-radiometric infrared videos, this could have affected the sensitivity of the measurements due to changes in light conditions (Jorquera-Chavez *et al.*, 2020).

### 2.3.6 Environmental parameters

Environmental parameters impact IRT temperature measurements significantly and therefore must be managed to ensure reproducible and accurate readings (Church *et al.*, 2014b). Terrain and climate influence ambient temperature, relative humidity, sunlight, wind and rainfall and IRT is sensitive to environmental changes such as weather fluctuations and radiation from adjacent surfaces. Overall, for the 107 papers in the review, across the 12 environmental parameters, 43.61% of expected data was reported (Figure 2-8). While some studies incorporated environmental parameters into calculations and analysis, none accounted for all types of environmental parameters, which will be necessary to attain the required disease surveillance accuracy, sensitivity and specificity (Bell *et al.*, 2020b). The camera must be allowed to habituate to the environmental conditions in which it is to be used. To achieve ambient

temperature compensation, the Teledyne FLIR user's manual[9] recommends measuring the temperature of the camera and optical path in up to three different locations. These data are then included in the internal calibration equation and can ensure accurate readings through the entire range of operating temperatures (typically -15 to 50 ºC). This is particularly relevant for using IR cameras outdoors. Additionally, cameras should be given time to warm up prior to taking any measurements. The camera and optics should be kept out of contact with other heat sources or direct sunlight as changing the temperature of either will adversely affect measurement uncertainty.

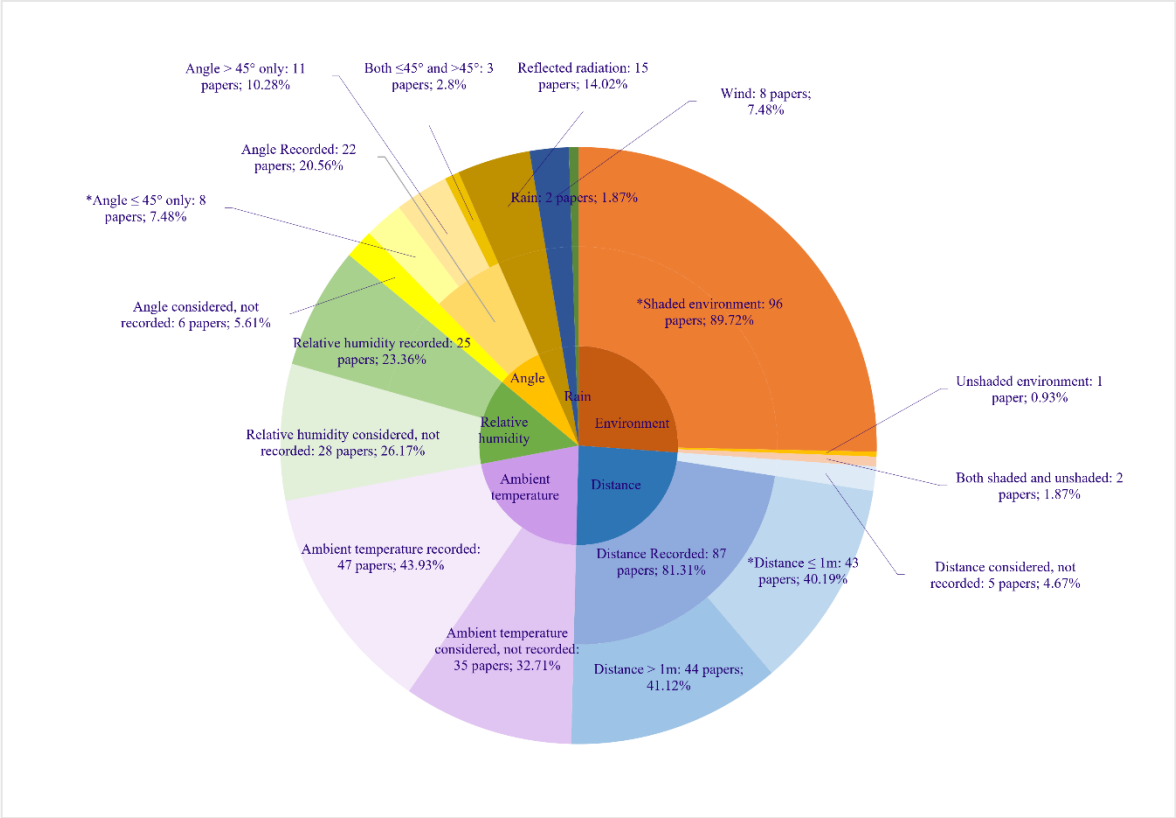



**Figure 2-8.** Environmental parameter reporting in the 107 studies included in the scoping review. Labels show the number and percentage of papers reporting each parameter or condition. Individual papers may contribute to several categories. An asterisk (*) denotes the recommended value or condition. Angle categories reflect values as reported by the authors and are not mutually exclusive; three publications reported angles in both categories (≤45° and >45°).

[9]Teledyne FLIR LLC. FLIR Ex Series User Manual. https://www.flir.com/globalassets/imported-assets/document/flir-ex-series-user-manual.pdf [Accessed June 6, 2022 ].

#### 2.3.6.1 Wind, rain, ambient temperature, reflected radiation and relative humidity

Wind, rain and ambient temperatures can affect animals' skin temperature due to evaporation and blood flow to the skin. Temperature assessments were undertaken in a variety of environments: either indoors in a closed room, outdoors in a shaded barn or in the field in direct sunlight. Church *et al.* (Church *et al.*, 2014b) found that in the presence of a 7 km/h wind, mean eye temperature difference was 0.43°C but that at higher wind speeds of 12 km/h, mean difference was 0.78°C when compared with no wind. The presence of wind at both higher and lower speeds resulted in a statistically significant decrease of cattle IR eye temperature. Internal body temperature monitoring revealed that cows exposed to wind and rain could be either hotter or colder than cows indoors due to an increase in the amplitude of the circadian body temperature rhythm (Webster *et al.*, 2008). Bewley, Einstein et al. (169) found that both rectal and reticular temperatures were influenced by season, milking, housing system and parity and so IR estimates of these temperatures would be similarly affected. Church *et al.* (2014) worked with different humidity settings on the cameras, finding that as humidity accounts for only a 0.1°C temperature change over its range (0–100% humidity), the setting had very little effect at 1 m at a constant room temperature. As humidity is expected to affect the transmission of IR radiation, humidity corrections may become more pronounced at greater distances and higher temperatures (Church *et al.*, 2014a). Sunlight and reflected radiation from other surfaces can interfere with the temperature on the IR image collected. For instance, an object that is cool to touch may show a higher temperature on a thermogram if a nearby heat source (such as the operator, or other animals) was reflecting off the surface. Sunlight will also adversely affect the result, with direct sunlight increasing IRT eye temperature by 0.56±0.36°C (Church *et al.*, 2014b). These environmental influences act in two distinct ways: they can change the animal's actual surface temperature, or affect the estimation of that temperature from the radiation reaching the camera. Wind and wetting, for example, can alter surface temperature through heat loss, while reflected radiation and atmospheric transmission can affect the temperature estimated by the camera. An environmentally induced change in surface temperature may therefore be measured accurately but misinterpreted as a change associated with disease. Controlling or recording environmental

conditions is consequently necessary both to minimise measurement error and to distinguish environmental effects from physiological changes associated with disease.

#### 2.3.6.2 Distance and angle

Variations in the distance between the subject and the camera as well as the angle of the image can affect the accuracy of the measurements. The AAT recommend a patient to camera distance of between three and eight feet (0.91 to 2.44 m), as needed to allow the ROI to fill approximately 75% of the image but make no recommendations as to angle of assessment. Church *et al.* investigated the effect of distance to object and found that as camera to object distance increased from 0.5 to 3.0 m, IR temperature decreased by as much as 2.0°C (Church *et al.*, 2014b). Okada, Takemura and Sato found that temperatures were significantly lower at distances of 2 and 3 m away from the object of interest (cattle) but that there were no significant differences between distances of 0.5 and 1 m (Okada, Takemura and Sato, 2013). Just under half of the papers reporting distance used distances of 1 m or less. Playà-Montmany and Tattersall demonstrated that even when incorporating the appropriate object parameters in the thermal image software, increasing the distance away from their calibration source (a blackbody of known temperature and emissivity) led to a linear increase in the apparent error in temperature (Playà-Montmany and Tattersall, 2021). As the eye to camera distance increased, the IR temperature value decreased for all settings (Playà-Montmany and Tattersall, 2021).

Ijichi *et al.* aimed to validate a standardised protocol for the use of IRT eye temperature measurement in mammals with anterolateral eyes, such as horses and cows (Ijichi *et al.*, 2020). In horses, they found a significant strong positive correlation between eye temperature taken from an angle of 90° to the sagittal plane but observed no such correlation from 90° to the nasal plane or eye, suggesting the optimal position would be 90° in relation to the sagittal plane. Jiao *et al.* found that an angle greater than 45° away from the area of interest yielded significant differences in temperature measurement (Jiao *et al.*, 2016). Eleven papers reported at least one angle of 45° or less (Krogbeumker *et al.*, 2009; Alsaaod and Büscher, 2012; Alsaaod *et al.*, 2014a; Amezcua *et al.*, 2014; McCoard *et al.*, 2014; Talukder, Gabai and Celi, 2015; Jiao *et al.*, 2016;

Kleinhenz *et al.*, 2019; Bell *et al.*, 2020a; Reppert *et al.*, 2020; Warner *et al.*, 2021). However, angle reporting was inconsistent: some papers reported a 90° angle to an object, but this was actually a 0° angle to the object and *vice versa*. A paper documenting areas for error when using IRT in ecology found that angles greater than 55° led to a decrease in emissivity when testing with mink fur, along with other biological and non-biological materials (Playà-Montmany and Tattersall, 2021). Vardasca *et al.* (Vardasca *et al.*, 2017) found that the mean temperature of the inner canthi of the eye of humans varied by 0.1ºC at distances between 0.8 and 1.2 m when compared with the reference distance and angle of 1 m and 90º, and by 0.4°C and 0.5°C at angles of 105º and 75º, respectively. They concluded that to minimise measurement error, distances between 0.8 and 1.2 m and angles as close as possible to 90° should be used to obtain the temperature of the medial canthus of the eye. There are now developed methods to account for angles greater than 45° (Jiao *et al.*, 2016). However, where possible, aiming to record thermal images at distances of 0.5 to 1 m and at angles of 0 to 45° to the ROI would be ideal. A unified approach to recording angle, with supporting images, would be useful.

## 2.4 Discussion

### 2.4.1 Recommended parameters

In recent years, IRT has progressed as a diagnostic and clinical tool in both the medical and veterinary spheres, although differences exist between these applications. Within a hospital environment, IRT can be performed in highly controlled laboratory-like conditions, with patients capable of describing symptoms to medical practitioners. As such, the use of IRT in humans has become more specialised than in livestock, with the AAT producing separate guidelines for neuro-musculoskeletal10, dental-oral and systemic health11 and breast health12 examinations for cancer screening (Kennedy, Lee and Seely, 2009). For use of IRT in livestock, the veterinary AAT guidelines are more geared

[10] American Academy of Thermology. Guidelines for Neuro-Musculoskeletal Infrared Medical Thermology (2022). https://aathermology.org/wp-content/uploads/2018/04/AAT-Oral-Systemic-Guidelines-2022.pdf [Accessed July 6, 2022].

[11] American Academy of Thermology. Guidelines For Dental-Oral And Systemic Health Infrared Thermography (2022). https://aathermology.org/wp-content/uploads/2018/04/AAT-Breast-Guidelines-2021v2.pdf [Accessed July 6, 2022].

[12] American Academy of Thermology. Guidelines for Breast Thermology (2022). https://aathermology.org/wp-content/uploads/2018/04/AAT-Breast-Guidelines-2021v2.pdf [Accessed July 6, 2022].

towards equine thermography, with a focus on sport horses. However, in general terms, indications are similar for use of IRT in humans and animals, i.e. as a diagnostic aid, to enhance clinical assessment and to assess thermal, functional and musculoskeletal stress in animals. While this review focusses on disease detection in livestock, there has also been extensive research undertaken on evaluating IRT to detect heat stress in animals (Weschenfelder *et al.*, 2013; de Souza *et al.*, 2018; Wildridge *et al.*, 2018) and to assess the reproductive health of sires (Menegassi *et al.*, 2015; Rode *et al.*, 2016).

Early disease detection using IRT has the potential to yield significant benefits for both animals and humans. A system that uses IRT to detect disease could reduce farm labour, improve animal welfare and increase production yields. To our knowledge, this is the first study to collate and summarise these parameters in an attempt to provide a reference guide. To improve reporting guidelines, researchers should provide parameter data to enable like-for-like comparisons and ensure that the evidence underpinning IRT for use in disease detection for livestock is harmonised, robust, reproducible and repeatable.

Creation of a disease surveillance system incorporating IRT for early detection depends on several parameters to optimise accuracy (see Tables 2-4, 2-5 and 2-6). These include but are not restricted to: ambient temperature, relative humidity and radiated temperature. In an ideal experimental scenario, the first two can be achieved using a data logger habituated to the environment to record ambient temperature and relative humidity, while the third can be carried out using a Lambert radiator. A Lambert radiator is an object that reflects incident radiation in all directions and represents optimum diffusion. The temperature of the reflected radiation can be measured using a Lambert radiator in conjunction with a thermal camera. Using a crumpled and unfolded piece of aluminium foil (which has a high reflectance and its crumpling allowing for near-perfect diffuse reflection) as a suitable substitute for a Lambert radiator, the foil should be placed on or in the same area as the object one wishes to image. Camera emissivity should be set to 1.0. The temperature of the Lambert radiator as it appears in the image can be input into the thermal camera as the radiated temperature. The camera must be habituated to the environment and ideally personnel trained in IRT should be involved in and/or

carry out procedures. Imagery should be collected at 1 m or less and at angles of 45° or less from the ROI.

The IR camera should have a resolution of at least 640×480, an NETD of 50 mK at 30°C, a spectral range of 8 to 14 μm, an IFOV of ≤2.6 mRad at 40 cm minimum focus and a spot size of at least 3×3 pixels (ideally 10×10 pixels of homogeneous temperature of which the area used for temperature should be positioned at least seven pixels from the edge of the ROI). Blackbody calibration of the camera to reference object temperature and for camera stability and drift should be carried out once per year. Fixed cameras would reduce differences between human operators and would lend the IRT system to automation. The temperature range of the camera and its setting prior to use should include the ranges users are interested in, i.e., between 30 and 45°C, and the lens should have a field-of-view of 25°. If using video, a frame rate of at least 50 Hz and precision autofocus are recommended. However, many commercial thermal cameras offer 30 Hz as the maximum frame rate. For temperature analysis, radiometric files are preferred. However, some video file formats are proprietary and require specific commercial software for analysis. Emissivity values should be established for livestock and researchers should endeavor to obtain training in and understand IR technology prior to its use. Obviously, researchers should strive to achieve all ideal parameters when planning future experiments, but practicalities and cost will influence experimental design. Cameras that have the capabilities as outlined above usually cost upwards of $23,000[13],[14]. However, technology is currently advancing at a rapid rate and smaller, lighter and cheaper instruments are being manufactured from year to year and so the ideal equipment is becoming ever more accessible.

### 2.4.2 Challenges and opportunities with regards to disease detection

This section discusses the opportunities and challenges that are likely to be encountered in the journey and the design stages of creating an IR system for disease detection. We reflect on three distinct but linked considerations: types of diseases (exotic, endemic and production diseases); absolute versus relative

[13]Teledyne FLIR LLC. FLIR A615. https://www.flir.co.uk/products/a615/?vertical=rd%20science&segment=solutions [Accessed June 8, 2022].

[14]PASS Equipment and Accessories. Price of FLIR A615. https://www.tester.co.uk/flir-a615-automated-process-r-d-thermal-camera-w-choice-of-lens [Accessed June 8, 2022].

temperatures; individual versus herd measurements, including animal identification, indoor and outdoor environments; and the implications of these considerations for UAV-based thermal imaging.

#### 2.4.2.1 Disease types

There is potential for IRT to be used to detect infectious and non-infectious diseases which affect production (mastitis, digital dermatitis), domestic markets (Bovine Viral Diarrhoea (BVD), Bovine Respiratory Disease (BRD)) and international markets (notifiable diseases such as FMD and Bluetongue (BTv)). IRT may be particularly useful for diseases which affect the blood supply or cause focal areas of inflammation such as digital dermatitis, laminitis and FMD of the hoof and mastitis of the udder. Nikkhah et al. investigated IRT for detection of inflammation associated with laminitis in dairy cattle, concluding that IRT may have potential as a detection tool for laminitis (Nikkhah *et al.*, 2005). Further research was recommended to investigate the relationship between IRT and hoof abnormalities and to identify other diseases affecting hoof temperature (Nikkhah *et al.*, 2005).

A 2009 study assessed IRT as a screening tool for FMD, before and after development of clinical signs (Rainwater-Lovett *et al.*, 2009). Eye and hoof temperatures were analysed and the feasibility of IRT as a screening tool for FMD in cattle was demonstrated finding that IR foot temperatures increased in FMD-infected animals (Rainwater-Lovett *et al.*, 2009). The authors recommended further research to enable differentiation between foot-associated conditions (i.e. to differentiate FMD from digital dermatitis using an IR image) and the development of computational algorithms to assess signature temperature patterns of specific diseases (Rainwater-Lovett *et al.*, 2009). Results demonstrated IRT to be a promising screening technology to quickly identify potentially infected animals for confirmatory diagnostic testing during FMD outbreaks. Dunbar *et al.* evaluated the use of IRT in detecting heat changes associated with affected sites of FMD infection, namely the feet and mouth, while also recording body temperature from a surgically implanted abdominal temperature logger and eye IRT (Dunbar *et al.*, 2009). In that study, Mule Deer experimentally infected with FMD experienced a significant foot temperature rise over the course of the infection. The authors highlighted that thermograms of the eye may have use in detecting changes in general body temperature by

use of the eye as an index of body temperature. IRT may thus have potential as a rapid and remote screening tool for FMD infection and research focused on the correlation of eye temperature and body temperature will determine the practical use of IRT in screening for FMD and other pyrogenic diseases (Dunbar *et al.*, 2009). However, a later experiment which evaluated eye and foot IRT in cattle concluded that IRT would "be at best a modest predictive indicator of early FMD" (Gloster *et al.*, 2011). It was noted that activity (or lack thereof) influences the temperature of the hoof and as such a period of acclimatization is required prior to imaging. In agreement with Dunbar *et al.* (Dunbar *et al.*, 2009), this study also suggested that IRT of the eye may be a good proxy for core body temperature (Gloster *et al.*, 2011). The study was completed under ideal field conditions, so this will not necessarily translate to real-life farming and veterinary work (Gloster *et al.*, 2011).

Berry *et al.* used IRT to gather baseline information on the magnitude and pattern of daily variation in udder temperature and tried to determine the influence of environmental temperature parameters on udder temperature (Berry *et al.*, 2003). The authors concluded that IRT showed promise as an early detection method for mastitis when coupled with environmental temperature monitoring. Polat *et al.* aimed to determine interrelationships among mastitis indicators and evaluate the subclinical mastitis detection ability of infrared thermography (IRT) in comparison with the California Mastitis Test (CMT) (Polat *et al.*, 2010). The study found that as a non-invasive and rapid tool, IRT could potentially be employed for screening for subclinical mastitis via measuring udder surface temperature with a high predictive diagnostic capability, similar to the CMT when microbiological culture is unavailable. Polat *et al.* stated that the receiver operating characteristic curve "revealed that sensitivity and specificity of IRT (95.6 and 93.6%, respectively) were not different from those for CMT (88.9 and 98.9%, respectively)". In addition to being non-invasive and relatively fast, IRT was sensitive enough to detect thermal changes on udder skin caused by subclinical mastitis (Polat *et al.*, 2010).

IR eye temperature has been highlighted as a potentially useful indicator of core body temperature that is not affected by ambient temperature (Dunbar *et al.*, 2009; Gloster *et al.*, 2011). The temperature of the posterior border of the eyelid and the medial canthus have been found to be the most representative of

core body temperature due to rich capillary beds (Stewart *et al.*, 2007). There have been a number of studies investigating eye temperature using IR sensors in cattle (Schaefer *et al.*, 2004, 2007, 2012; Stewart *et al.*, 2017) to ascertain its feasibility and accuracy for fever, disease, pain and stress detection. Bell *et al.* found a weak correlation between thermal eye and rectal temperature of r=0.28 (Bell *et al.*, 2020a), which is similar to the findings of Scoley *et al.* of r=0.24 (Scoley, Gordon and Morrison, 2019). Bleul *et al.*, however, established a stronger correlation of r=0.37 (Bleul, Hässig and Kluser, 2021). Bell *et al.* posit that sex, age and parity of an animal are all differences which warrant consideration in attempting to solve this problem as they likely influence the thermoregulation of an animal (Bell *et al.*, 2020a). Continuous temperature measurement of individual animals would give confidence that changes in temperature are due to disease rather than natural body rhythms and temperature set points.

Cook *et al.* investigated radiated surface temperature measurements of groups of piglets and found that a febrile response to vaccination was detectable on thermal imaging when compared with control groups (Cook *et al.*, 2014). Two experiments thus far have measured respiratory rate by IRT to assess stress and discomfort in cattle. The first attempted to validate IRT as a method of respiratory rate measurement in adult cows by measuring respiratory rate with continuous IRT imaging of airflow through the nostrils and by counting flank movements from video and live recordings (Stewart *et al.*, 2017). The authors concluded that IRT can be used reliably to measure respiratory rate and that with further development, the technology could be integrated into existing systems for remote monitoring of dairy cows' health and welfare on-farm. The second study recorded air exhaled from nostrils in calves and found IRT to be a suitable method for recording respiratory rate in calves (G. Lowe *et al.*, 2019). The authors write that once this method is validated, the future application of IRT will rely on the development of algorithms to automate recording and analysis.

#### 2.4.2.2 Absolute and relative temperatures

Farmers and animal health professionals will look to identify normal and abnormal temperatures in livestock, using acquired thermal imagery to differentiate between diseased and non-diseased animals. Fever screening based

on a fixed temperature cut-off would require absolute temperature estimates. However, if one is looking for a change over time, it may be possible to use relative temperatures of individual animals or the herd as a whole. Here, absolute and relative temperatures describe how temperature is assessed, whereas surface and core temperatures describe where it is measured. Absolute thermographic measurements provide numerical estimates of surface temperature, while relative measurements concern differences between anatomical sites, animals or time points. Neither directly measures core body temperature. Using surface temperature as an indicator of fever therefore requires validation against an appropriate reference measure, such as rectal temperature.

For example, a relative change or increase may be enough to present a signal to detect signs of mastitis or digital dermatitis at an individual animal level, provided animals can be identified. Radiometric JPEGs (RJPGs) are thermal images with temperature information embedded into the image as metadata. These give absolute temperature measurements for each pixel within the image. RJPGs retain radiometric data that allow surface temperature estimates to be extracted from individual pixels using compatible software. Standard non-radiometric JPEGs retain the displayed image without the underlying radiometric data. Quantitative temperature analysis therefore requires a radiometric format, such as RJPG; however, the file format alone does not ensure measurement accuracy. Systems using RJPGs instead of JPGs will produce more data for storage and analysis. Systems requiring absolute temperature measurements for livestock should aim to use RJPGs. An option to use relative temperatures instead of absolute would involve building a bank of images over a set time period representing 'normal' or 'non-diseased' for an individual animal or for the herd. The IR system would update this bank of images/data once or twice per day and then would be able to identify a change from the norm using relative temperatures. The accuracy of IR cameras must be considered and included in models if disease threshold temperatures are to be established.

#### 2.4.2.3 Individual or herd measurements

While the studies included in this review primarily focus on thermographic assessment at the level of individual animals or specific anatomical sites, rather than herd-level surveillance, herd-level measurement is considered here as a

potential future application. This may be particularly relevant where individual animal identification is not feasible or where group-level changes may indicate the need for further investigation. At the individual-animal level, a thermal finding can prompt further assessment of that animal, and repeated monitoring requires measurements to be linked to the same individual. At the herd level, a change in the group's thermal pattern could prompt investigation of the herd without necessarily identifying which animals are affected.

Translation of IRT into a surveillance or monitoring system raises the practical challenge of animal identification, particularly where thermographic measurements are intended to inform decisions at the level of individual animals. In the UK, most livestock are identifiable by individual ear tags but only sheep are legally required to have electronic tags that can be read with a radio frequency identification reader. Many farms, however, are already using sensor-based technology for estrus detection, such as pedometers or collars. This ID or the ear tag ID for each animal could be read and uploaded to the system when animals enter the race to identify time of entry and therefore matched with time when the IR image or video was taken. If it is not possible to identify individual animals in this manner, an alternative would be to collect information concerning the whole herd and to monitor for any relative change outside of the norm. As previously mentioned, sunlight and reflected radiation can interfere with the temperature on the IR image. This will likely make outdoor data collection unreliable and further research may conclude that these technologies are only suitable for indoor implementation in, for example, barns and milking parlours. This will have an impact on the species and production type of animal that can be monitored.

#### 2.4.2.4 Implications for UAV-based thermal imaging

The preceding considerations are particularly relevant to the use of UAV-acquired thermal imagery for animal health surveillance. The reviewed literature demonstrates that thermography has been applied to disease detection in livestock, but also shows that interpretation of thermographic measurements is affected by environmental conditions, emissivity, anatomical site selection, image acquisition protocols, distance from the target, and validation against appropriate reference measures. These issues limit the extent

to which absolute or apparent surface temperatures can be interpreted as direct indicators of disease across different settings.

These constraints are amplified in UAV-based thermal imaging, where images are acquired from a moving platform and at greater distance from the animal. Flight altitude, viewing angle, atmospheric conditions, animal size, movement, and pixel size may all affect temperature estimation. This informed the methodological decision in Chapter 4 to use UAV-acquired thermal imagery primarily for livestock detection based on relative temperature differences between animals and their surrounding environment, rather than as a direct measure of disease status. This does not remove the longer-term relevance of absolute thermography for disease detection, but positions reliable animal detection and localisation as a necessary step before animal-level thermal data can be extracted, standardised, validated, and interpreted in relation to health or disease.

In this way, the review provides both a set of methodological considerations for future studies seeking to use absolute thermography for livestock disease detection and a rationale for the subsequent experimental focus on UAV-based data acquisition and machine learning-based livestock detection.

### 2.4.3 IRT system considerations

Useful real-time reporting would demand on-site (i.e., farm, abattoir) data capture and processing as part of any IRT system. Zhang *et al.* (Zhang, Guo and Li, 2019) outlined the necessary components of an IR diagnostic system, including: an IR optical system, an uncooled focal plane array, a signal processing system and a display terminal. Implementation of this system for use with livestock will require some adjustments. Animal identification would ideally be built into the system and the system would need to be autonomous for users to benefit.

Video allows repeated observations of animals over time, providing opportunities to select suitable frames and assess temporal changes. For moving animals, sufficiently short exposure times and fast detector responses can reduce motion blur and associated temperature measurement errors; a higher frame rate alone does not guarantee these improvements. IR cameras record at high frame rates,

creating large quantities of data, which pose a challenge for data processing, analysis and storage.

Opportunities for data reduction should be explored and exploited. Within the medical field of IRT, researchers apply methods including the subtraction of background from each frame of interest (Gulyaev *et al.*, 1995), Fast Fourier Transform (Lewis, Gatto and Porges, 2011; Lahiri *et al.*, 2012) and Principal Component Analysis (Gauci, Camilleri and Falzon, 2020). Consideration will need to be given to whether the original raw image data will need to be retained in case of future enquiry, for example if there is an exotic disease outbreak and data needs to be kept for future lessons learned or future interrogation.

Colour palette is a consideration for processing, illustration and interaction purposes. A 'false' colour scale can be selected to represent the image for thermal image processing. Different colour scales are appropriate for different uses. The 'rainbow' palette is generally the preferred colour scale for thermography in medicine and biology (Ammer, 2014). Ammer used processed images to demonstrate that false colourings impacted resolution, gray levels and the likeness of the imaged object (Ammer, 2014). Howell *et al.* used the rainbow palette with five cameras from both FLIR and Infratec and found that equine images were incomparable due to different colour choices with increasing temperatures from the two manufacturers (Howell, Dudek and Soroko, 2020). They suggested that a solution would be to apply a linear grayscale to all images when thermal images from different software packages are to be compared. Vardasca carried out research into which false 'rainbow' colour scales work best as a visual aid for human interpretation and recommended an internationally accepted standard false colour scale to ensure agreement across studies (Vardasca and Gabriel, 2014). Olalia *et al.* found that in hot tropical areas, where the temperature of the scene may match the object being imaged, the more colour a palette has, the more noise it generates (Olalia *et al.*, 2021). As a result, they recommended the use of minimal contrasting colours to render solid detailed images, using palettes such as 'black-hot' and 'white-hot'. Ultimately, selection of colour palette will depend on the task, the environment and user need. If a machine is interpreting and processing thermal imagery, grayscale may be best, but a 'rainbow' palette may be more useful to display results to human users.

Cuthbertson *et al.* (Cuthbertson, Tarr and González, 2019) explored different avenues to process thermal video imagery of cattle. The authors used line plots to isolate different periods when the animal was either in the field-of-view or not, when the preferred ROI (ocular in this case) was within the field-of-view or whether no animal was present within the field-of-view. Using histograms, they illustrated these three different data scenarios. These mixed distributions allow for fitting of probability density functions to collected video imagery to obtain threshold points so that a data point is assigned to one of three populations. This would enable automation of the system, only collecting the relevant data when the ideal ROI of the animal is within the field-of-view. The authors also had some success with using statistical pre-processing techniques of a 1-second rolling median and quantiles to smooth the temperature data and account for outliers. Outliers in the data were defined as unpredictable movements, such as the animal blinking or shaking its head.

Image analysis techniques have traditionally utilised manual techniques to highlight regions of interest (Metzner *et al.*, 2014a) and commercial IR camera software for image processing (Schaefer *et al.*, 2007, 2012). More recent studies have made advances in terms of advanced statistical predictive modelling (Bell *et al.*, 2020b) and algorithm development (Jaddoa *et al.*, 2019). To act autonomously and yield real-time results, it is likely that techniques incorporating computer vision and neural networks will be necessary. Jia *et al.* constructed body temperature prediction models for pigs to compare three machine learning algorithms (Back Propagate Neural Net (BPNN), Random Forest (RF), and Support Vector Regression (SVR)) and found that all three models performed better when environmental parameters were considered and that SVR outperformed the other two models in terms of accuracy (Jia *et al.*, 2020). Two customised Matlab® algorithms were developed and used by Jorquera-Chavez *et al.* to process RJPGs and non-radiometric thermal video in cattle (Jorquera-Chavez *et al.*, 2020). The first algorithm extracted the radiometric information from each image and then selected the ear and eye as ROIs. The second algorithm was used to assess the breathing rate from non-radiometric thermal video, identifying changes in pixel intensity values within the ROI of the nose, which show air exchange during inhalation and exhalation. Computer vision and

machine learning techniques are likely to propel this area of research forward in the next few years.

## 2.5 Conclusion

Precision livestock farming is becoming popular in food production and favours non-invasive techniques of monitoring for animal health and welfare. IRT offers a potential solution using existing technology to monitor and surveil for livestock disease. However, it has been posited that "knowledge of thermal imaging camera accuracy in the scientific literature are limited, poorly investigated and rarely questioned" (Pušnik and Geršak, 2021). In this review, we find parameter reporting to date to be insufficient with high numbers of reporting inaccuracies and we recommend that standardised methodology and reporting for IRT measurements are adopted to enable robust comparisons of future investigations. Due to the lack of emissivity values for animals, further research is required to establish accurate values for use with livestock in field settings. It is essential now that research teams attempting to use and validate IR techniques for disease detection include individuals with physics expertise and experience operating IR technology. Without high-level comprehension of the multiple parameters that influence the final image and temperature estimation, it will be impossible to develop reliable disease detection systems. Automation is the obvious next step to achieve functioning IRT systems, but methods need to be tested and validated before this can happen. Managing and processing the large datasets that IRT systems will produce is now possible with sophisticated computer algorithms and machine learning image analysis methods. While research interests range from production to both endemic and exotic diseases with researchers attempting to use both relative and absolute thermal values, IRT may be most useful in its current form to detect mastitis and hoof-related diseases. Within the wider surveillance technology pipeline outlined in Chapter 1, these findings support the need to treat reliable image acquisition, animal detection, validation, and interpretation as sequential steps before thermographic data can be used within operational disease surveillance systems. We conclude that an IRT system to continuously monitor housed livestock as a group or individuals may be the natural next step, with due consideration given to farm layout, animal identification and specific diseases that are important to detect.

# 3 Data Journeys in Veterinary Surveillance: Informing Integration of Novel Data

## 3.1 Introduction

Sensors have become ubiquitous in the current world, and the livestock farming sector offers multiple research avenues for the application of sensor technology, from early disease detection to virtual fencing (Halachmi *et al.*, 2019). National animal health surveillance in Scotland currently relies on post-mortem examinations of animals either on-farm or at Scotland's Rural College (SRUC) sites and on data derived from laboratory-submitted clinical samples (Scottish Government, 2020). Within the surveillance framework adopted in Section 1.1, these diagnostic activities contribute to surveillance when their findings feed into the systematic collection, analysis, interpretation and dissemination of animal health data. An on-farm post-mortem is primarily a diagnostic investigation, but it also contributes to surveillance when its findings are reported and used to identify disease patterns or emerging threats. This contribution is not limited to the detection of a particular disease: routine diagnostic findings can also inform surveillance when considered alongside information from other animals and farms. Sensor-driven syndromic surveillance of livestock has been identified as a gap in Scotland's current animal health surveillance capabilities. Real-time data collected from herds on-farm has the potential to underpin improved disease detection and management at the farm level and the allow earlier identification and investigation of potential outbreaks at the national level.

Previous research undertaken by Boden *et al.* (2017) explored five potential future scenarios with regards to trade policy, data collection and sharing, and resourcing in order to better prepare a resilient surveillance model for Scotland, following its exit from the European Union. As we have now entered the 'post-Brexit' era, it is important not only to undertake essential research of novel technologies for use in the agricultural sector within the UK, but also to ensure that these technologies are developed with future use and application in mind from the outset, fostering resilience at both the farm level and the surveillance level.

Using the "data journeys" approach (Edwards, 2010), the aim of the present research study was to elucidate the conceptual passage of novel data from farm

to policy. This approach aims to identify and define various forms of data across interconnected sites of practice. It highlights the movement of data within and between sites, in response to calls for the development of "a methodological repertoire that can match the geographic and temporal scale of emerging knowledge infrastructures" from the critical data studies field. The term "data friction", first coined by Edwards (2010), is used to describe the complex factors (political, social and economic) that conspire to slow down and restrict data generation, movement and use. Enabling data to move from on-farm use to national surveillance use is likely to generate multiple points of data friction across different sites of practice.

A number of research questions were posed:

(i) what data are currently being used for animal health surveillance purposes in Scotland?

(ii) how is this data being utilised?

(iii) how might thermal and drone-derived data be a useful addition?

(iv) who within the existing surveillance structures might use this form of data?

In this chapter, methodology is presented first followed by findings. The methodological approach is based on semi-structured stakeholder interviews, designed to capture perspectives across the data journey and to explore challenges associated with novel data collection and use. The results outline the initial data journey "mapping", the thematic coding and analysis informed by interview data, and then moves on to descriptions of the identified themes. Potential implications of areas of data friction identified through thematic analysis are subsequently discussed, before the chapter concludes with explicit proposals for mitigating identified areas of data friction, which are focused on governance, technical and institutional interventions for novel data use. The chapter therefore contributes both an empirical mapping of frictions and a targeted set of mitigation measures linked to those identified frictions across the data journey.

Tables 3-1 and 3-2 below summarise key terms relating to data journeys, governance and the qualitative research methods used in this chapter.

**Table 3-1.** Data journey and governance terminology used in Chapter 3.

| **Term** | **Meaning** |
|---|---|
| Data journey | The movement and transformation of data within and between sites where they are generated, interpreted and used. |
| Data friction | Factors that slow down or restrict the generation, movement and use of data, including technical, social, political, and economic factors. |
| Data ecosystem | The interconnected people, organisations, technologies and arrangements through which data are generated, shared, and used. |
| Data infrastructure | The technical systems supporting data collection, storage, processing, transfer, and access. |
| Interoperability | The ability of systems and organisations to exchange and meaningfully combine or use data through compatible formats, standards, and shared meanings. |
| Metadata | Data describing other data, which may be embedded within a file or stored separately, providing information about their characteristics, context, or origin. |
| Data provenance | Information about where data originated and how they have been processed or transformed. |
| FAIR data principles | Principles supporting data that are findable, accessible, interoperable, and reusable. |
| Data governance | The frameworks, roles, processes, and decision-making arrangements through which data are managed across their lifecycle. |
| Data stewardship | Responsibility for the ongoing care and management of data, including their quality, documentation, security, and appropriate use. |

**Table 3-2.** Qualitative research terminology used in Chapter 3.

| Term | Meaning in this chapter |
|---|---|
| Semi-structured interview | An interview guided by common topics and questions, with flexibility for participants to introduce issues and for the researcher to explore responses. |
| Snowball sampling | Identifying additional potential participants through recommendations from existing participants. |
| Thematic analysis | An approach to identifying, reviewing and interpreting patterns across qualitative data. |
| Code | A label assigned to a passage of data to identify content relevant to the analysis. |
| Deductive coding | Coding informed by the research questions or initial categories established before detailed analysis of the transcripts. |
| Inductive coding | Developing codes through reading and interpreting the data, allowing unanticipated issues to be identified. |
| Theme | A pattern of meaning developed by grouping and interpreting related codes in relation to the research questions. |
| Coding tree | A structured representation of the themes and associated subthemes developed through the analysis. |

## 3.2 Methods

### 3.2.1 Ethical statement

This study was approved by the University of Glasgow Research Ethics Committee (Project Code: 200200119). Participants were provided with information describing the project prior to agreeing to be interviewed. The interview and the purpose of the project was further discussed before each interview commenced. Participants were informed that their interview transcripts would be anonymised, stored securely and that any material potentially leading to identification would be removed. Consent forms, signed by each participant, specified that they could terminate the interview or withdraw from the study at any time.

### 3.2.2 Study Design

The project was structured in four phases, which are outlined below. While phase one and two are described as separate entities below, they were in reality

performed concurrently, with one informing the other. While this study focuses on animal health surveillance data journeys within Scotland, livestock production systems and disease risks frequently extend beyond national administrative boundaries. Many farms engage in cross-border movements with England and Wales, and responses to notifiable and exotic diseases are coordinated at the UK level, led by the Department for Environment, Food and Rural Affairs (Defra) through the Animal and Plant Health Agency (APHA).

The Scottish focus reflects the primary researcher's location, the practical ease of access to relevant stakeholders, and Scotland's devolved animal health governance context. Within this, organisations such as EPIC (Epidemiology, Population Health and Infectious Disease Control) contribute to the coordination of animal health surveillance. EPIC is the Scottish Government–funded Centre of Expertise on Animal Disease Outbreaks. It provides epidemiological analysis, risk assessment, modelling and scientific advice to support preparedness and response to animal disease outbreaks in Scotland, working closely with government, surveillance bodies and regulatory agencies. This focus does not imply that animal health surveillance or disease response activities operate independently of wider UK frameworks, but rather that Scotland provides a well-defined case study within a multi-level governance system.

#### 3.2.2.1 Phase 1: Creation of data journey map

Data journeys were mapped for exemplar data streams, illustrating two different forms of animal health data. The first was the journey of data pertaining to sick animals on the farm. This was followed to multiple end-points, depending on whether the animal had a notifiable disease or not. The second data journey followed stock location data as collected by the Scottish Electronic Identification Livestock Traceability Research (ScotEID). ScotEID provides access to a database where users and others can register their livestock and record movements, Bovine Viral Diarrhoea (BVD) status, BVD Persistently Infected (PI) locations and Quality Meat Scotland (QMS) status. It was initially set up as a research and development project in 2008 by the Scottish Agricultural Organisation Society (SAOS), working in partnership with the Animal Health and Welfare Division of Scottish Government and an industry working group, to find practical ways to deal with a new EU regulation for sheep movement and flock registers.

The initial data journey map was used to identify relevant organisations and stakeholder roles. Potential participants were identified through this mapping and the researcher's professional contacts, with further participants identified through snowball sampling, whereby interviewees suggested other individuals with relevant knowledge or experience. Recruitment concluded after 14 interviews because the available recruitment list had been exhausted within the study timeframe. A small number of additional prospective participants did not respond to further follow-up, and these interviews did not proceed.

This approach sought perspectives from different points in the data journey. However, recruitment through professional contacts and participant referrals may have favoured individuals within connected networks, limiting the range of perspectives represented. Not all invited stakeholders participated, and the findings therefore reflect the perspectives of those who took part rather than all organisations represented in the data journey.

#### 3.2.2.2 Phase 2: Stakeholder interviews

Using semi-structured conversational interviews, stakeholders were engaged at all levels to explore concerns and attitudes towards the uptake of precision and smart farming, data sharing, data protection regulations, and perceptions of data sharing and of algorithms in animal health decision-making with respect to imagery derived from stationary or drone-mounted devices. Semi-structured interviews were selected to explore stakeholder perspectives on an emerging topic for which the relevant concerns and barriers were not fully established. This format gave participants freedom to explain their experiences and introduce unanticipated issues, while a common topic guide ensured coverage of the research questions. Other approaches were considered, including fixed-response questionnaires and a consensus-focused Delphi approach, but interviews were judged more appropriate for obtaining rich, nuanced accounts and exploring the reasons underlying participants' views. The purpose was to understand the range of stakeholder perspectives rather than to establish agreement between participants. These interviews also informed the development of the data journey map. The interview topic guide is provided in Appendix 3. Interviews were conducted online using the Zoom platform between the 18th of January 2022 and the 10th of August 2022. Meetings were held in private sessions, which were password protected, and recordings were stored

securely in accordance with University of Glasgow data protection and research governance requirements. At the time of data collection, Zoom was widely used within academic and public-sector contexts and supported encrypted data transmission. Recordings were downloaded promptly after each interview and stored on secure institutional systems, with access restricted to the research team. Recordings were deleted after transcription. The same core interview topic guide (Appendix 3) was used across interviews, with flexibility to explore issues raised by participants. However, not every question was asked of every participant because of time constraints and differences in their areas of experience and expertise. Open-ended questions allowed participants to explain their views in their own terms, with follow-up prompts used to explore their responses. The order and direction of discussion remained flexible, allowing participants to introduce issues they considered relevant. This approach supported consistency in topic coverage while allowing participants to shape the discussion. Nevertheless, the interviewer's questioning and follow-up prompts may have influenced the accounts produced. The interviewer also had pre-existing professional relationships with some participants. These relationships may have supported rapport but may also have influenced what participants felt comfortable disclosing or assumed the interviewer already knew.

#### 3.2.2.3 Phase 3: Thematic analysis of interview text

All interviews were recorded and transcribed verbatim, after which transcripts and associated documents were analysed using NVivo 14 (Lumivero, 2023) to support the thematic coding and organisation of qualitative data. Thematic analysis was selected to identify patterns across stakeholder accounts while retaining differences in participants' experiences and perspectives on the generation, movement and use of animal health data. The thematic analysis was conducted according to the outline proposed by Braun and Clarke (2006). This involved a six-step process: (i) familiarisation with the data; (ii) generation of initial codes; (iii) searching for themes; (iv) reviewing themes; (v) defining and naming themes; and (vi) writing the report. Familiarisation involved reading the interview transcripts to develop an understanding of their content. Initial codes were then assigned to relevant passages. Coding combined deductive codes informed by the research questions with inductive codes developed through reading the transcripts, maintaining a focus on the study objectives while

allowing unanticipated issues to be incorporated. Related codes were grouped into potential themes. These groupings were reviewed against the transcripts and refined before the final themes were defined and named. The analysis was then written up as a narrative account, supported by participant quotations and interpreted in relation to the research questions. During this analysis and the creation of the data journey map, a range of primary and secondary data sources was drawn upon. Stakeholder interviews constituted the primary data for thematic analysis, while policy, scientific and legal documents that interviewees referenced were used as secondary sources to contextualise the themes identified and to support further exploration of them. The results are therefore presented in a narrative format, with the issues raised in the stakeholder interviews integrated with the secondary material to form a synthesis and with the various emergent themes being discussed in turn. Coding and theme development were undertaken by the primary researcher alone. Potential themes were checked against the interview transcripts and refined to ensure that interpretations remained grounded in participants' accounts. Nevertheless, the analysis reflects the researcher's interpretive perspective, and the absence of review by another researcher is acknowledged as a limitation.

#### 3.2.2.4 Phase 4: Updated map with areas of data friction

After the completion of phase three, the initial data journey map was updated. The updated map accounted for potential novel data created by agritech companies that were included as a site of practice. This map was then used to identify areas of potential data friction for novel data.

## 3.3 Results

Results are presented in four phases: (i) data journeys; (ii) stakeholder interviews; (iii) generation of codes for thematic analysis; and (iv) thematic analysis of areas of data friction.

### 3.3.1 Phase 1: Data journeys

#### 3.3.1.1 Data journey 1: Sick animal data

The first data journey that was examined focused on data from sick animals as it travelled from the farm to various other stakeholders. Using the Scottish Government's Exotic Disease Contingency Framework Plan and Department for Environment Food and Rural Affairs' (Defra) Foot and Mouth Disease (FMD)

Control Strategy for Great Britain, pathways through which data concerning a sick animal would travel were identified and described (Scottish Government, 2022; Defra, 2025). In the first instance, it would travel from the farm to a private veterinary service provider. Depending on whether there was a suspicion of a notifiable disease or not, the journey may reach an end-point at that stage or extend, with a sample and its metadata travelling to an external lab or to the Animal and Plant Health Agency (APHA) and Defra.

#### 3.3.1.2 Data journey 2: Animal location data

Using stakeholder interviews, the journey of the animal location data was mapped as it travels through multiple institutions which would have access to that information. ScotEID is an entity, established in the aftermath of the foot and mouth disease (FMD) epidemic of 2001 to better monitor livestock movements within Scotland. It is a quango (quasi-autonomous non-governmental organisation), which is a semi-public administrative body outside the civil service but receiving financial support from the government, which can make senior appointments to it. It was created to monitor sheep, then pig, then cattle movements using Electronic Identification (EID) tags. These have become compulsory for cattle from 2024 in Scotland and are already mandatory for sheep and pigs.

#### 3.3.1.3 Composite map

Using these two data journeys, a map was constructed (Figure 3-1) illustrating the data journey of animal health surveillance data from farm through to policy in Scotland and beyond that would occur in the event of a FMD outbreak in Scotland. While this project initially mapped data for both “peace time” and outbreak situations, Figure 3-1 illustrates the journey of animal health surveillance data from farm through to policy and beyond that would occur in the event of an FMD outbreak in Scotland. FMD was chosen as an example disease for this project due to the number of times it was mentioned during interviews with stakeholders. Data moves through multiple sites of practice and stakeholders, with arrows showing the direction of data movement. This map was further used to highlight areas of data friction from thematic analysis of stakeholder interviews. Table 3-3 illustrates the assignation of data producer or data consumer to each site of practice. Data consumers were defined as those who consume data provided by the data producer and data producers were

defined as those that collect, store and process data from their data domain, in addition to monitoring and ensuring the quality of their data assets. When there is a suspicion of FMD in Scotland, the person who discovers it is duty-bound to inform the competent authority, which in the UK is the Animal and Plant Health Agency (APHA). The APHA then sends a veterinary inspector to the site of disease suspicion. Samples are taken and sent to the national reference laboratory at Pirbright for confirmation of disease. If disease is confirmed, the results are communicated to the Chief Veterinary Officer (CVO) for Scotland and the CVO for the UK, who then notifies international bodies, namely the World Organisation for Animal Health (WOAH) and the European Commission (EC). Local authorities, private veterinarians and farmers are also informed of the results and of the control measures to be implemented. EPIC advises the Scottish government and other stakeholders on the risk of spread of the disease and on how to control this risk. Data on animal movements are collected by ScotEID and are used by EPIC and other stakeholders.

**Table 3-3.** Classification of sites involved in the animal health surveillance data journey as data producers, data consumers or both. Data consumers are defined as those who consume data provided by the data producer and data producers are defined as those that collect, store and process data.

| Site | Data Producer | Data Consumer |
|---|---|---|
| Farm | ✓ | ✓ |
| Private Veterinary Services | ✓ | ✓ |
| ScotEID | ✓ | |
| National Reference Laboratories | ✓ | |
| EPIC | ✓ | ✓ |
| Scottish Government | | ✓ |
| APHA | ✓ | ✓ |
| Local Authorities | | ✓ |
| Defra | | ✓ |
| European Commission | | ✓ |
| WOAH | | ✓ |

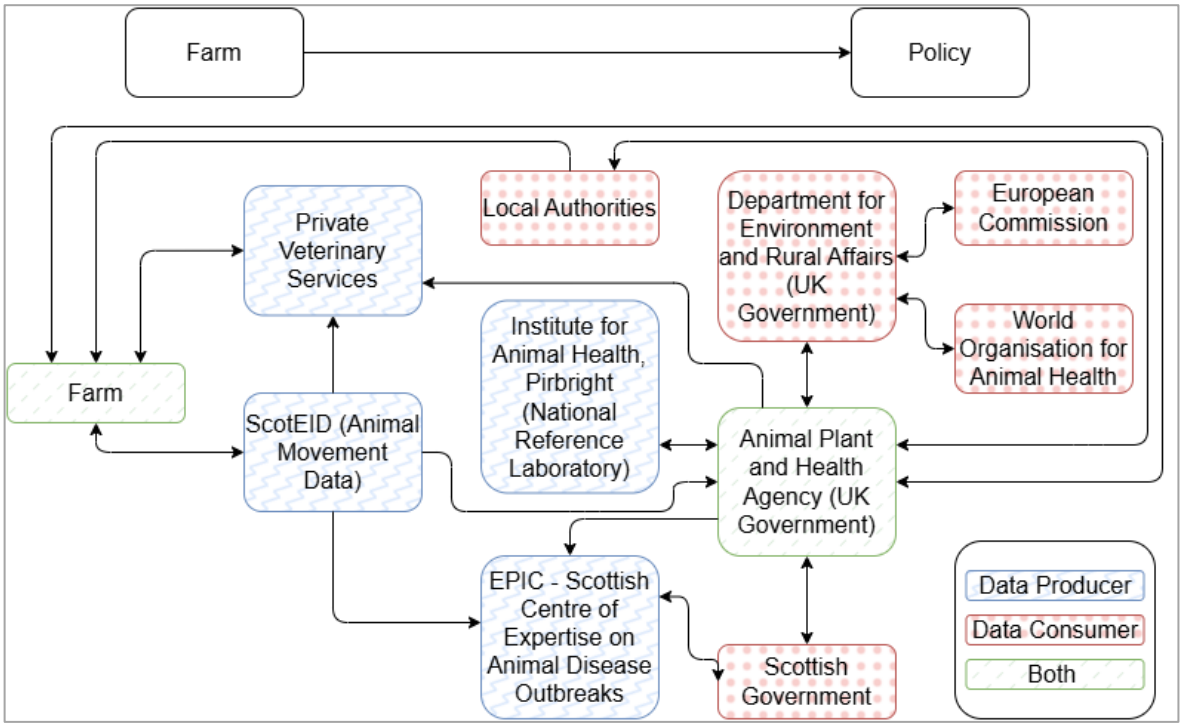



**Figure 3-1.** Preliminary map illustrating the data journey of animal health surveillance data from farm to policy in Scotland, UK in the event of an outbreak of foot and mouth disease (FMD). Data moves through multiple institutions and stakeholders. Arrows show the direction of data movement and information communication from data processing (data can flow in both directions). In this context, data consumers are defined as those who consume data provided by the data producer and data producers are defined as those that collect, store and process data from their domain.

### 3.3.2 Phase 2: Stakeholder interviews

Stakeholders were identified using the above map and through suggestions from interviewees, a process known as 'snowball sampling'. Fourteen interviews were conducted with stakeholders from a variety of institutions. Interviews were conducted using an online platform (Zoom), for a duration of between 30 and 95 minutes. Interviews were semi-structured and included open-ended questions to elicit discussion around complex topics and explore areas of interest. Interview questions are available in Appendix 3. Because this research investigated a range of issues related to existing and novel data in the field of animal health surveillance and outbreaks, participants were necessarily drawn from a wide range of backgrounds. Table 3-4 summarises the backgrounds, affiliations and expertise of the 14 participants. Individual participants could contribute experience across several categories. Hence, while some interviews focused on

issues directly related to animal health surveillance, others only briefly addressed this topic. Policy documents, scientific publications and reports of inquiries were identified using a combination of internet search engines (Google and Google Scholar), online databases (Pubmed, Web of Knowledge and Scopus), citations in identified key publications and by recommendation from study participants.

**Table 3-4.** Professional backgrounds, organisational affiliations and areas of expertise of the 14 interview participants at the time of interviewing. Entries include current and previous affiliations and experience. Categories are not mutually exclusive.

| Participant | Professional background, affiliations and expertise |
|---|---|
| I-01 | Business; Farming; Agritech; Legal |
| I-02 | Academia; EPIC; Veterinary; Epidemiology |
| I-03 | Agritech; Academia; Farming |
| I-04 | SRUC; Veterinary; Epidemiology; Academia |
| I-05 | Agritech; Animal Science |
| I-06 | Agritech; Farming; Animal Science |
| I-07 | Farming |
| I-08 | Veterinary |
| I-09 | APHA; Agritech; Epidemiology; Animal Science |
| I-10 | EPIC; SRUC; Academia |
| I-11 | Legal |
| I-12 | Veterinary; Epidemiology; EPIC; Academia |
| I-13 | EPIC; Epidemiology; Academia |
| I-14 | ScotEID |

### 3.3.3 Phase 3: Generation of codes for thematic analysis

Following the thematic analysis process described in Section 3.2.2.3, transcripts were coded line by line, examining their content and explicit and implicit meanings. Coding combined deductive codes informed by the research questions with inductive codes developed from the transcripts. Related codes were grouped into potential themes, which were reviewed against the transcripts and refined before being defined and named. The resulting themes and subthemes were organised into a coding tree illustrating the areas of data friction identified in relation to animal health surveillance (Figure 3-2).

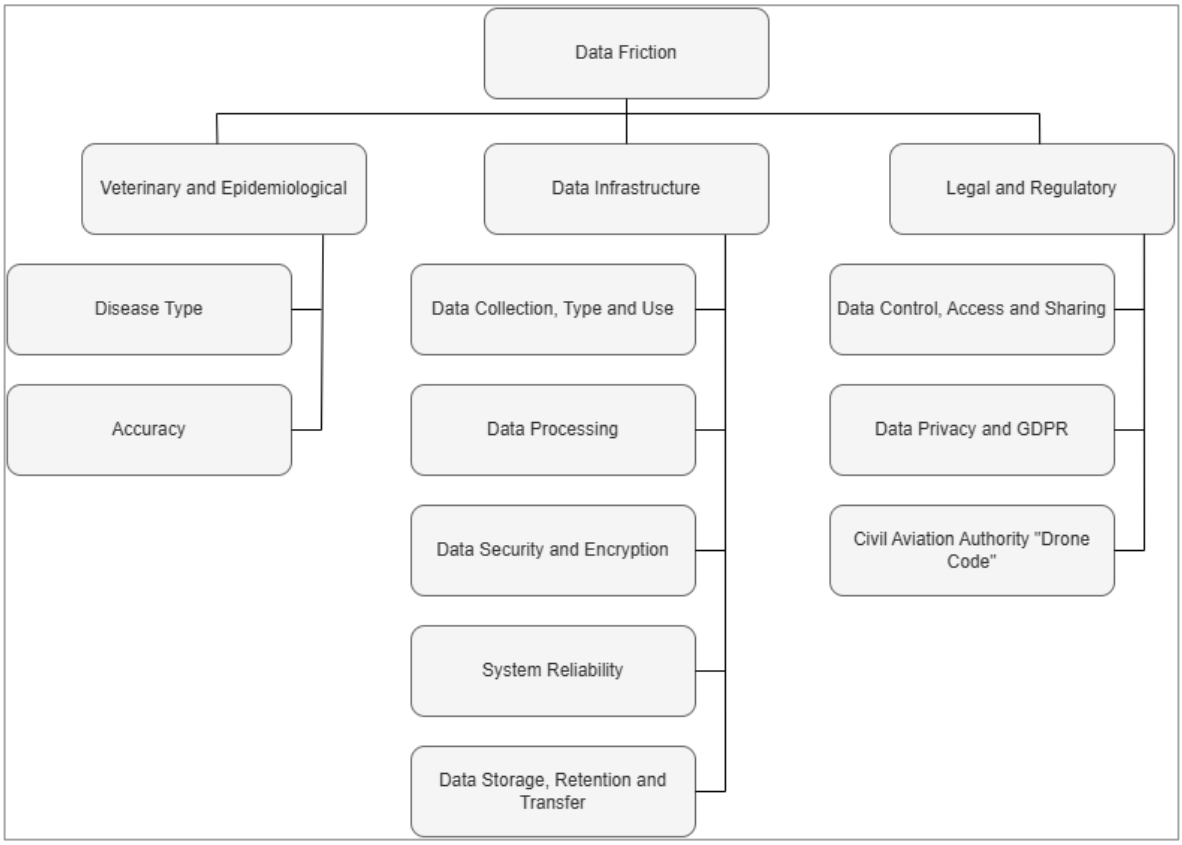



**Figure 3-2.** Coding tree denoting the themes and subthemes identified through thematic analysis of stakeholder interviews concerning data friction in animal health surveillance.

### 3.3.4 Phase 4: Thematic analysis with areas of data friction

In this section, the concept of data friction is used as an analytical lens to interpret the themes emerging from the stakeholder interviews. Rather than treating data friction as an abstract condition, the thematic analysis identifies how frictions arise in practice as data move between actors, institutions and technical systems involved in animal health surveillance in Scotland and beyond. The following themes highlight where, how and why frictions emerge across the data journey, and how these frictions shape the feasibility of integrating novel data streams into surveillance systems. Participant counts indicate how many interviewees expressed a view or discussed an issue. As not all questions were asked of every participant, absence of a topic from an interview should not be interpreted as disagreement. Percentages refer to all 14 participants unless another denominator is specified.

### 3.3.4.1 Theme 1: Veterinary and epidemiological concerns

Stakeholders discussed multiple potential purposes for drone- and thermal-derived data within animal health systems. These ranged from on-farm support for clinical assessment and routine disease management, to population-level surveillance and outbreak response at regional and national scales. The relative value and interpretation of such data depend on the disease context, particularly whether a disease is endemic or exotic, as this influences both the intended use of the data and the decisions taken in response to detected signals.

From a veterinary and epidemiological perspective, an area of data friction was identified where novel data is moved from the farm to a technology provider (Figure 3-3). Veterinary stakeholders expressed concerns about sensitivity and specificity of thermal and drone technology, the cost of such a system, data quality and trustworthiness, and how many participating farms would be necessary to enable meaningful data analysis. Speed to detection also emerged as an issue and posed the question as to whether a system like this truly speed up detection of a disease like FMD, whether by identifying suspicious FMD lesions or by detecting herd or individual animal temperature increases. Some interviewees thought that such a system may be helpful in providing data about disease spread but that it may not be an improvement on the current surveillance system for early disease detection.

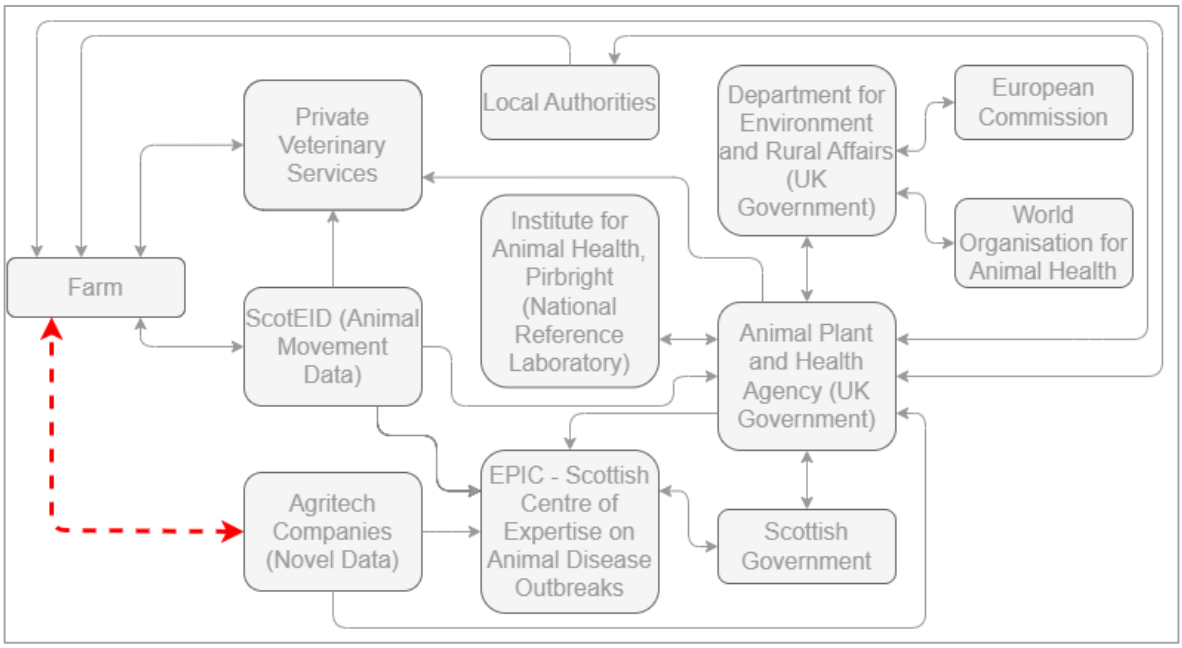



**Figure 3-3.** Map identifying area of data friction related to veterinary and epidemiological concerns (Theme 1). Data friction was found to occur at the

point where on-farm observations and clinically informed practices are translated into technology-mediated data streams managed by commercial providers, reflecting epistemic uncertainty around data accuracy, clinical relevance and trust in novel sensing technologies. This is denoted by the red broken arrows.

#### 3.3.4.1.1 Disease type

Six of the 14 interviewees (42.86%) mentioned foot and mouth disease during interviews, four unprompted and two following a prompt from the researcher. It was chosen as the sample disease for discussion and planning throughout this study. Other diseases that were discussed were bovine viral diarrhoea, porcine reproductive and respiratory syndrome, infectious bovine rhinotracheitis, African horse sickness, African swine fever, sheep scab, lameness, digital dermatitis and pneumonia, all of which could instigate episodes of pyrexia in production animals. When speaking in more general terms, stakeholders discussed respiratory diseases, emerging endemic versus exotic animal diseases and, also, zoonotic diseases.

#### 3.3.4.1.2 Accuracy

In epidemiological terms, accuracy refers to the proportion of test results that are correctly classified, comprising both true positives and true negatives. For diagnostic tests, sensitivity, specificity, positive predictive value and negative predictive value are used to describe test performance and to inform their practical usefulness within a given epidemiological context. Sensitivity is the probability that a test will identify a diseased animal as positive and specificity denotes the probability that a test will correctly identify an animal without the disease as negative. Positive predictive value (PPV) is the probability that an individual who tests positive truly has the disease and the negative predictive value (NPV) is the probability that an individual who tests negative truly does not have the disease. Seven interviewees (50%) said that novel technologies should be used as support measures rather than diagnostic tools, and that they would be more usefully considered as indicators for clinical assessment. Eight interviewees (57.14%) considered that it would be difficult to build a system that would predict disease. When discussing the creation of animal surveillance systems, one interviewee said that they would want to maximise the sensitivity of the system but that false positives would be inevitable:

*"but yet I want to detect them, I want to take them all, because I know that within that big group of positives, there's going to be some true positives and I want to sift through the data to find the true positives"* (I-04);

with another stating,

*"you don't mind being wrong"* (I-07);

further echoing the sentiment that one would prefer a system that gives false positives rather than false negatives, that the sensitivity of a surveillance system would be more important than specificity. Depending on the disease, one might favour sensitivity over specificity based on the control policy and the cost of control measures. For example, culling rare breeds at the tail end of an outbreak of a non-notifiable disease would not be considered a proportionate response. However, for FMD, high sensitivity is important, but in low-prevalence settings the positive predictive value is also critical due to the consequences of false positives. In contrast, for production diseases such as mastitis, the emphasis may be on identifying or predicting the majority of cases to support routine management decisions.

When discussing whether any technological surveillance system would be useful in the context of the current reporting system within Scotland, one interviewee said that:

*"but you're never going to beat the farmer"* (I-04),

Expressing the view that the current disease reporting system is very effective and that new technologies may not represent an improvement on the *status quo*. One interviewee said that

*"there needs to be an element of stockmanship for it to be beneficial"* (I-07);

and

*"the next step after you use that technology - after that technology brought that cow to our attention - is to check it yourself anyway"* (I-07).

Another interviewee suggested that any novel surveillance system would need to be tested against existing methods,

*"If you're going to get any data from new technology, you need to make sure it's cross-referenced with your own ways of collecting that information previously so that you could trust it."* (I-08);

and

*"You don't want to go straight into a new technology without making sure it marries up with what you already know"* (I-08).

#### 3.3.4.2 Theme 2: Data infrastructure concerns

The second area of data friction identified relates to data management and curation. Figure 3-4 focuses on data moving from the technology provider to public-sector analytical, regulatory and research infrastructures such as EPIC and APHA. A recurring issue raised by interviewees across multiple stages of the data journey was interoperability, not only between technologies and data formats, but also between institutions, databases and governance contexts in which animal health data are collected, processed and repurposed.

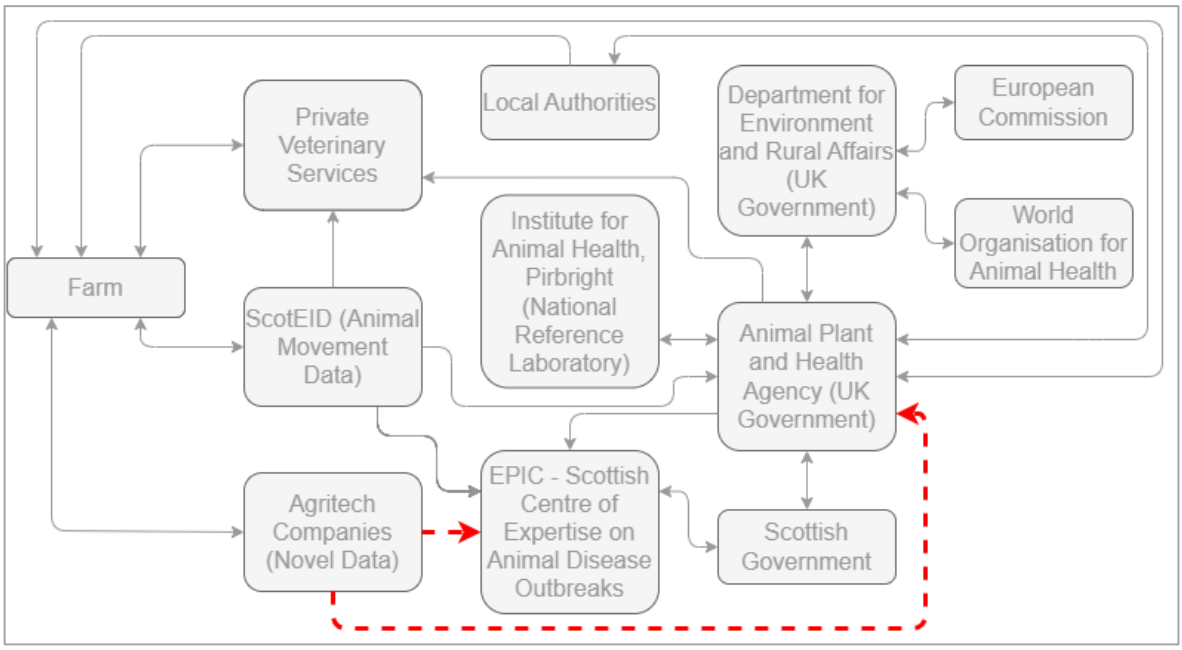



**Figure 3-4.** Map identifying area of data friction related to data infrastructure (Theme 2). Data friction was found to occur as data move from commercial technology providers into shared analytical and public surveillance infrastructures, particularly at the point of integration into institutions such as EPIC. At this transition, frictions arise from interoperability between systems, data processing capacity, cybersecurity requirements, access control and trust, and in data stewardship. These frictions are denoted by the red broken arrows.

#### 3.3.4.2.1 Data collection, data types and data use

Data is collected by multiple stakeholders in Scotland for animal health surveillance. It may be collected on-farm by farmers, veterinary surgeons and external animal management companies, with official livestock movement data being collected by ScotEID.

On farms, data is recorded using a mix of pen and paper, whiteboards and electronic formats. Paper-based or digital medicines logbooks and a large daily diary were described as methods of recording data on farms. Farmers and stockpersons carry personal diaries to make notes of animals that need to be checked and procedures that need to be undertaken. Some data sensors are already in use, for example to collect milk information in the parlour or individual cattle ambulatory data via sensors attached to their legs (e.g. technological livestock companies such as ICERobotics), with data uploaded initially to on-site servers and then to off-site locations. In Scotland, farmers record cattle births, deaths and movements through ScotEID (via the ScotMoves+ service). Farmers manually input data to ScotEID when on-farm, while off-farm movements at cattle marts can be automatically recorded using EID readers. Movements involving England and Wales are captured through data exchange with the Cattle Tracing System (CTS), the Great Britain–wide cattle movement database maintained by the British Cattle Movement Service on behalf of the Rural Payments Agency. CTS records cattle births, deaths and movements across Great Britain and provides a centralised dataset to support livestock traceability, disease control and regulatory functions. This highlights the need for interoperability between devolved Scottish systems (such as ScotEID/ScotMoves+) and Great Britain-wide cattle movement databases. The UK food quality assurance scheme “Red Tractor” may audit data that is collected on the farm. This is a not-for-profit company set up in 2000 by the food industry to transform and rebuild trust in British farming and food quality.

Based on interview data and internal EPIC documentation, EPIC uses the following data for animal disease risk assessments: animal agricultural censuses for Scotland, cattle population data for Scotland, the Scottish Sheep and Goat Annual Inventory (ScotEID), animal agricultural censuses for England and Wales, registered pig keepers in Great Britain (GB), the Great Britain Poultry Register, recorded movements of cattle for all of GB (the Cattle Tracing System),

recorded movements of cattle, sheep and pigs in Scotland (ScotEID), recorded movements of sheep and goats (and deer) in England via the Livestock Information Service (LIS) and recorded movements of pigs in England and Wales via electronic Animal Movement Licence, Version 2 (eAML2), Bovine Viral Diarrhoea (BVD) testing data for Scottish farms, the list of linked holdings for purposes of cattle movement reporting, PRIMO-approved pig pyramid premises (approved under the Pig Records, Identification and Movement Order), Red Tractor quality assurance scheme members, and information on agricultural holdings from the Scottish Integrated Administration and Control System (IACS). In private veterinary practices, data is uploaded to veterinary electronic patient record (EPR) software such as RoboVet to log farm visits, procedures and medications. Practices also maintain a written daily diary, with scheduling information for each veterinary surgeon in the practice. Shorthand notes may be written which will be typed up electronically at a later date. This extensive data list illustrates the interlinkages between demographic data, movement data, disease data, production data and animal health surveillance in Scotland.

Interviewees were supportive of novel data streams but seven (50%) raised interoperability concerns between systems and data formats. These concerns extended beyond technical compatibility to include institutional interoperability, as data relating to the same animals may be held in separate databases across devolved and Great Britain–level systems, and processed differently depending on whether they are used for surveillance, regulatory compliance or epidemiological risk assessment.

Wilkinson *et al.* (2016) proposed that data must be findable, accessible, interoperable and reusable (FAIR data principles) emphasising that data must be accompanied by appropriate metadata, persistent identifiers and clear access conditions in order to be discoverable and usable beyond their original context. In this framework, findability and accessibility relate to whether data can be located and retrieved by relevant users, while reusability depends on sufficient documentation, provenance information and clarity regarding permitted uses. Interoperability, in particular, requires not only compatible data formats and standards, but also shared vocabularies and frameworks that allow data generated for different purposes, such as regulatory compliance, surveillance and epidemiological risk assessment, to be meaningfully combined and re-used

across institutional boundaries. More recently, Devaraju *et al.* (Devaraju *et al.*, 2021) show that applying the FAIR principles in practice requires turning them into clear criteria that can be assessed. They demonstrate how repositories must document metadata standards, licensing information and access conditions in a structured way so that data can be evaluated against FAIR principles in a consistent and transparent manner.

A report from the International Organisation for Standardisation Strategic Advisory Group on Smart Farming similarly noted that while automating farming practices could help producers of all sizes, large-scale implementation remains difficult, because equipment and software from different manufacturers are often unable to communicate (International Organisation for Standardisation, 2023). The report therefore recommends the implementation of common data standards, standard vocabularies, improved communication between technology developers and end-users, and greater support for user communities to enable more consistent, transparent and reusable data practices across the sector.

#### 3.3.4.2.2 Data processing

Four of the five interviewees involved in data analytics of livestock (80%) reported using R or Python for data processing. Some also use bespoke software, C++ or SQL to process data. Within EPIC, a primary dataset is curated and cleaned to produce a secondary dataset for analysis, and scientists are not permitted to generate new datasets on their own machines in order to maintain data security, version control and auditability. For novel data, it is likely that very large datasets would be generated—for example, continuous high-resolution thermal or video imagery collected at herd scale—which could slow down or even overwhelm existing computational infrastructure. One interviewee suggested that pre-processing data prior to transfer could help mitigate some of these computational challenges; however, this raised further questions about where such processing should occur, who would be responsible for undertaking it, and how data quality, transparency and reproducibility would be maintained when data are transformed before reaching analytical or regulatory bodies.

#### 3.3.4.2.3 Data security and encryption

Password protected systems were mentioned by two interviewees, although participants were not systematically asked about their use. EPIC scientists use GitLab as a secure way to share code, but researchers can only access data

through a data repository. Data is not to be saved to hard drives in order to reduce the risk of data loss, unauthorised access and version fragmentation, and to ensure that sensitive datasets remain within centrally managed, auditable and secure environments. Amazon Web Services was mentioned as a service used by commercial businesses to store data. Some data transfers between the Animal and Plant Health Agency (APHA) and EPIC were described as taking place via physical media. This practice can be interpreted as reflecting legacy data-sharing arrangements and constraints associated with accredited secure transfer mechanisms, network segregation and organisational policy, rather than the absolute size of the datasets involved. Reliance on physical media may also introduce additional logistical and security considerations. Such practices may persist due to infrastructure limitations or institutional inertia, but it should be noted that data-sharing arrangements are subject to ongoing review and change.

One interviewee noted that the Scottish Government is aiming for the gold standard in terms of data management and safety protocols. In this context, "gold standard" can be understood as adherence to established government best practice, including the use of secure research environments, strict access controls, audit trails, compliance with data protection and cybersecurity legislation (e.g. General Data Protection Regulation and the UK Network and Information Systems Regulations 2018), and the routine use of governance mechanisms such as Data Protection Impact Assessments for high-risk or novel data streams. These will be further discussed below.

For novel data, interviewees raised questions about how data could be stored securely. One interviewee mentioned that it is a:

*"balancing act between the level of security, cost and convenience and other forms of functionality*" (I-01);

suggesting that the most secure method would be not to use any wireless broadcast and to store it locally on physically secure devices. However, this cannot be said to be a practical solution if data is to be utilised to further research, understanding and policy. The same interviewee said that,

*"I think this fits into a larger discussion about those kinds of technologies, I don't think agriculture in any way is going to lead that"* (I-01).

They also recommended considering “secure development life cycles” (I-01) for the novel equipment as it is in development. Secure Software Development Life Cycle (Secure SDLC) is an approach that emphasises integrating security practices throughout the traditional Software Development Life Cycle (SDLC) (de Vicente Mohino *et al.*, 2019). Applied to farm-based sensing and animal health surveillance systems, Secure SDLC would embed security considerations across the software development process to proactively identify and mitigate vulnerabilities before systems are deployed on farms or integrated into surveillance infrastructures. Regulation (EU) 2019/881 (2019), also known as the “EU Cybersecurity Act”, is a legislative framework adopted by the European Union (EU) to strengthen the EU’s cybersecurity capabilities and response mechanisms. It became law in June 2019 and its main objectives include the establishment of a European Cybersecurity Certification Framework, strengthening the EU’s cybersecurity Agency (ENISA), encouraging EU-wide co-operation and information sharing between member states and with the private sector, certification schemes and market surveillance to ensure products and services meet specific cybersecurity requirements and standards.

The relevance of this framework to Scotland and to the UK post-Brexit therefore warrants consideration. Interviewees noted that it is important for the UK to maintain similar legislation to the EU to ensure ease of business between jurisdictions. Although the EU Cybersecurity Act does not apply directly in the United Kingdom following Brexit, it remains relevant to UK agricultural technology developers and livestock surveillance system providers that supply digital products or services into EU markets. It continues to shape expectations around cybersecurity standards and certification for farm-based sensing and data systems. In parallel, the UK Government has signalled its intention to strengthen domestic cybersecurity requirements through proposed legislation, including the Cyber Security and Resilience Bill (2022), reflecting a policy direction towards enhanced resilience and assurance for digital systems operating in critical and regulated sectors, including agri-food and animal health surveillance.

The Network and Information Systems (NIS) Directive is a European Union (EU) directive, Directive (EU) 2016/1148 (2016), which aims to enhance the cybersecurity of critical infrastructure and essential services It requires member states to establish cybersecurity measures and incident reporting procedures for

organisations operating in sectors such as energy, transportation, healthcare and banking. This helps protect vital services and infrastructure from cyber threats, contributing to overall digital resilience and security within the EU. In the United Kingdom, the requirements of the NIS Directive were transposed into domestic law through the Network and Information Systems Regulations SI 2018/506 (2018). The EU NIS Directive was updated by Directive (EU) 2022/2555 (2022), known as NIS2, which entered into force in January 2023 and repeals the NIS Directive on the NIS2 timetable, but the UK will not be implementing the changes outlined by NIS2. The UK government is, however, in the process of strengthening the NIS Regulations.

The UK Network and Information Systems Regulations and the EU Cybersecurity Act address cybersecurity through distinct but complementary approaches. The UK NIS Regulations impose mandatory, sector-specific obligations focused on the resilience and incident reporting of critical infrastructure, whereas the EU Cybersecurity Act establishes a broader, cross-sector framework centred on voluntary cybersecurity certification and standards for digital products and services.

One interviewee suggested that it would make sense for novel data and systems for animal health surveillance to be managed by the government, as security systems are already in place to manage data of this nature. Many proposed surveillance technologies, including thermal cameras and on-farm sensors, would form part of a broader Internet of Things (IoT) ecosystem, in which physical devices are embedded with sensors, software and other technologies for the purpose of connecting and exchanging data with other devices and systems over the internet. The Government published a voluntary Code of Practice for Consumer IoT Security in 2018, providing manufacturers and others with guidance on good practice to ensure that connectable products were secure (Department of Digital and Media and Sport, 2018). At the time the interviews were conducted, the UK Product Security and Telecommunications Infrastructure Bill (2021) was progressing through Parliament, aiming to address recognised security weaknesses in consumer connectable products but had not yet been enacted or brought into force. The Bill proposed mandatory baseline security requirements for connected devices, including restrictions on default passwords, requirements for vulnerability disclosure policies, and transparency around

security update support periods. Although primarily framed around consumer IoT products, interviewees highlighted its relevance to agricultural sensing technologies, given the potential risks that insecure devices pose to data integrity, system reliability and trust in surveillance outputs. The Bill has since been enacted as the Product Security and Telecommunications Infrastructure Act (2022), establishing a statutory framework for IoT product security in the UK. The discussion above therefore reflects the policy and regulatory context at the time of data collection, rather than the fully implemented post-enactment regime.

The Act provides for regulation-making powers for the Secretary of State to introduce security requirements for consumer connectable products sold in the UK. Some products are excluded, such as smart meters, medical devices, and smart charge points for electric vehicles. The Government has used the powers under Section 1 via regulations made under the Act to introduce statutory security requirements, implemented through regulations and derived from the Code of Practice: a ban on default passwords, a requirement for products to have a vulnerability disclosure policy whereby any security weakness in a product is identified and notified, and a requirement for transparency about the time period for which a manufacturer provides security updates for the product. It also places duties on manufacturers, importers, and distributors of these products to ensure compliance with the statutory requirements and to take action where a compliance failure has occurred. For serious issues of non-compliance, the Act sets the maximum penalty at £10 million or 4% of the company's worldwide revenue.

In the context of animal health surveillance, insecure or poorly governed IoT devices pose risks not only to data privacy but to the integrity and reliability of surveillance systems themselves, as compromised, incomplete or manipulated data could influence regulatory decision-making and outbreak response. Unlike many consumer IoT applications, failures in farm-based sensing technologies may therefore have consequences that extend beyond individual users, affecting disease detection, risk assessment, and trust in surveillance outputs at regional or national scales.

When asked about the unintended consequences of interconnected data collection devices on farms, interviewees raised concerns about ransomware

attacks by cyber criminals and the potential misuse of surveillance footage by animal activists to discredit and attack farming practices. These concerns are reflected in the findings of Hazrati *et al.* (2022) who examined cybersecurity risks associated with digital technologies in agricultural settings and identified three interrelated categories of vulnerability: human error (such as poor password practices and lack of user awareness), technological threats (including insecure devices, software vulnerabilities and weak network configurations), and physical threats (such as unauthorised access to equipment or infrastructure). The authors emphasise that farms are often particularly exposed due to the combination of limited cybersecurity expertise, reliance on third-party technologies and the increasing deployment of networked sensors and devices. They recommend a combination of technical safeguards which comprised improved user training, clearer responsibility for security across the supply chain, and the adoption of recognised cybersecurity standards to reduce these risks.

In the context of animal health surveillance, such vulnerabilities have implications not only for farm-level privacy and security, but also for the integrity, reliability and trustworthiness of data that may feed into disease detection, risk assessment and regulatory decision-making. Hazrati *et al.* (2022) show that cyber risks arising from human error, insecure devices and physical access vulnerabilities on farms have implications beyond individual holdings, aligning with the rationale underpinning both the UK Network and Information Systems Regulations and the EU Cybersecurity Act, which seek to mitigate systemic risks to data integrity, service continuity and trust where digital systems support critical or regulatory functions.

#### 3.3.4.2.4 System reliability

Ten interviewees (71.43%) discussed equipment reliability, connectivity or technical support. It was noted that an animal health system going offline for any reason would be detrimental to farmers, animals and any end-users of the system. One interviewee (7.14%) wondered whether the technology for a fully integrated animal health system is “there yet” (I-03) in terms of development.

In this context, stakeholders used ‘reliability’ to refer to the operational robustness and continuity of the technical infrastructure required to support data collection, transfer and use. The issue of technology breakage or disruption

was raised, with one interviewee with previous experience noting that mites can penetrate cameras and cables in barns and eat through equipment. It was also proposed that some types of substrate encountered in the farm environment (e.g. sand) can be corrosive to equipment. Stakeholders viewed system reliability as a prerequisite for adoption and emphasised the need for ongoing technical support, including regular follow-up between farmers and technology providers, to ensure appropriate and effective system use. The need for effective connectivity on farm to pick-up data from sensors (within-farm and off-farm) was highlighted, together with a reliable connection to servers.

#### 3.3.4.2.5 Data storage, retention, and transfer

Ten interviewees (71.43%) discussed data storage, retention or transfer. Interviewees imparted that EPIC uses a main server in SRUC in Inverness to store and manage its data and this data is mirrored by a server at the University of Glasgow. Interviewees described variation in access to computers and wireless internet on farms. One interviewee (7.14%) questioned whether data infrastructure could be affected by the weather on-farm and also noted that there are not generally huge servers designed for the on-farm storage of data. While it was suggested that a commercial company or research institute undertake an initial analysis, the alternative of cloud storage and processing was suggested as an option for storage. Cloud-based storage was described as being used by commercial companies. One such service is Amazon Web Services (AWS), which has good scalability, is managed and updated by Amazon and can be more cost effective than some other services as you only pay for what you need. However, there can be limited internet access on farms in rural areas and stakeholders expressed differing views on whether it would be necessary to move collected data to another site. For example,

*"I don't think you need to get it off the farm"* (I-04);

and

*"there's no hard rules, each system is going to be different"* (I-04).

Interviewees hypothesised about how to move data from the farm to arenas potentially more suited to its analysis. It was also suggested, however, that it would be easier to transmit results (i.e. analysed data), rather than raw imagery from the farm and to process the imagery on-site, although the question of what

to do with the raw data remains. Photographic and video imagery data are very demanding in terms of data storage needs and would require:

> *"enormous storage, multiple people and very high computational power, probably some artificial intelligence to analyse it as well"* (I-09).

One interviewee relayed that current 'animal wearables' are recognised by an EID sensor which takes the collected information from the wearable sensor and then uploads it to the cloud. One suggestion was to bring this data to a centralised place, to save it and to try to achieve this in real-time, while another suggestion was to consider 'data lakes' to store such data but again, interviewees maintained that one would need to consider the format of the data. A data lake is a centralised repository that allows organisations to store vast amounts of structured and unstructured data. Unlike traditional databases or data warehouses, data lakes are designed to store data in its raw or native format, without the need for predefined schema or data structure. Data lakes are typically used for storing diverse data types, such as text, images, videos, log files, sensor data and other forms of information, providing a flexible and cost-effective way to store and analyse large volumes of data.

From a commercial provider perspective, it was suggested that an enterprise providing storage would require business continuity and disaster recovery planning and that the industry should aim to avoid vendor 'lock-in' issues to protect farmers. The vendor lock-in problem in cloud computing occurs when clients become reliant (i.e. locked-in) on a single cloud provider's technological implementation and are unable to switch vendors in the future without incurring significant fees, legal restrictions or experiencing technical incompatibilities. There was also some concern about concentration risk within the livestock sector, which would mean reduced competition between commercial providers of cloud technology to farmers; such a phenomenon has previously been observed in the financial sector.

These questions extend beyond technical storage capacity and raise issues of structured data stewardship across the research lifecycle. As articulated in work associated with the UK Digital Curation Centre, responsible research data management requires clearly defined roles, institutional support and lifecycle

planning to ensure that data remain usable and accountable beyond their initial point of creation (Davidson, 2015).

In high-volume surveillance contexts, such as continuous thermal imagery and sensor streams, decisions about retention, documentation and responsibility therefore become governance questions rather than purely technical ones. The infrastructural frictions identified by interviewees thus reflect not only technical incompatibilities, but the need for structured, assessable data management practices capable of sustaining reuse at scale.

#### 3.3.4.3 Theme 3: Legal and regulatory concerns

The third area of data friction identified relates to legal and regulatory issues. Regulations and laws surrounding data privacy, data control, access, and sharing and the Civil Aviation Authority's Drone Code were discussed by interviewees with regards to slowing down and restricting the movement of novel data. Unlike veterinary or infrastructural frictions, legal and regulatory frictions do not arise at a single point in the data journey, but operate across multiple transitions where data are collected, transferred and repurposed, shaping whether and how data can move between actors and be reused for surveillance or regulatory purposes. Figure 3-5 shows that areas of data friction relating to legal and regulatory concerns were found to operate across multiple stages of the data journey, particularly where data move off-farm, are transferred between commercial and public actors, or are repurposed for surveillance and regulatory use. These frictions reflect uncertainty around data protection, consent, ownership, and compliance obligations.

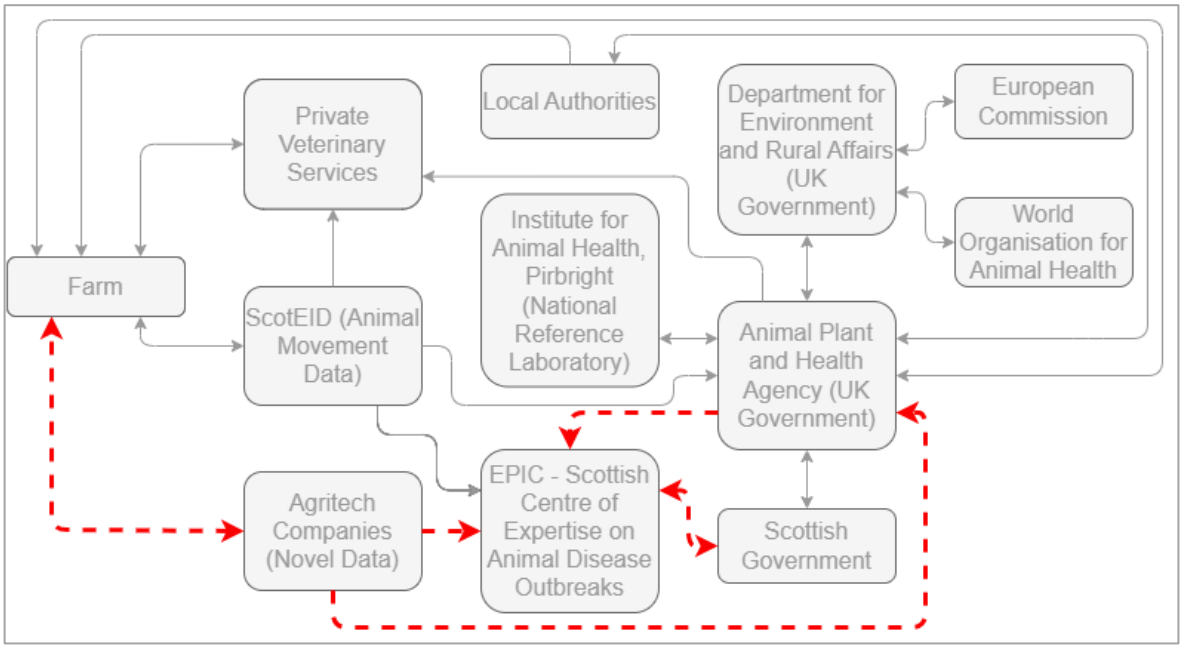



**Figure 3-5.** Map illustrating areas of data friction related to legal and regulatory concerns (Theme 3). Legal and regulatory data frictions were found to operate across multiple stages of the data journey, particularly where data move off-farm, are transferred between commercial and public actors, and are repurposed for surveillance and regulatory use. These frictions reflect uncertainty around data protection, consent, ownership, and compliance obligations, and are denoted by the red broken arrows across the data journey.

#### 3.3.4.3.1 Data privacy

Incidental collection of personal information was raised by six interviewees (42.86%) as a possible issue, with three discussing imagery and three other participants discussing other types of collected animal health data.

> *"You've got to separate animal data from personal data. Animal data is not personal data"* (I-14).

County Parish Holding (CPH) numbers are used in Scotland and across the UK to identify agricultural holdings. One interviewee (7.14%) suggested that CPH numbers are treated as personal data in England and Wales, but not in Scotland, raising concerns about differences in data protection treatment across jurisdictions. However, under data protection law, a CPH number is not inherently personal data. Rather, it may constitute personal data in any UK jurisdiction where it can be linked, directly or indirectly, to an identifiable natural person. The perception of jurisdictional difference therefore reflects

uncertainty among stakeholders regarding the application of data protection law, rather than a formal legal distinction.

The General Data Protection Regulation (GDPR) was introduced as Regulation (EU) 2016/679 (2016b) to protect the personal data and privacy of natural persons within the European Union. Following the United Kingdom's withdrawal from the EU, Regulation (EU) 2016/679 was retained and amended in domestic law, where it now applies as the "UK GDPR", pursuant to the European Union (Withdrawal) Act (2018). The UK GDPR operates alongside the Data Protection Act 2018 (2018), which supplements the retained regulation by providing UK-specific provisions, exemptions and enforcement mechanisms. Together, the UK GDPR and the Data Protection Act (2018) form the principal legislative framework governing the collection, processing and protection of personal data in the United Kingdom. Regarding national animal health surveillance in the UK, if such surveillance involves the collection and processing of personal data, it is subject to the UK GDPR and the Data Protection Act (2018). This means that entities involved in animal health surveillance, such as government agencies, veterinary authorities, research institutions and any other organisations handling personal data related to animal health, must comply with national data protection regulations. Organisations are required to ensure that personal data is collected and processed lawfully, fairly and transparently, and must also implement appropriate security measures to protect the data from unauthorised access, disclosure or loss.

Incidental data collection was raised by stakeholders as a possible issue. This refers to the collection of data that is not the primary focus of a particular activity or process but is gathered as a byproduct or side effect. Stakeholders were concerned that people's privacy could be invaded if imagery was to be taken above homes or farms.

Under data protection laws, organisations are generally required to collect and process personal data for specified, explicit and legitimate purposes (Article 5(1)(b) GDPR). Incidental data collection occurs when personal data is collected unintentionally while pursuing another legitimate purpose. However, the key legal question is not whether the collection is "incidental", but whether the personal data collected is necessary for those specified purposes. When personal data is collected incidentally, organisations must identify an appropriate lawful

basis for processing, which may in some circumstances include consent from individuals for such data processing. Consent requirements can vary depending on the nature of the data and the purposes for which it is collected.

The principle of data minimisation encourages organisations to collect only the data that is strictly necessary for the intended purpose. Pursuant to Article 5(1)(c) GDPR, personal data must be adequate, relevant and limited to what is necessary in relation to the purposes for which it is processed. In the case of incidental data collection, organisations should review their procedures and take steps to minimise the collection of unnecessary data. If imagery of private homes or farms is not required to achieve the defined objective, its collection may exceed what is permissible under the GDPR.

Organisations are typically required to inform individuals about the data they collect, including any incidental data. This information is usually provided through privacy notices or policy information issued to these individuals. In cases where incidental data collection may result in high risks to individuals" rights and freedoms, organisations may be required to conduct Data Protection Impact Assessments (DPIAs) to assess and mitigate such risks. Where the lawful basis relied upon is legitimate interests (Article 6(1)(f) GDPR), the organisation must also demonstrate that the processing is necessary for that purpose and that its interests are not overridden by the rights and freedoms of affected individuals. Google Maps was raised as an example of an organisation that collects imagery, and which has stakeholders who are keen to understand how data privacy is maintained.

*"For a project the scale of Google Maps, there's probably many, many data protection impact assessments…….and the systems and processes in place for rooting out any incidental data capture would effectively form part of a DPIA"* (I-11).

Google's "Street View" imagery has previously been subject to regulatory scrutiny in the UK and several EU Member States, leading to requirements such as facial and licence plate blurring and enhanced opt-out mechanisms, although no major GDPR-era enforcement action has prohibited the service on the basis of imagery capture alone.

Incidental data, like any other personal data, needs to be appropriately secured to prevent unauthorised access, disclosure or misuse. It is important for organisations to be aware of incidental data collection and take steps to ensure compliance with data protection regulations. Failure to do so can result in legal and financial consequences, including fines and penalties. Therefore, organisations collecting imagery for animal health surveillance should have robust data protection policies and practices in place to address incidental data collection and protect individuals' privacy rights.

Stakeholders discussed current data anonymisation techniques and how they might be applicable to novel data. Anonymisation of data can be achieved through multiple methods, but some expressed the belief that true anonymisation is not always possible and that if someone wanted to find out the identity or location of a farm or farmer, this may be possible. Three stakeholders (21.43%) also expressed the belief that it may be important to analyse un-anonymised data to better understand a dataset:

*"sometimes I think to get down to the nitty gritty of it, it's good to get that understanding, that granular understanding before you then anonymise it"* (I-10)

Again, DPIAs were suggested as mitigation to avoid any data privacy issues. One stakeholder recommended:

*"systems and processes in place as early as possible to anonymise - to the extent that there's any risk of incidental personal data capture – you'll just be ruling that out"* (I-11).

Data breaches and the potential for collecting commercially sensitive data were also raised as issues by stakeholders.

#### 3.3.4.3.2 Data control, access and sharing

Interviewees stated that farmers share data with ScotEID, Red Tractor, farming software providers (e.g. providers of DairyComp (Valley Agricultural Software, n.d.a) and GEA Group's DairyPlan software (Clarkson Dairy Services, n.d.)), and veterinary practices. ScotEID shares data with EPIC, APHA, farmers, veterinary practices, and data companies like MapofAg. Veterinary practices share data with veterinary software providers such as RoboVet together with organisations such as the APHA, Defra, and external laboratories. EPIC members work in

various institutions such as Scotland's Rural College (SRUC), the University of Glasgow, the Global Academy for Agriculture and Food Systems and Roslin at the University of Edinburgh, the James Hutton Institute, Biomathematics and Statistics Scotland (BioSS), and the Moredun Research Institute.

Interviewees were asked whether farmers "own" their data and whether they should do so. Nine interviewees (64.29%) responded that farmers should own the data concerning their livestock. But do farmers own their data currently? The concept of "data ownership" is often used as a convenient shorthand, but in UK law, control over data arises through a combination of legal regimes rather than through ownership of the data itself. Instead, rights and control arise through intellectual property law (including database rights), contractual arrangements, confidentiality, privacy and data protection law.

One legally trained interviewee discussed database rights in detail as a potential mechanism through which control over aggregated livestock data might be asserted. Legally in the UK, databases may attract copyright protection where the selection or arrangement of material is original, and a separate *sui generis* database right where there has been substantial investment in obtaining, verifying or presenting the contents. The *sui generis* right protects against the extraction or re-utilisation of all or a substantial part of the database. In practice, this means that the person or organisation that has made the relevant investment in compiling and maintaining a structured dataset may exercise legal control over its substantial use, even where the underlying data originates from farmers.

This illustrates that what interviewees described as "data ownership" is more accurately understood as a shorthand for a range of legal rights, such as intellectual property, contract, confidentiality, privacy, and data protection law, which together determine who may access, use or share data. In agricultural data ecosystems, where information is often aggregated and managed by intermediaries, such control may not rest with individual farmers, with implications for data access and onward sharing.

Discussions about sharing data elicited very different responses. Eleven interviewees (78.57%) perceived farmers, as a group, as cautious about sharing data.

*"it depends on who the third party is that has access to that data"* (I-06).

In the event of an outbreak, three of the four participants with a farming background expressed that they would be happy to share data. Three non-farming interviewees also expressed support for sharing data in this context, while a further interviewee described sharing as compulsory. This suggests that caution about data sharing could coexist with willingness to share during an outbreak.

#### 3.3.4.3.3 The Civil Aviation Authority "Drone Code"

Interviewees had concerns over whose responsibility it would be to collect drone-acquired data; would it be necessary for the farmer to gain the qualifications necessary to fly or could an autonomous system be created for data collection? For stationary ground-based cameras it is likely an autonomous system could be created, akin to systems that already exist for robotic milkers. For drone-acquired data, UK Civil Aviation Authority (CAA) regulations generally require the pilot to maintain visual line of sight with the aircraft. While permissions can be granted for Beyond Visual Line of Sight (BVLOS) operations in tightly controlled circumstances (such as site-specific authorisations involving defined airspace, enhanced safety systems and continuous human oversight), truly autonomous flights remain largely impractical under current regulatory conditions.

Current drone regulations require a person to obtain certification to demonstrate adequate knowledge and skill with regards to flying, drone regulations and safety. The CAA has set guidelines for the safe and responsible use of drones, known as the "Drone Code"(Civil Aviation Authority, 2022). The Drone Code applies to all drone users in the UK, whether these are being flown for recreational or commercial purposes. The code is designed to ensure the safety of people, property and other aircraft while also promoting responsible drone operation. Where a drone is equipped with a camera, the operator must be registered with the CAA and display a unique operator identification number on the aircraft, regardless of weight. Given that agricultural drones would be typically deployed for imaging, monitoring, or surveying purposes, this requirement would apply in most farm-based use cases. In addition, pilots must hold appropriate competency certification, which is mandatory for drones

weighing 250 g or more and for certain operations involving lighter aircraft. These requirements apply to both recreational and commercial drone operators.

Operators must have adequate training and competency to fly the drone safely and should familiarise themselves with rules and best practice before flying. Operators should be respectful of people's privacy and avoid flying over people, private property or sensitive areas without permission, but there is no specific guidance about what would qualify as an invasion of privacy. Currently, subject to specific flight restriction zones, there is no generally enforceable prohibition against flying a drone over privately-owned land. Operators must keep drones within their visual line of sight during flights to ensure identification and avoidance of potential hazards. Care must be taken to avoid flights near airports, aircraft or areas where emergency services are operating and to maintain a safe distance to avoid collisions and interference. If flying near an airport or flight path, or within a certain zone near the airport, it is advisable to call the local Air Traffic Control tower to advise of start and finish times. Unless special permissions have been granted, the operator must keep the drone"s altitude below 400 feet (120 meters) to avoid potential collision with manned aircraft. Drones must not be flown over crowded areas, such as concerts, sports events or gatherings, where people's personal safety could be put at risk. Flying a drone at night is generally not permitted unless specific permission from the CAA has been obtained. A safe distance from people, buildings and vehicles should be maintained to reduce the risk of accidents. Operators should check for any local restrictions or bylaws that may apply to drone flights in a particular area.

If the drone is to be used for commercial purposes (e.g. photography or surveying), additional regulations and permissions may apply, and commercial operators must also obtain appropriate insurance. Failure to comply with the Drone Code may result in legal consequences and pose a risk to public safety. Non-compliance constitutes a breach of the Air Navigation Order SI 2016/765 (2016) relating to small, unmanned aircraft amount and is an offence punishable on summary conviction by a fine not exceeding level four on the standard scale (up to £2,500), pursuant to Article 265(6). Notably, while core requirements such as visual line-of-sight operation and pilot certification have been established for several years, the regulatory framework governing drone use is

evolving rapidly in response to technological development and expanding commercial applications. As such, current regulatory constraints should be understood as reflective of the present policy landscape rather than fixed long-term limitations on future autonomous drone use in agriculture.

### 3.4 Discussion

The thematic analysis identified three interrelated domains of data friction with respect to hypothetical novel data streams: (i) veterinary and epidemiological data frictions, (ii) data infrastructure frictions, and (iii) legal and regulatory frictions. These frictions emerge at specific transition points as data move between sites of practice, most notably from farms to technology providers, from commercial or private systems to public surveillance infrastructures, and from data collection to regulatory or analytical use. Understanding where friction occurs is critical for identifying appropriate mitigation measures, as different forms of friction arise at different stages of the data journey.

Veterinary and epidemiological data frictions (Theme 1) were most evident at the interface between on-farm observations and clinically informed husbandry practices, and their translation into population-level surveillance outputs used by epidemiological and regulatory institutions. At this boundary, friction arose from differing expectations around data accuracy, sensitivity and specificity, trust in novel technologies, and uncertainty over whether remotely sensed data could meaningfully augment, or outperform, existing farmer-led detection and reporting systems. These frictions reflect differing epistemic priorities (differences in what stakeholders consider reliable and meaningful evidence) between farmers, veterinarians and epidemiologists, particularly in how uncertainty, false positives, and clinical relevance are evaluated within disease-specific surveillance contexts.

Data infrastructure frictions (Theme 2) occurred primarily as data moved from farm-level systems and commercial platforms into shared or public analytical environments, including research institutions and government agencies. These frictions were associated with interoperability between databases, limits on processing capacity, uncertainties over data stewardship, and concerns regarding cybersecurity and trust.

Legal and regulatory frictions (Theme 3) became most visible at the point where data were transferred beyond their original context of collection, particularly when repurposed for surveillance, research or regulatory decision-making. In these cases, uncertainty surrounding data protection obligations, data ownership, and compliance with aviation and product security regulations shaped decisions about whether, how and by whom data could be shared or used.

Framing these challenges as forms of data friction highlights that they are not inherent limitations of novel sensing technologies, but arise from the interaction between data, infrastructures and governance contexts. The mitigation measures outlined in Table 3-5 are therefore targeted not at eliminating friction entirely, but at reducing its constraining effects at key transition points in the data journey.

The findings should be interpreted in light of the researcher's role in both interviewing and analysis. Pre-existing professional relationships with some participants may have influenced what they chose to disclose, while coding and theme development were undertaken by a single researcher. Although potential themes were reviewed against the transcripts, the resulting interpretation remains shaped by the researcher's perspective.

### 3.4.1 Data friction mitigation

The future of animal health surveillance is likely to be shaped by a combination of technological advancements, data-driven approaches and a growing awareness of the importance of animal health and welfare as objectives in their own right, alongside their wider implications for human and ecosystem well-being. The IoT and sensor technologies are likely to play a significant role. Novel data access has the potential to (i) increase the timeliness of surveillance information; (ii) improve temporal and/or spatial resolution of surveillance; (iii) add surveillance to places lacking existing systems; (iv) improve data dissemination; (v) measure unforeseen outcomes of interest; (vi) measure aspects of a transmission/disease process not captured by traditional surveillance; and, (vii) increase the population size under surveillance (Althouse *et al.*, 2015; Dórea and Revie, 2021). In order to ensure that novel data is usable, it is imperative to identify potential obstacles to the development and deployment of new surveillance systems.

Many areas of data friction with respect to data infrastructure, legislation and regulation could be mitigated by implementing appropriate data governance. Data governance is a principled approach to managing data during its life cycle, from its acquisition to its subsequent uses and to its possible disposal or storage. In this context, data governance is used as an overarching concept rather than as a synonym for regulation or infrastructure. It refers to the frameworks, roles, processes and decision-making structures through which data is managed across its lifecycle, including how legal requirements are interpreted and operationalised, how technical systems are designed and used, and how responsibilities are allocated between actors. While legislation and regulation set formal legal obligations, and data infrastructure provides the technical means through which data is handled, data governance links these elements by translating regulatory requirements into organisational practice and technical implementation. It therefore encompasses, rather than duplicates, aspects of infrastructure, legislation and regulation. Data governance is considered a crucial aspect of effective management in any organisation, whether commercial or semi-state, playing a pivotal role in its ability to serve the public good. Organisations generate and manage vast amounts of data, ranging from sensitive personal information to insights about public services and infrastructure. Implementing robust data governance practices is essential to ensure that data is handled responsibly, securely and ethically. In this study, governance appears most critical at the farm to technology provider and technology provider to public surveillance transitions.

These transitions can involve farm-management software, which forms part of the wider data ecosystem by supporting routine recording and reporting. A farming interviewee identified DairyComp and DairyPlan as systems used on their farm and described that the software exchanges information. DairyComp supports dairy herd recording, health and reproductive management (Valley Agricultural Software (n.d.a), while GEA's DairyPlan supports herd management using data from animals and the milking parlour (Clarkson Dairy Services, n.d.). Integration between the systems is documented by Valley Agricultural Software, including the transfer of animal identification and reproductive information and access to milk-production data (Valley Agricultural Software, n.d.b). This

illustrates how connections between commercial systems can support the movement and use of farm data.

Beyond the examples raised in the interviews, FarmIT 3000 supports broader farm-management activities, including cattle and sheep recording alongside arable and financial management. It supports livestock movement, treatment, weight and breeding records, with links to recording systems including ScotEID and CTS (Border Software, n.d.). Such software provides a potential connection between everyday farm records and surveillance workflows. Movement reporting can support traceability, while treatment and production records could provide additional information for animal health monitoring if suitable arrangements for access and interpretation were established. These potential uses do not imply that all records held within these systems are routinely available for surveillance.

Another possible solution to areas of identified data friction is use of blockchain technology (Chattu *et al.*, 2019). As the importance of data security and traceability increases, blockchain technology could be utilised to secure and manage health records for animals. This could ensure the integrity of data related to vaccinations, treatments and disease outbreaks. Blockchain is a decentralised and distributed digital ledger technology that records transactions across multiple computers in a way that ensures the security, transparency and immutability of data that relies on a distributed network of nodes, consensus mechanisms, cryptographic techniques and immutability to record and verify transactions. It has the potential to provide a tamper-resistant and transparent record of transactions and data. Unlike traditional centralised systems where a single entity (like a bank or a company) controls the data, blockchain operates on a decentralised network of computers, often referred to as nodes. Each node has a copy of the entire blockchain ledger. Blockchain technology could be valuable in managing and securing animal health surveillance data, as a potential mitigation for several data frictions identified in the results, particularly those relating to traceability of animal movements, interoperability between heterogeneous databases, and trust in data handling between farmers, technology providers and public institutions. Animal health data can be recorded on the blockchain as immutable records. Once recorded, data are typically immutable in the sense that original entries cannot be altered or deleted

without trace. Corrections are made through additional records, preserving an auditable history and supporting data integrity. Sensitive data can be encrypted, and only authorised parties with the appropriate encryption keys can access it. Blockchain enables tracking the provenance of data. Each data entry includes information about who recorded it, when it was recorded and any updates or transfers. This traceability can be crucial for identifying the source of diseases or monitoring the movement of animals. Access to the blockchain can be restricted to authorised participants, such as government agencies, veterinarians, farmers and researchers. This ensures that only trusted parties can view and contribute to the data. Blockchain could facilitate interoperability between different systems and databases, making it easier to share data across organisations and regions, and could support data sharing while allowing individuals (e.g. farmers) to have control over their data. Users can grant and revoke access to their data, enhancing privacy and consent management. Smart contracts can be used to automate compliance with regulations and standards. For example, they can ensure that certain health checks or vaccinations are performed on animals before they are allowed to be transported or sold. Blockchain could enable real-time monitoring of animal health data, allowing for the early detection of disease outbreaks. When an abnormal pattern or a potential disease outbreak is detected, relevant stakeholders could be notified instantly.

Blockchain could also be of assistance in contact tracing during disease outbreaks by providing a transparent history of an animal's movement and interactions with other animals. Researchers could access historical and real-time data on animal health trends for epidemiological studies and policy planning. Organisations could choose to share aggregated, anonymised data with researchers or other stakeholders and potentially receive compensation through blockchain-based microtransactions. Blockchain's transparent and immutable ledger allows for easy auditing of data activities, enhancing accountability and reducing fraud and data manipulation risks. The decentralised nature of blockchain makes it easier for different countries and regions to collaborate on animal health surveillance, enabling a more comprehensive approach to global health challenges. While blockchain can offer numerous benefits for animal health surveillance data, it is important to consider the practical challenges,

such as data standardisation, scalability and the need for consensus among participants. Additionally, implementing blockchain solutions should align with regulatory frameworks and privacy requirements to ensure the responsible use of data.

Although blockchain has frequently been proposed as a solution to data security and traceability challenges in agriculture, its adoption has remained limited in practice due to technical, organisational and regulatory barriers, including infrastructure constraints, interoperability issues, costs, and a lack of clear legal frameworks, which must be addressed before blockchain can offer practical value in animal health surveillance systems (Mohammed, Potdar and Quaddus, 2023; Liu *et al.*, 2024; Stanescu *et al.*, 2025).

Together, these mitigation measures demonstrate that data friction is not an inevitable consequence of integrating novel sensing technologies into animal health surveillance, but could be proactively managed through coordinated technical, organisational and governance interventions. Table 3-5 outlines mitigation measures for identified areas of data friction. While the thematic analysis is organised around three domains of data friction, Table 3-5 reframes these findings around key transition points in the data journey, linking specific sites of friction to targeted mitigation measures.

**Table 3-5.** Mapping identified data frictions to mitigation measures across the data journey

| Site of friction | Theme | Type of Data Friction | Mitigation |
|---|---|---|---|
| Farm → Technology provider | Theme 1: Veterinary & epidemiological | Epistemic uncertainty; trust; interpretability/clinical validity | Data governance; shared standards; validation against gold standards |
| Technology provider → Public surveillance | Theme 2: Data infrastructure | Security; access control; processing capacity; interoperability | Data governance; public-private coordination; secure environments |
| Data collection → Regulatory use | Theme 3: Legal & regulatory | Legal uncertainty; compliance burden; liability; consent | Regulatory alignment; sector-specific guidance; DPIAs |
| Cross-system reuse | Themes 2 & 3 | Traceability; provenance; accountability | Blockchain; audit mechanisms; metadata standards |

### 3.4.2 Data for public good

During interviews, support was expressed for data being used for the public good. Here, "public good" is used in both a policy and an economic sense. Improved animal health surveillance can generate collective benefits that are non-rivalrous and largely non-excludable, such as reduced disease spread, improved biosecurity, and protection of national livestock populations, while also delivering broader societal benefits. Although such benefits may be publicly valued, the data used to generate them are often privately collected and commercially controlled, raising questions about how privately held data can contribute to outcomes that function as public goods. This study recognises that novel data collection may be facilitated by either commercial companies or public-sector bodies. However, whether data collection is commercially driven or state-led, the central challenge lies in ensuring that the associated data flows, access arrangements and governance structures are aligned to deliver public benefit.

A recent literature review conducted on behalf of the Scottish Government examined how the public sector can share personal data with the private sector in publicly trusted ways, in order to unlock the public benefit of this data

(Suman and Switzer, 2023). The report found that the public sector typically lags behind the private sector in developing and implementing data-sharing regimes, and that public support for the use of health and social care data is contingent on demonstrable public benefit rather than private commercial gain.

Commercial data for public use typically refers to datasets and information collected or generated by private companies or organisations that are made available to the public, often for a fee or under specific licensing terms. While such data are commercially controlled, this does not preclude them from being managed in ways that align with the FAIR data principles: findability, accessibility, interoperability and reusability. For example, commercial datasets may be made *findable* through metadata catalogues and persistent identifiers, *accessible* via controlled access mechanisms rather than open release, and *interoperable* through the use of common data standards and vocabularies.

Reusability may be supported through clear licensing terms, documentation and provenance information that specify permissible uses, even where access is restricted. In this sense, FAIR does not necessarily imply open or free data, but rather data that are well-described, discoverable and usable under clearly defined conditions. Applying FAIR-aligned practices to commercially held agricultural data could help mitigate some of the access and interoperability frictions identified in this study, while allowing data providers to retain commercial control and still meet regulatory and contractual obligations.

Data can originate from a wide range of sources, including private companies, research institutions, government agencies and non-profit organisations. Access to commercial data typically involves purchasing a license or subscription from the data provider. Licensing terms can vary widely and may include restrictions on data usage, redistribution and the duration of access. Commercial data is often valued for its accuracy and reliability, as it is frequently subject to rigorous data collection and verification processes. However, the quality of commercial data can vary, and users should carefully evaluate the data source and methodology. Privacy concerns can arise when dealing with commercial data, particularly if it includes personal or sensitive information. Companies collecting and distributing data are often subject to data privacy regulations, and users must handle such data responsibly and ethically. Companies

specialising in data collection, analysis and aggregation often make available commercial datasets.

## 3.5 Conclusion

This study set out to examine how animal health surveillance data are currently generated, managed and used in Scotland, and to explore whether and how novel data streams, such as drone- and sensor-derived data, might augment existing surveillance systems. Through qualitative interviews with key stakeholders, the study identified three interrelated domains of data friction that shape the integration of novel data into animal health surveillance: veterinary and epidemiological frictions, data infrastructure frictions, and legal and regulatory frictions.

Importantly, these frictions were found to emerge at specific transition points as data move between sites of practice, particularly from farms to technology providers, from commercial systems into public surveillance infrastructures, and from data collection into regulatory use. Veterinary and epidemiological frictions reflected uncertainty over data validity, trust and clinical relevance, highlighting tensions between on-farm judgement and population-level surveillance requirements. Data infrastructure frictions centred on interoperability, processing capacity, data stewardship, and cybersecurity as data moved across organisational boundaries. Legal and regulatory frictions operated across multiple stages of the data journey, shaping whether data could be collected, shared or repurposed, and reflecting uncertainty around data protection, ownership, consent and compliance obligations.

Framing these challenges as forms of data friction highlights that barriers to integrating novel data are not solely inherent to the technologies themselves, but also arise from interactions between data, institutions and governance arrangements. Rather than proposing universal solutions, this study examined mitigation approaches as context-dependent ways of reducing friction at specific points in the data journey. These include the use of data governance frameworks, more structured public–private coordination and, in some cases, technologies such as blockchain.

Overall, the findings suggest that the future value of novel sensing technologies for animal health surveillance will depend not just on technical capability but on

the parallel development of governance arrangements and institutional relationships that allow data to move, to be trusted and to be reused across sectors.

# 4 Drone-Mounted Livestock Detection Using YOLOv8: Data Collection and Establishment of an Animal Thermal Dataset, Model Training and Testing with Sensitivity Analysis

## 4.1 Introduction

Computer vision is increasingly being applied to livestock with the aim of automating tasks that traditionally require manual labour such as animal counting, posture estimation and behavioural observations (Natho *et al.*, 2025; Rahman, Asaari and Ibrahim, 2025). Convolutional neural networks (CNNs), a class of machine-learning models that learn to recognise patterns by progressively combining simple visual features into more complex representations, have significantly improved the capability of computer vision systems by learning directly from image data. At the same time, unmanned aerial vehicles (UAVs) equipped with thermal cameras have increased the feasibility of remote livestock monitoring. Thermal infrared imagery (TIR) enables animal detection even in low-light or visually obstructed conditions, offering additional robustness for pasture-based systems where traditional visible light (optical) imagery (VLO) may fail due to vegetation cover, shadows or large spatial areas. Detecting animals automatically within these aerial thermal scenes provides the foundation for locating individuals, estimating group sizes and eventually inferring biological or health-related indicators such as heat stress signatures, behavioural anomalies or activity pattern deviations.

YOLOv8 (You Only Look Once) is an object-detection algorithm released by Ultralytics in 2023 (Jocher, Chaurasia and Qiu, 2023). It is most often used for object detection in digital images and uses a supervised learning approach. Supervised learning is a dominant paradigm in the field of machine learning where an algorithm is trained on input data that has been “marked up” or labelled with the correct output. YOLOv8 is open source, “anchor-free” and capable of processing images in a single inference step. Anchor-free means that YOLOv8 predicts bounding boxes directly without using predefined anchor boxes as templates. Also, instead of proposing regions and refining them iteratively, YOLO predicts bounding boxes, class scores and confidence values across an entire image grid simultaneously. This is known as single-stage detection. This architecture provides high processing throughput, making YOLO particularly suitable for aerial monitoring of livestock where images may contain many small, spatially dispersed animals. Providing dense predictions in real-time is

advantageous for drone-based workflows that may require dynamic flight-path adjustment, live monitoring or rapid decision-making. YOLOv8's inference speed and detection reliability make it an appropriate tool for fully automated livestock detection in drone imagery.

To achieve strong baseline performance, YOLOv8 is commonly pretrained on the COCO (Common Objects in Context) dataset, a large collection of labelled images used to teach object-detection models to recognise general visual features (Lin *et al.*, 2014). However, COCO datasets contain well-lit, high-resolution visible light (optical) objects (encoded in RGB colour-space) occupying significant image proportion, which differs greatly from TIR UAV imagery where targets are small, low-contrast and can be partially occluded. These differences meant that effective detection in TIR UAV imagery could not be assumed from performance on COCO alone, motivating the development of an annotated thermal dataset for this application. Publicly available livestock thermal datasets remain scarce and generally limited in scale and annotation detail, although this area is beginning to grow with emerging datasets for cattle, pigs and sheep (Bhole *et al.*, 2019, 2022; Ma *et al.*, 2024; Pham *et al.*, 2025; Botsoglou *et al.*, 2026).

Addressing this gap forms a central component of the present study. The work focuses on constructing an annotated thermal dataset and evaluating detection performance for small-target animals in drone-acquired imagery. By establishing a dataset and baseline model performance in this domain, the study contributes toward future systems capable of supporting automated livestock detection, monitoring and health assessment.

As outlined in Section 1.4, this chapter addresses the data acquisition, detection and processing stages of the wider surveillance pipeline. UAV-mounted sensing provides a mobile platform for targeted data collection across grazing areas, whereas stationary cameras provide observations within fixed fields of view. The choice of a UAV platform was also motivated by its potential application to monitoring livestock in the Scottish Highlands, where animals may be dispersed across extensive areas of difficult-to-access terrain. A mobile aerial platform could survey different locations, whereas stationary cameras would provide coverage limited to their installed positions. The present study investigated the animal-detection component needed to support that longer-term application.

Although livestock detection using VLO imagery had already been explored, this study focused on establishing detection performance within thermal imagery as a preliminary step towards future temperature-based animal health applications. The thermal images acquired in this study also had smaller file sizes than the corresponding VLO images, reducing storage and data-handling requirements.

The findings of Chapter 2 informed the decision to focus on locating animals using relative thermal contrast. The review highlighted how camera-to-target distance and environmental conditions constrain the reliable estimation and interpretation of animal surface temperatures. Under the aerial acquisition conditions used in this study, sufficiently accurate absolute temperature measurements for health assessment could not be assumed. The study therefore evaluated animal detection using thermal contrast with the surrounding scene, while future applications involving absolute temperature measurements would require separate validation of measurement accuracy.

The study therefore addressed the following research question: how accurately can YOLOv8 detect sheep in UAV-acquired thermal imagery under the field conditions studied? For reference, Table 4-1 outlines definitions for commonly used terms that appear throughout this chapter. Model performance metrics are defined separately in Table 4-4.

**Table 4-1.** Terms used in the course of Chapter 4.

| Term | Meaning |
|---|---|
| Artificial Intelligence | A broad field of computer science aimed at creating systems capable of performing tasks that typically require human intelligence, such as perception, reasoning and learning. |
| Computer Vision | A field of artificial intelligence concerned with enabling computers to interpret, analyse and understand visual information from images and videos. |
| Machine Learning | A subset of artificial intelligence that focuses on developing algorithms that allow computers to learn patterns from data and make predictions or decisions without explicit programming. |
| Supervised Learning | A machine learning paradigm in which models are trained using labelled data, where each input is paired with a known output. |
| Convolutional Neural Network | A class of neural network that analyses images by applying the same learned pattern detectors across an image to identify relevant visual features |
| YOLOv8 | An object detection model from the 'You Only Look Once' family that performs real-time object detection by predicting bounding boxes and class labels in a single forward pass. |
| COCO Dataset | An abbreviation of Common Objects in Context; a large, publicly available labelled dataset, widely used for training and evaluating object detection, segmentation and captioning models. |
| UAV | An abbreviation of Unmanned Aerial Vehicle, commonly known as a drone, which operates without a human pilot onboard. |
| Thermal Infra-Red Imagery | Images formed from infra-red radiation emitted by objects due to their temperature, representing relative heat differences. |
| Visible Light (optical) Imagery | Images formed from light in the visible spectrum reflected by objects and captured by optical sensors. |
| RGB | A colour representation commonly used in visible light imagery where each pixel is defined by the intensities of red, green and blue light channels. |
| Epoch | One complete pass of the entire training dataset through a machine learning model during training. |

| Table 4-1 (continued) | |
|---|---|
| **Term** | **Meaning** |
| Patience Parameter | A training parameter that specifies the number of epochs to wait for improvement before stopping training early in order to prevent overfitting. |
| Confidence (YOLO) | A value between 0 and 1 representing the model's estimated probability that a predicted bounding box contains an object of the specified class. |
| Non-maximum Suppression (NMS) | A post-processing technique used in object detection to remove redundant bounding boxes by retaining only the highest-confidence prediction for overlapping detections. |
| Confusion Matrix | A table used to visualise the performance of a classification model by comparing predicted labels with ground-truth labels. In object detection, includes True Positives (TP), False Positives (FP) and False Negatives (FN). True Negatives (TN) are not normally counted. |
| Ground-truth | Refers to the reference labels assigned through annotation or verification procedures that represent the best-available class and location of each object in an image, and which are used as the benchmark for evaluating model predictions. |
| Training Set | The training set is a subset of data used to estimate the model's internal parameters by learning the relationship between the input images and their annotations. |
| Validation Set | The validation set is a subset of data used during model development to tune model settings and assess performance, without being used to estimate the model parameters. |
| Test Set | The test set is an independent subset of data used to evaluate and compare trained checkpoints on images not used during training. |
| Bounding Box | A rectangular annotation used in image analysis to indicate the location and extent of an object by enclosing it within the smallest possible axis-aligned rectangle. |
| Anchor-free (YOLO) | A YOLO object detection approach that predicts bounding box locations directly from feature map points without using predefined anchor boxes. |

## 4.2 Methods

All aerial data collection and animal monitoring procedures complied with relevant animal welfare regulations and UK UAV flight legislation. No handling of or interference with livestock occurred at any stage. The study was approved by the Ethics Committee of the School of Biodiversity, One Health and Veterinary Medicine at the University of Glasgow: Ethics Approval Designation EA32/20.

### 4.2.1 Aerial surveys

Image acquisition was conducted using a UAV, the DJI Matrice 300 RTK (Real-Time Kinematics-enabled), released in May 2020. The platform provides a maximum flight time of approximately 55 minutes without payload and supports a maximum take-off weight of 9 kg. It has a wind resistance of up to 15 m/s and an operating temperature range of −20°C to 50°C, allowing safe and reliable deployment under a wide range of environmental conditions. The multi-rotor UAV is shown in Figure 4-1.



**Figure 4-1.** DJI Matrice 300 RTK at the University of Glasgow's Cochno Farm and Research Centre before take-off for data collection.

TIR and visible light (optical) images were captured using the Zenmuse™ XT2 gimbal and imaging system, which integrates a dual-sensor camera designed jointly by FLIR and DJI. The XT2 incorporates a FLIR long-wave infrared sensor (~8-14 µm) alongside a visible light sensor (~0.4-0.7 µm), enabling simultaneous acquisition of thermal and visible light imagery. The FLIR thermal camera uses an uncooled VOx microbolometer operating within the spectral range 7.5–13.5 µm and has a thermal sensitivity of <50 mK @ f/1.0. Images were saved in JPEG format; although TIFF and radiometric JPEG outputs are possible, JPEG was selected because relative rather than absolute temperature values were required. Data were stored internally on a microSD card. The camera was fitted with a 19 mm lens and the payload mass was 588 g. When mounted on the Matrice 300 RTK, the estimated endurance of the UAV was reduced to approximately 45 minutes.

Flight control and mission planning were conducted using the DJI Smart Controller Enterprise operating DJI Pilot software. Autonomous missions were executed with the sensor positioned at nadir (90° downward orientation), with 90% forward and side overlap, and in accordance with relevant civil aviation authority legislation. The high overlap was selected to support the original intention of combining adjacent images into a single map of the surveyed area for locating and counting animals. Shared features between overlapping images would allow them to be aligned. The selected 90% forward and side overlap is consistent with guidance for thermal image reconstruction published by Pix4D (2016). However, the resulting maps were not sufficiently accurate for reliable animal counting, and the analysis therefore focused on detecting animals in individual images using machine learning.

Data were collected at the University of Glasgow's Cochno Farm and Research Centre, which covers approximately 850 acres. The site is predominantly south-facing, with an elevation gradient ranging from ~400 ft near the West Lodge Gate to >1,200 ft at the northern extent of the estate. After assessment of logistics, airspace restrictions and livestock location, Field 30 was selected as the primary survey area (see Figure 4-2). Sheep were the target livestock species, based on seasonal availability and accessibility.

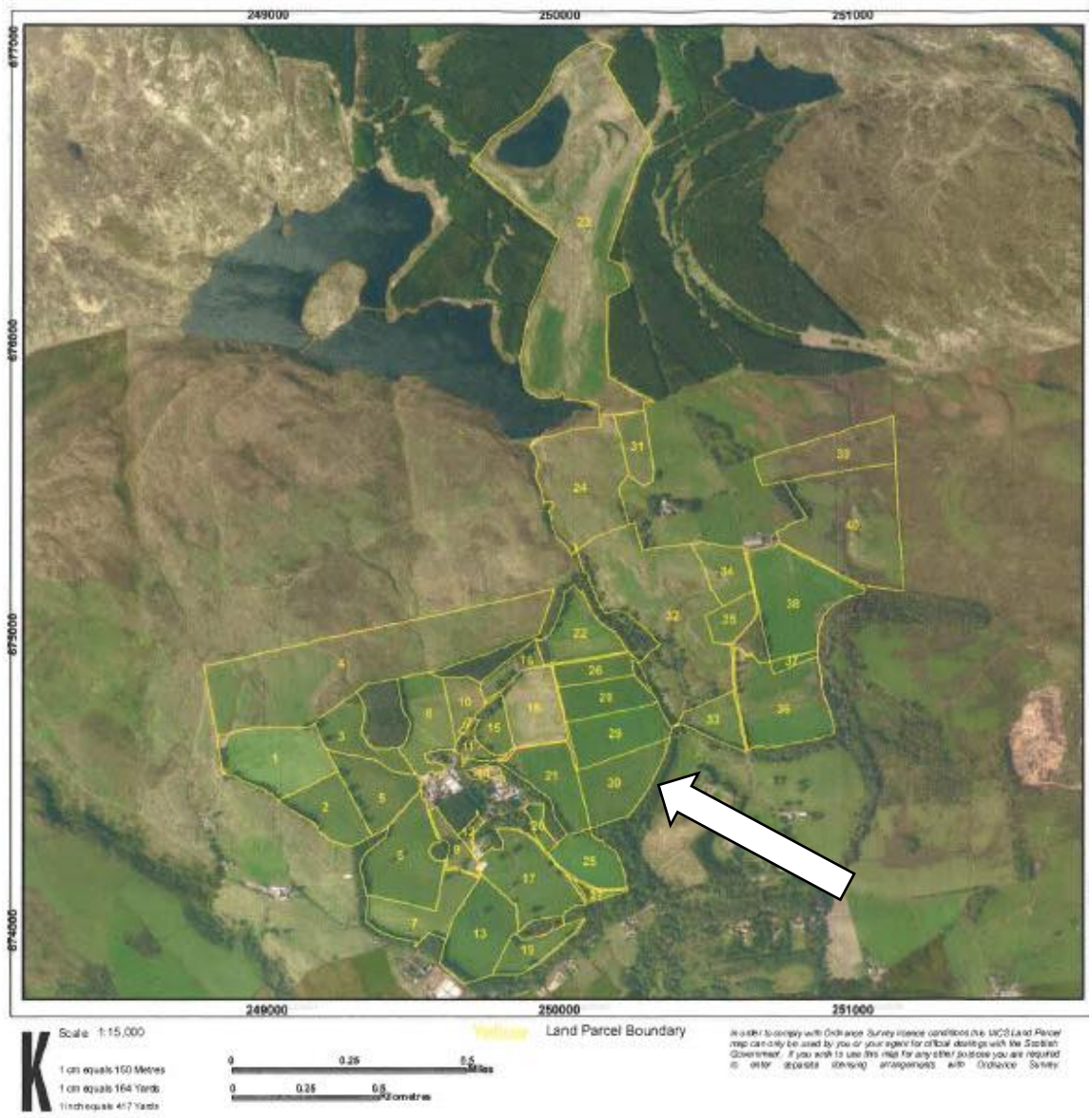



**Figure 4-2.** Area for data collection at the University of Glasgow's Cochno Farm and Research Centre, which covers approximately 850 acres. The site is predominantly south-facing, with an elevation gradient ranging from ~400 ft near the West Lodge Gate to >1,200 ft at the northern extent of the estate. After assessment of logistics, airspace restrictions and livestock location, Field 30 was selected as the primary survey area (white arrow). Land parcel boundaries are denoted by yellow lines.

A total of ten flights were conducted over two consecutive days. Four flights took place on 03/05/2022 and six on 04/05/2022. The timing and duration of data collection were determined by the combined availability of the UAV operator, equipment, livestock and survey field, together with suitable weather conditions. Ten flights were undertaken to collect enough images of sheep to support the development and evaluation of an automated animal-detection

model. The high overlap between successive images also increased the number of images available for this purpose. All flights were undertaken at an altitude of 80 m above ground level. This altitude was selected as a practical compromise between ground coverage and retaining sufficient image detail to discern animals. An altitude of 80 m was also identified as suitable for thermal detection and identification of cattle by Longmore *et al.* (2017), although its suitability depends on the imaging system and target species. Images were collected under clear, dry and low-wind conditions.

### 4.2.2 Image sets for analysis

Raw images were grouped by flight and date. Images were divided into a training set, a validation set and a test set (Table 4-2). The intended target sizes were approximately 1,000 images for both the training and validation sets and 100 images for the test set, following accepted machine-learning conventions and practical considerations around model development and independent evaluation. Dataset splitting was performed at the flight level, such that no flight contributed images to more than one dataset. This group-wise splitting reduced direct data leakage and temporal dependence between training, validation, and test sets, while acknowledging that spatial correlation remained due to repeated coverage of the same area across flights. Each TIR image was manually assessed for the presence of sheep and verified against the corresponding VLO image. The TIR images were stored as non-radiometric, colour-mapped images using an "ironbow" palette, whereas the VLO images used standard RGB colour encoding. The TIR images (640 × 512 pixels, ~1 MB) had lower spatial resolution and a different aspect ratio than the VLO images (4000 × 3000 pixels, ~2.3 MB), reflecting differences in the thermal and optical camera sensors and optics. As a result, each TIR image covered only a portion of the corresponding VLO scene, and the two datasets were not directly comparable on a like-for-like basis in terms of ground coverage. This difference is illustrated in Figure 4-3.

**Table 4-2.** Numbers of thermal images collected and images containing sheep for each flight, showing allocation to the training, validation and test sets. Images were grouped by flight to reduce the risk of overfitting associated with closely related images appearing in different sets.

| Date | Flight Number | Total Thermal Images | Images Containing Sheep | Set |
|---|---|---|---|---|
| 03/05/2022 | 1 | 617 | 347 | Training Set |
| 03/05/2022 | 2 | 618 | 316 | Training Set |
| 03/05/2022 | 3 | 616 | 265 | Training Set |
| 03/05/2022 | 4 | 621 | 221 | Training Set |
| 04/05/2022 | 5 | 602 | 183 | Validation Set |
| 04/05/2022 | 6 | 608 | 225 | Validation Set |
| 04/05/2022 | 7 | 619 | 216 | Validation Set |
| 04/05/2022 | 8 | 615 | 224 | Validation Set |
| 04/05/2022 | 9 | 618 | 385 | Test Set |
| 04/05/2022 | 10 | 619 | 375 | Test Set |

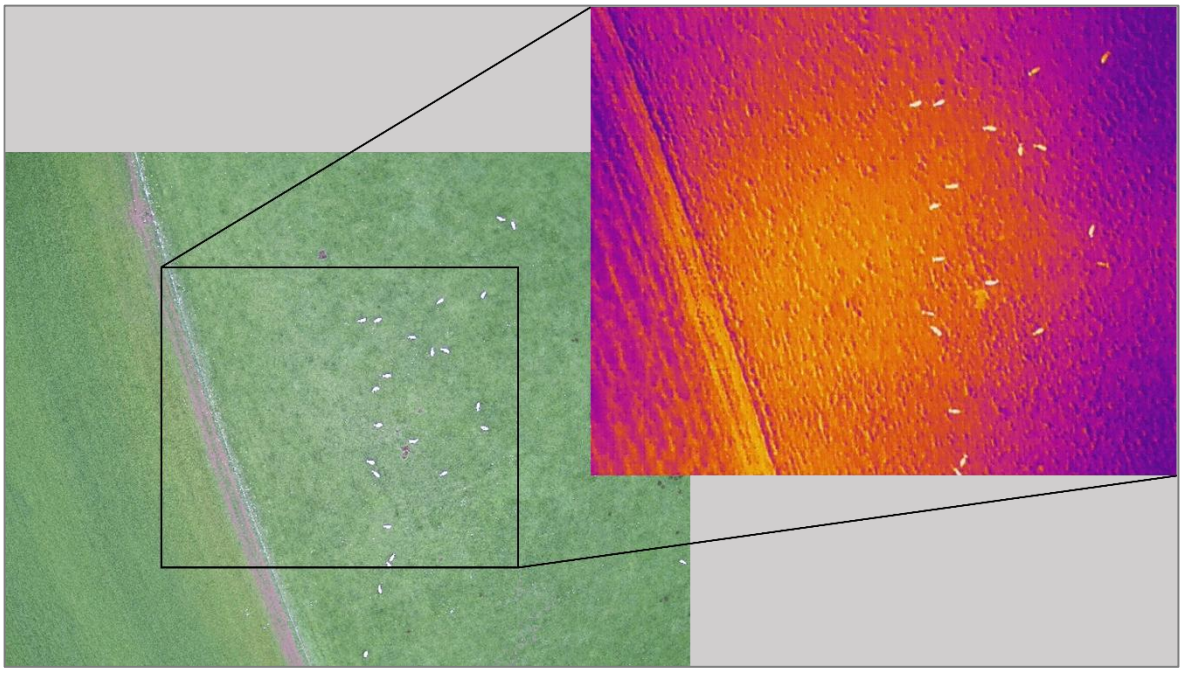


**Figure 4-3.** A drone acquired thermal infrared (TIR) image and its corresponding visible light (optical) image (VLO). The TIR image has a lower pixel resolution and covers only a portion of the corresponding VLO scene.

### 4.2.3 Image annotation

Images containing sheep were uploaded to the Computer Vision Annotation Tool (https://www.cvat.ai/), a web-based, open-source platform for annotating images and video data for computer vision and machine learning tasks. Images were annotated using rectangular bounding boxes. Only one class was annotated: sheep. Full sheep, half sheep (situated at the edge of an image) and sheep lying and standing in different positions were all included. Differing animal positions are illustrated in Figure 4-4. Table 4-3 outlines the final number of images used in each set. The training set contained 11,098 annotated sheep instances, exceeding Ultralytics' recommendation of 10,000 labelled instances per class. These instances represent individual sheep appearances within images, including repeated observations of the same animals. The training set contained 1,132 labelled images, below the accompanying recommendation of 1,500 images per class (Ultralytics, n.d.). These recommendations provide guidance on dataset size; detection performance must still be evaluated using held-out data.

The reduced size of the final validation set arose from image quality limitations specific to the flights allocated to this set. In these images, background thermal noise from vegetation and soil made it difficult to confidently identify sheep in a substantial proportion of thermal frames, preventing reliable ground-truth annotation. Although the validation flights covered the same ground as the training flights, differences in environmental conditions and acquisition timing affected image clarity. This challenge is illustrated in Figure 4-5.

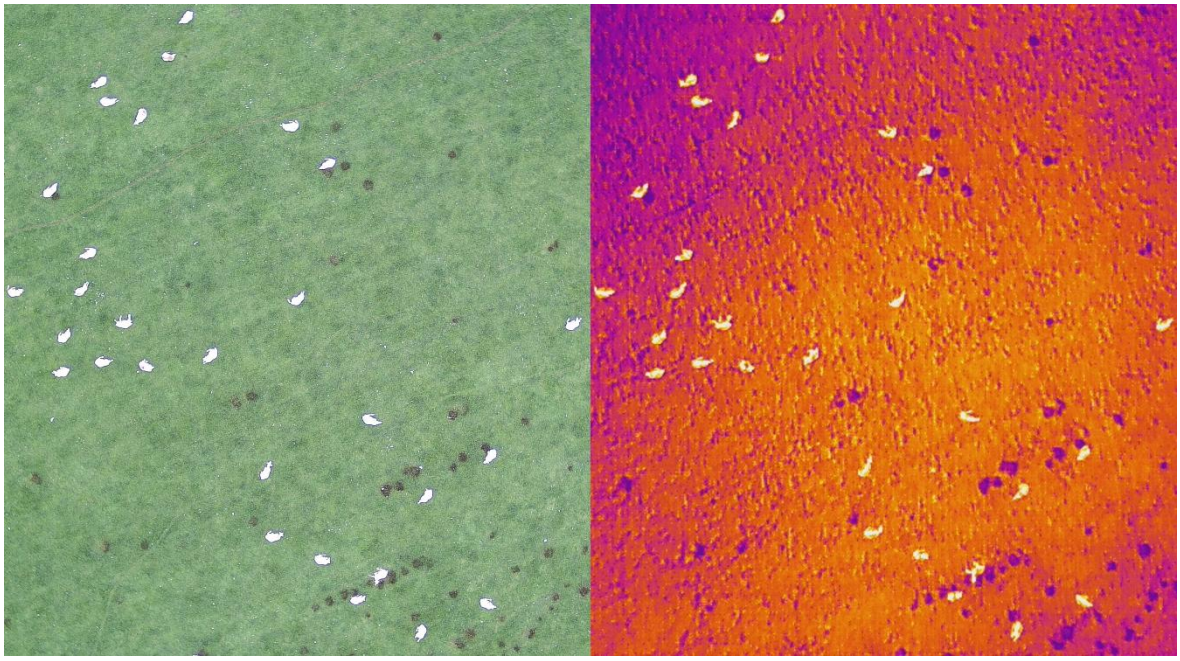


**Figure 4-4.** Different lying and standing positions of sheep in a thermal infrared (TIR) image and its corresponding visible light (optical) image (VLO).

**Table 4-3.** Final numbers of background images, labelled images and annotated sheep instances in the training, validation and test sets. Annotated instances include repeated appearances of the same animals across different images.

| Set | Number of Background Images (no labels) | Final Number of Labelled Images | Final Number of Objects Annotated in Images |
|---|---|---|---|
| Training | 103 | 1132 | 11098 |
| Validation | 50 | 313 | 3238 |
| Test | n/a | 100 | 736 |

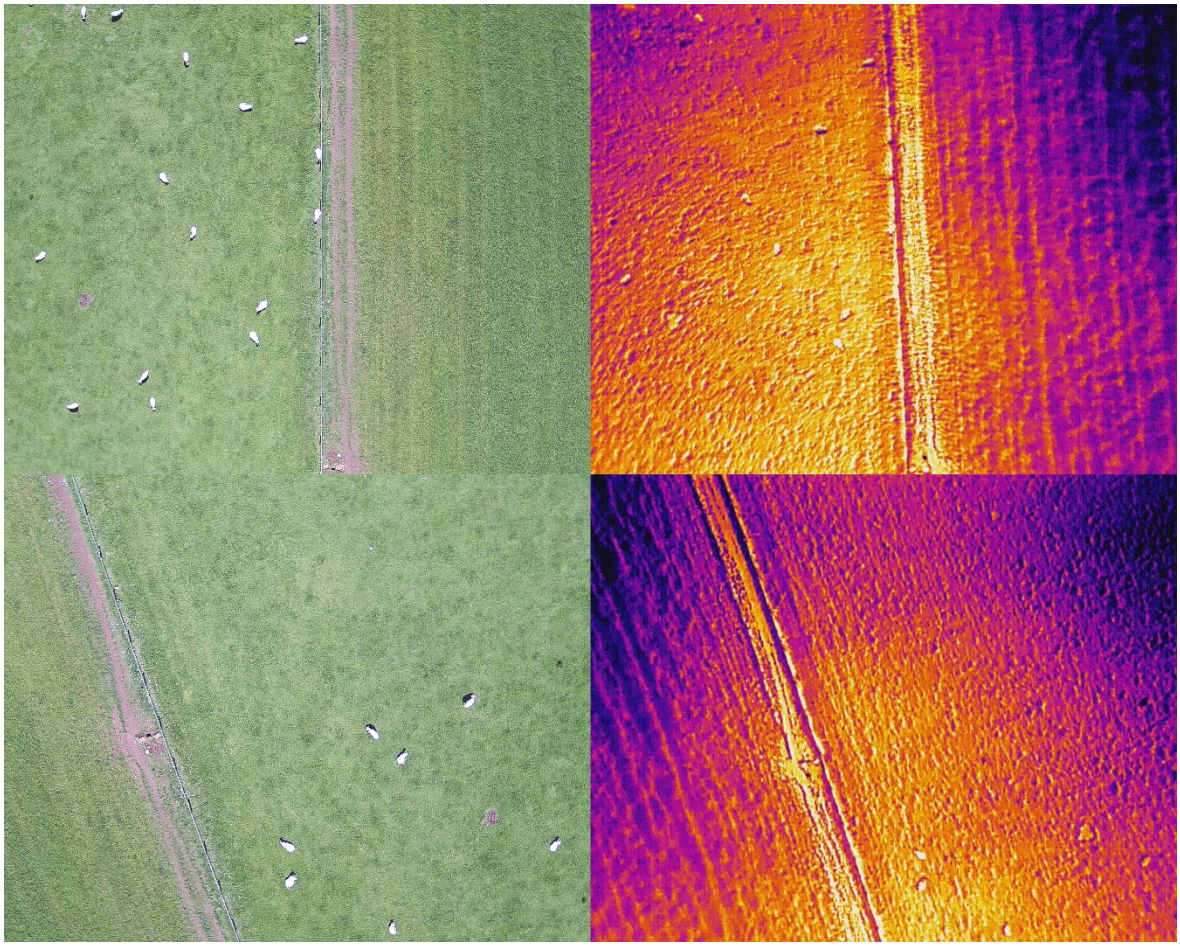


**Figure 4-5.** Thermal infrared images are shown alongside their corresponding visible-light images. In some cases, animals could not be clearly identified in the thermal imagery, making those images unsuitable for annotation. For example, in the top thermal image, it is difficult to identify those sheep which stand along the fencing area. In the bottom thermal image, three sheep which can be seen in the visible light (optical) image (VLO) are not identifiable in the corresponding thermal image.

### 4.2.4 Model architecture

YOLOv8 belongs to the "You Only Look Once" family of single-stage object detectors. "Single-stage" means the model does not first generate region proposals and then classify them; instead, it predicts object locations and labels them in one pass through the network. This design allows rapid processing, which is important for UAV applications where large numbers of images may be collected. The YOLOv8 network follows the typical three-part structure used in modern object detectors: a 'backbone', a 'neck' and a 'head'.

The backbone is responsible for feature extraction. As an image passes through this part of the network, the algorithm learns increasingly complex visual

patterns, from simple edges and heat contrasts to more abstract shapes associated with animals. The neck combines these features at several different resolutions. This structure, known as a feature pyramid, allows information from coarse, low-resolution layers, which is useful for large shapes, to be merged with fine, high-resolution details which is important, for example, for sheep in the distance that appear very small. This multi-scale representation is critical in UAV thermal imagery where animals appear at different sizes within the same frame. Finally, the detection head produces the model's output, i.e. the predicted bounding boxes and confidence scores.

A key architectural change in YOLOv8 compared with earlier versions is the use of an anchor-free detection head**.** Earlier YOLO models (e.g. YOLOv3–YOLOv5) were "anchor-based", meaning they relied on predefined "anchor boxes" of fixed shapes that acted as starting templates for each bounding box. During training, the model learned how much to adjust each anchor to match an object. This approach required manual tuning of anchor shapes to suit each dataset, which could be time-consuming, dataset-specific and could reduce performance when objects were very small, irregularly shaped or only partly visible. In contrast, YOLOv8 predicts object centres directly and then learns the distances from the centre to the edges of the bounding box. Because it no longer depends on fixed templates, this anchor-free approach simplifies optimisation and adapts more readily to variable object sizes and postures. For thermal UAV imagery, where sheep often appear as small, low-contrast shapes, this flexibility is advantageous because bounding boxes are fitted to the data rather than constrained by preset anchor shapes.

The model was implemented using the Ultralytics YOLOv8 framework with default architectural settings unless otherwise stated.

### 4.2.5 Model training and testing

The model was trained on the training set, tuned using the validation set, and final performance was reported on an independent test set that was never used during training**.** The model was trained from random initialisation, meaning no pretrained weights were used. This means that all model parameters were learned solely from the data in this study, rather than inherited from a previously trained neural network. Training from random initialisation was selected because no pretrained weights specifically developed for sheep

detection in aerial thermal imagery were known to the researcher at the time of model development. This allowed baseline performance to be established using the study's own thermal dataset. Fine-tuning weights pretrained on VLO imagery was an alternative, but was not evaluated; the study therefore does not establish whether training from random initialisation performs better than that approach. A smaller subset of "background images" that contained no sheep and corresponding blank annotation files were added to both training sets and validation sets to aid learning. Each training sample consisted of a greyscale thermal image and an accompanying YOLO-format label file containing the class index and normalised bounding box coordinates. Training was set to run for 300 epochs, but a patience parameter was set at 40, meaning that the model would automatically stop training once it had observed no improvement for 40 epochs. After each epoch during training, YOLOv8 evaluates the model on the validation set and computes a single performance score, referred to as the 'fitness function'. By default, YOLOv8 defines this fitness function as the validation mAP50–95, and the checkpoint with the highest value is saved as the "best" model.

Final model performance was quantified using standard object detection metrics: mAP50 (mean Average Precision at IoU=0.50), mAP50–95 (mean Average Precision averaged over IoU thresholds from 0.50 to 0.95 at intervals of 0.05), precision, recall and F1-score. Precision, recall and F1-score metrics provide complementary perspectives on model performance and are more commonly used in fields of ecology, with mAP50 and mAP50–95 being more common assessment metrics in the field of computer vision and offering stricter assessments of localisation accuracy. The detection outcomes and performance metrics used in this study are defined in Table 4-4.

**Table 4-4.** Definitions of detection outcomes and performance metrics used to evaluate sheep detection.

| Term | Meaning |
|---|---|
| Intersection over Union (IoU) | A metric used to measure the overlap between two regions, defined as the ratio of the area of their intersection to the area of their union, with values ranging from 0 to 1. |
| True Positive (TP) | A predicted sheep detection correctly matched to an annotated sheep at the specified IoU threshold. |
| False Positives (FP) | A predicted sheep detection without a matching annotated sheep, including additional detections of an already matched sheep. |
| False Negatives (FN) | An annotated sheep for which no matching detection is produced at the specified IoU threshold. |
| Precision | The proportion of predicted sheep detections that correctly match an annotated sheep: TP / (TP + FP). |
| Recall | The proportion of annotated sheep correctly detected: TP / (TP + FN). |
| F1-Score | The harmonic mean of precision and recall: 2 × precision × recall / (precision + recall). |
| Average Precision | A summary of the precision–recall curve obtained by varying the detection confidence threshold, at a specified IoU threshold. With one class (sheep), mean Average Precision equals that class's AP. |
| mAP50 | Mean Average Precision calculated using an Intersection over Union (IoU) threshold of 0.50, commonly used to evaluate object detection performance. |
| mAP50–95 | Mean Average Precision averaged across multiple IoU thresholds from 0.50 to 0.95 in increments of 0.05, providing a more comprehensive evaluation metric. |

When assessing model performance, a confusion matrix can be used to summarise detection outcomes. It consists primarily of true positives (TP), false positives (FP) and false negatives (FN). True negatives are not typically reported in object detection due to the very large proportion of background pixels. From

these values, precision, recall and F1-score are calculated per the formulae below.

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1} = 2\,x\,\frac{Precision\ x\ Recall}{Precision\ +\ Recall}$$

Precision gives an idea of how many detections are correct, whereas recall indicates how many of the true objects were found. The F1 score is the harmonic mean of precision and recall, reflecting the balance between correctly identifying objects (recall) and avoiding incorrect detections (precision). Because the harmonic mean penalises extreme imbalances, a model only obtains a high F1-score when both precision and recall are simultaneously high. It can be particularly useful in object detection problems where false positives and false negatives do not have equal consequences, and where accuracy alone may be misleading due to the large amount of background (true negatives).

Intersection over Union (IoU) measures how well a predicted bounding box overlaps the ground-truth box. It is defined as the area of the overlap between the two boxes divided by the area of their union, i.e. the total area covered by either box. IoU values range from 0 to 1, where 1 indicates perfect alignment and 0 indicates no overlap.

$$IoU = \frac{Area\ of Overlap}{Area\ of\ Union}$$

In object detection, a prediction is counted as correct only if its IoU with the ground-truth object is greater than or equal to a chosen threshold, e.g. 0.50. Mean Average Precision at IoU = 0.50 (mAP50) was used to evaluate overall detection performance. Because only one class (sheep) was considered, mAP50 here corresponds directly to the Average Precision of that class at IoU ≥ 0.50. mAP50 is the mean Average Precision calculated using a fixed IoU threshold of 0.50. A detection is counted as being correct if its predicted box overlaps the

ground-truth box by at least 50% (IoU ≥ 0.50). Because the mAP50 IoU requirement is moderate, mAP50 rewards detectors that can find objects even if their bounding boxes are not perfectly tight. Mean Average Precision at IoU from 0.5 to 0.95 (mAP50-95) was also used as a model performance metric. mAP50–95 is the mean Average Precision calculated across multiple IoU thresholds, from 0.50 to 0.95 in steps of 0.05. It measures how well a detector both finds objects and accurately localises them across increasingly strict overlap requirements. This metric was popularised by the COCO benchmark and is considered much tougher and more realistic than mAP50.

During evaluation, the trained YOLOv8 model produces a set of predicted bounding boxes, each with an associated confidence score. Non-maximum suppression (NMS) is applied to remove duplicate detections based on overlap and confidence, ensuring that each sheep is represented by just a single bounding box.

Model performance was evaluated using two approaches on the same test dataset. First, the standard YOLOv8 validation procedure was used to obtain mAP50, mAP50–95, precision and recall. The default validation settings are a minimum confidence threshold of 0.001 and an NMS IoU threshold of 0.7. Ordinary prediction uses the same default NMS threshold but a higher minimum confidence threshold of 0.25. The lower confidence threshold used in validation retains detections so that performance can be assessed across a range of confidence thresholds. Average precision summarises the resulting precision–recall curve, while the reported precision and recall correspond to a confidence threshold selected to maximise F1. F1 was then calculated from those reported precision and recall values. The validation summary therefore does not simply describe predictions generated at confidence=0.25 and NMS IoU=0.7.

As outlined above, YOLO produces multiple candidate bounding boxes for each object, often with small variations in position and confidence. Non-Maximum Suppression (NMS) is the post-processing step that filters these candidates by removing redundant overlapping boxes. It works by selecting the highest-confidence prediction for a region and suppressing any neighbouring boxes whose Intersection-over-Union (IoU) with it exceeds a defined threshold. This reduces redundant bounding boxes in the final output.

Second, a separate sensitivity analysis examined performance at fixed prediction settings. The default YOLOv8 prediction settings are a confidence threshold of 0.25 and an NMS IoU threshold of 0.7; this combination was used as the baseline. Three alternatives were tested by lowering the NMS threshold to 0.4, lowering the confidence threshold to 0.175, or lowering both. The lower NMS threshold was intended to reduce duplicate detections, while the lower confidence threshold retained less confident predictions.

For each combination, predictions were compared with the annotated sheep. A prediction was counted as correct if it matched an annotation at an IoU of at least 0.50, with each annotation matched at most once. This matching threshold assessed agreement with the annotations and was separate from the NMS threshold used to remove overlapping predictions. True positives, false positives and false negatives were summed across all test images, and precision, recall and F1 were calculated from those totals. These results describe performance at the specified prediction settings, whereas the validation summary reports precision and recall at a confidence threshold selected by the evaluation procedure.

### 4.3 Results

Training ran for 69 epochs and then stopped automatically, due to a patience parameter of 40. This indicates that no further improvement was observed after approximately epoch 29 according to the validation fitness function. Epoch 28 was saved as the “best” checkpoint according to the YOLOv8 internal selection criterion (validation mAP50-95).

All 69 checkpoints were subsequently evaluated against the independent test set, which contained 736 annotated sheep. Table 4-5 presents the results for the two best-performing checkpoints on the test set, epoch 39 and epoch 53. For comparison, epoch 28 achieved an mAP50-95 of 0.177 and an mAP50 of 0.5511, substantially lower than those of epochs 39 and 53.

**Table 4-5.** Performance metrics for the two best checkpoints from epochs 39 and 53 evaluated on the test set containing 736 annotated sheep instances. Metrics were obtained using the Ultralytics validation procedure, with F1 calculated from the resulting precision and recall. mAP denotes mean average precision; mAP50 is calculated at an intersection-over-union (IoU) threshold of 0.50, while mAP50–95 averages performance across IoU thresholds from 0.50 to 0.95 in steps of 0.05. IoU measures the overlap between a predicted bounding box and its reference annotation, calculated as the area of their intersection divided by the area of their union. F1 is the harmonic mean of precision and recall.

| Checkpoint | mAP50 | mAP50-95 | Precision | Recall | F1 |
|---|---|---|---|---|---|
| Epoch 39 | 0.7654 | 0.2935 | 0.8090 | 0.6726 | 0.7345 |
| Epoch 53 | 0.7621 | 0.2955 | 0.7772 | 0.7106 | 0.7424 |

Epoch 39 achieved the highest precision (0.809) and slightly higher mAP50 (0.7654), while Epoch 53 achieved higher recall (0.7106), slightly higher mAP50–95 (0.2955) and the highest F1-score (0.7424). An image from the test set is presented in Figure 4-6 to illustrate the differences in annotation versus prediction for Epoch 39 and 53.

Tables 4-6 and 4-7 present detection outcomes under alternative post-processing thresholds. For both epoch 39 and epoch 53, changing the NMS IoU threshold and confidence value altered the number of true positives, false positives and false negatives, consequently affecting precision, recall and F1-score. Among the four combinations tested, the highest F1-score for both checkpoints occurred at confidence 0.25 and NMS IoU 0.4: 0.7311 for epoch 39 and 0.7119 for epoch 53. At confidence 0.25, reducing the NMS IoU threshold from 0.7 to 0.4 reduced false positives substantially, with a small reduction in true positives. These results were calculated using the fixed-threshold evaluation described in Section 4.2.5, separately from the Ultralytics validation summary in Table 4-5.

**Table 4-6.** Detection outcomes for epoch 39 using different confidence thresholds and non-maximum suppression intersection-over-union thresholds (IoU_NMS). Predictions were compared with 736 sheep annotations across the test images. A prediction was counted as a true positive if it matched an annotation at IoU ≥ 0.5, with each annotation matched only once. Precision, recall and F1 were calculated from counts pooled across the test images. TP = true positives, FP = false positives, FN = false negatives.

| IoU_NMS | Confidence | TP | FP | FN | Precision | Recall | F1 |
|---|---|---|---|---|---|---|---|
| 0.7 | 0.25 | 561 | 336 | 175 | 0.6254 | 0.7622 | 0.6871 |
| 0.4 | 0.25 | 556 | 229 | 180 | 0.7083 | 0.7554 | 0.7311 |
| 0.7 | 0.175 | 593 | 633 | 143 | 0.4837 | 0.8057 | 0.6045 |
| 0.4 | 0.175 | 585 | 354 | 151 | 0.623 | 0.7948 | 0.6985 |

**Table 4-7.** Detection outcomes for epoch 53 using different confidence thresholds and non-maximum suppression intersection-over-union thresholds (IoU_NMS). Predictions were compared with 736 sheep annotations across the test images. A prediction was counted as a true positive if it matched an annotation at IoU ≥ 0.5, with each annotation matched only once. Precision, recall and F1 were calculated from counts pooled across the test images. TP=True Positives, FP=False Positives, FN=False Negatives.

| IoU_NMS | Confidence | TP | FP | FN | Precision | Recall | F1 |
|---|---|---|---|---|---|---|---|
| 0.7 | 0.25 | 588 | 383 | 148 | 0.6056 | 0.7989 | 0.6889 |
| 0.4 | 0.25 | 582 | 317 | 154 | 0.6474 | 0.7908 | 0.7119 |
| 0.7 | 0.175 | 609 | 678 | 127 | 0.4732 | 0.8274 | 0.6021 |
| 0.4 | 0.175 | 602 | 454 | 134 | 0.5701 | 0.8179 | 0.6719 |

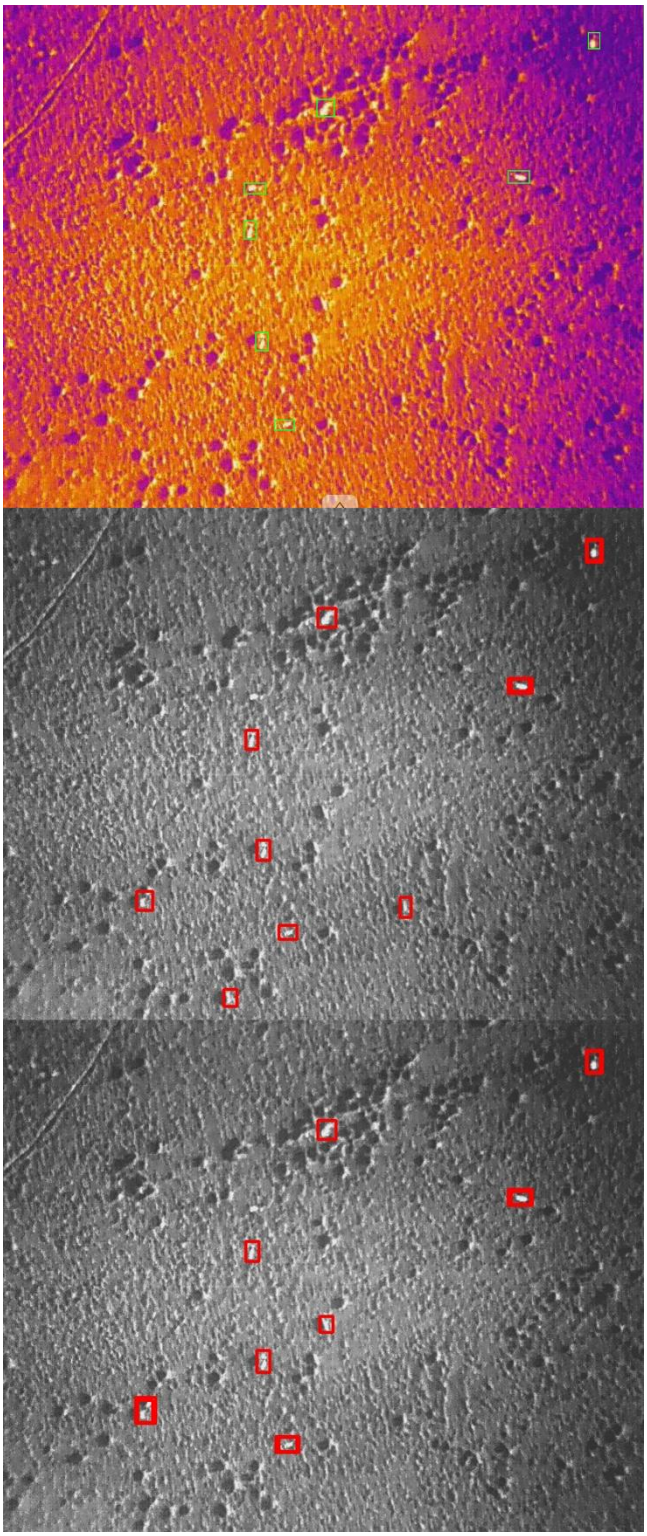


**Figure 4-6.** Illustrating the difference between an annotated test set image (top), an image with Epoch 39 predictions (middle), and an image with Epoch 53 predictions (bottom). The actual number of sheep in the image is equal to seven

## 4.4 Discussion

### 4.4.1 Model selection and generalisation

YOLOv8 identified epoch 28 as the best checkpoint based on validation mAP50–95. However, evaluation on the independent test set showed that later checkpoints (epochs 39 and 53) achieved substantially higher mAP50–95. This reflects the fact that the internal fitness function optimises validation performance, but without guaranteeing optimal test-set performance. This pattern is consistent with normal training variability: validation mAP can fluctuate across epochs, and a single early peak may be selected as "best" even though later models continue to improve in ways that are not captured by the fitness function. In addition, the fitness function is calculated entirely on the validation set, which represents only a subset of available imagery. Small differences in scene composition or animal appearance between validation and test samples can therefore favour different checkpoints. Evaluating all checkpoints can provide a clearer picture of downstream performance and avoid over-reliance on a single automatically selected model. This highlights the importance of explicitly validating model choice against task-specific metrics rather than relying solely on default training settings. The improved performance observed at later epochs suggests that a larger early-stopping patience value, or allowing training to continue for longer, may also have been appropriate.

Although the test set was excluded from training, it was subsequently used to compare all 69 checkpoints and identify the best-performing models. The test results therefore informed model selection, meaning that the reported performance of the selected checkpoints may overestimate performance on new data. These comparisons should consequently be interpreted as exploratory. Future evaluation should select checkpoints and post-processing settings using validation data, with final performance assessed on a separate test set that has not been used for training or model selection.

### 4.4.2 Mean average precision, F1-scores and sensitivity analysis

Epoch 39 and 53 performed similarly in terms of detection accuracy. Both achieved mAP50 values close to 0.76, with lower mAP50–95 values of around 0.30 indicating that performance declined when more precise localisation was required. This is consistent with the difficulty of fitting bounding boxes

accurately when animals occupy very few pixels. These scores summarise detection performance across confidence thresholds; recall indicates the proportion of annotated sheep detected. However, the two checkpoints differed in how they achieved these scores. Epoch 39 produced the highest precision, meaning that when it indicated a detection, it was more likely to be correct. In contrast, epoch 53 achieved higher recall and a slightly higher mAP50–95, indicating that it detected more true animals and maintained marginally better localisation across stricter IoU thresholds. As a result, epoch 53 achieved the highest F1-score, representing the best balance between precision and recall.

From a model-evaluation perspective, it is important to distinguish the roles of these metrics. Mean Average Precision (particularly mAP50–95) is widely used in research because it provides a consistent benchmark for comparing detectors across datasets and IoU thresholds, with a strong emphasis on localisation accuracy. However, in practical deployment settings, the primary concern is not whether bounding boxes align perfectly, but whether the system reliably detects animals without generating excessive false alarms. In this context, precision, recall and their harmonic mean (F1-score) offer a more operationally meaningful summary, as they directly capture the trade-off between missed animals and false positives.

From a practical perspective, this difference has implications for real-time deployment. A system based on epoch 39 would generate fewer false alarms but would miss a greater number of animals. In contrast, epoch 53 produces more detections overall, including some that require operator verification. For agricultural monitoring scenarios where detections can be reviewed, failing to detect animals poses a greater operational risk than occasionally flagging uncertain objects for review. On this basis, epoch 53 represents the more appropriate model for downstream use, offering better overall coverage, with additional false detections requiring review. The relative importance of false positives versus false negatives is inherently application-dependent, varying with whether the system is used for confirming livestock presence, detecting absence, or identifying livestock presence in restricted or environmentally sensitive areas.

The distinction between model performance and practical usefulness for surveillance is important when interpreting these results. Developing a thermal

dataset and demonstrating sheep detection under challenging aerial imaging conditions provides a foundation for further development. However, mAP50 of approximately 0.76 and mAP50–95 of approximately 0.30 do not, by themselves, establish whether the model meets the needs of farmers, veterinarians or surveillance practitioners. For example, locating groups of sheep to guide subsequent inspection may tolerate some missed detections, whereas a task requiring every animal to be located would demand greater completeness. False detections also create a verification workload that may reduce any time saved. Evaluation for practical use should therefore assess missed animals, verification time and benefit compared with existing practice, under the intended operating conditions. These requirements concern the animal-detection stage of the surveillance pipeline, but the effectiveness of subsequent health assessment and disease surveillance would require further evaluation.

As discussed in Section 3.3.4.1.2, the relative importance of missed cases and false alarms depends on the disease and the consequences of subsequent action. Here, however, recall describes the detection of sheep rather than diseased animals, and precision is not equivalent to epidemiological specificity. These detection metrics therefore cannot establish the disease-detection performance of a future surveillance system, which would require separate validation.

When animals occupy very few pixels, small bounding-box errors can substantially reduce IoU, lowering scores at stricter thresholds even when the animal has been detected. Comparisons with other studies should therefore account for differences in target size, image contrast and occlusion, as discussed further in Section 4.4.3. It is also relevant that the model was trained from random initialisation rather than using pretrained weights. This decision was made because no publicly available thermal livestock datasets closely matched the imagery used here, and conventional COCO-style pretraining is based on RGB, high-contrast objects that differ substantially from UAV thermal scenes. As a result, the model learned feature representations entirely from the custom dataset, which likely contributed to moderate but realistic mAP50–95 values while still achieving strong detection performance at IoU = 0.50.

The sensitivity analysis demonstrated that post-processing thresholds influenced performance more than the choice of checkpoint. Lowering the NMS IoU threshold from 0.7 to 0.4 reduced duplicate detections and lowering the

confidence threshold increased recall but also produced substantially more false positives. Among the fixed-threshold combinations tested, confidence=0.25 and NMS IoU= 0.4 produced the highest F1-score for both checkpoints, providing the best balance between precision and recall as measured by F1.

These findings suggest that a balanced inference configuration is preferable for operational use. Using confidence=0.25 and NMS IoU=0.4 reduced false detections while retaining most of the animals detected at the default prediction settings, with uncertain cases suitable for subsequent visual verification.

### 4.4.3 Comparisons with previous studies

Previous applications of UAV-based animal detection have reported performance using a wide range of object-based metrics (Table 4-8), but only a few of these studies are directly comparable to the results presented here. Models such as YOLOv5, YOLOv7 and enhanced RetinaNet variants have been evaluated using COCO-style metrics including mAP50, precision and recall (Krishnan *et al.*, 2023; Zhang & Cai, 2023; Xie *et al.*, 2023; Ulhaq *et al.*, 2021). Their reported performance, therefore, reflects similar IoU-based localisation criteria to those used in the present study.

In contrast, studies employing custom or tracking-oriented metrics, such as Hinke *et al.* (2022) for seabird colonies or Bárbulo Barrios *et al.* (2024) for cattle, use fundamentally different evaluation schemes. These include extended overlap tolerances, identity-tracking scores and measures such as user's and producer's accuracy. Such approaches assess broader behavioural or temporal objectives rather than strict per-object spatial agreement and are therefore not directly comparable with mAP50 or mAP50–95 benchmarks reported in this study.

Relative to datasets used in the most comparable published mAP-based studies, the imagery analysed here represents a more challenging detection scenario. In several previous datasets, animals were imaged at a closer range, exhibited stronger contrast or occupied a larger proportion of the frame. In contrast, sheep in UAV thermal imagery frequently appear as small, low-contrast targets and often occur in clustered groups, leading to overlapping bounding boxes and greater localisation ambiguity. Consequently, lower absolute mAP50 or mAP50–95 values do not inherently indicate poor model performance; rather, they

reflect the intrinsic difficulty of the detection task, object scale and posture variability.

It is also worth noting that several earlier studies benefited from pretrained weights derived from large RGB datasets, whereas the model presented here was trained entirely on a newly created thermal dataset. As a result, performance reflects genuine learning from domain-specific imagery rather than adaptation from COCO-style benchmarks. This context is important when interpreting mAP values, which should not be compared directly with models pretrained on substantially larger and visually richer datasets. Despite this constraint, the model achieved high precision and reasonable recall, indicating that YOLO-based detectors remain viable for livestock monitoring in thermal imagery even when object size and environmental conditions limit localisation accuracy.

**Table 4-8.** Studies utilising convolutional neural networks to analyse animal imagery acquired by unmanned aerial vehicles (UAVs), summarising species, imagery, tasks, models and reported performance metrics. TIR = thermal infrared, VLO = visible light (optical). AP (average precision) summarises the balance between precision and recall across confidence thresholds. mAP (mean average precision) averages AP across the evaluated object classes. Precision describes the proportion of detections that are correct, while recall describes the proportion of reference objects detected. F1 combines precision and recall using their harmonic mean. Evaluation methods differ between studies, so reported scores are not directly comparable.

| Paper | Species / Target | Imagery | Task | Model | Main metrics cited |
|---|---|---|---|---|---|
| Santhana Krishnan et al., 2023 | Deer, cattle, horses | VLO, TIR & both fused via multiple methods | Detection and classification | YOLOv5, YOLOv7 | mAP50 (highest = 0.97 for thermal imagery for horse with YOLOv5), precision, recall |
| Hinke et al., 2022 | Penguins, fur seals, some non-target classifications like rocks, nests, guano | VLO, TIR (separate models for comparison) | Detection and classification | YOLOv3 within VIAME v0.16.1 | Custom “mAP10-90”, accuracy, precision recall, F1 |

**Table 4-8 (continued)**

| Paper | Species / Target | Imagery | Task | Model | Main metrics cited |
|---|---|---|---|---|---|
| Bárbulo Barrios et al., 2024 | Dairy cattle | TIR video | Segmentation, detection and tracking | Track R-CNN and PWC-Net (Multi-Object Tracking and Segmentation) | 1) the soft Multi Object Tracking and Segmentation Accuracy (sMOTSA), 2) the Multi Object Tracking and Segmentation Accuracy (MOTSA), and 3) the Multi Object Tracking and Segmentation Precision (MOTSP). |
| Chen et al., 2023 | Cranes | TIR (night) & VLO (day) | Counting and classification | Classical image processing & modified YOLOv3 | Overall accuracy, user's accuracy and producer's accuracy |
| Zhang & Cai, 2023 | Elephants (from publicly available BIRDSAI dataset (Bondi *et al.*, 2020)) | TIR | Detection | RetinaNet with channel enhancement ("CE-RetinaNet") | AP @ 0.5 (0.751), AP @ 0.5:0.95, Recall |

| Table 4-8 (continued) | | | | | |
|---|---|---|---|---|---|
| **Paper** | **Species / Target** | **Imagery** | **Task** | **Model** | **Main metrics cited** |
| Xie et al., 2023 | Amur tiger & prey (deer species) | TIR | Detection and classification (by species) | YOLOv3, YOLOv5 variants (modified YOLOv5s) | "mAP%" and "mAP@0.5" (likely mAP50) (0.952 for YOLOV5x), precision, recall, and F1 |
| Ulhaq et al., 2021 | Rabbits (and their warrens), feral pigs, and kangaroos | TIR | Detection and counting | Modified YOLOv3 (Distant-YOLO) | mAP50 (0.871), per-class accuracy, precision, recall, and F1 |

### 4.4.4 Dataset limitations

Several factors inherent to the dataset influenced model performance. First, the animals are small in pixel terms, often occupying less than 10 × 10 pixels. Under these conditions, modest positional errors translate into substantial changes in IoU, which disproportionately penalises localisation metrics. Low thermal contrast and occasional motion blur from either animal or UAV movement further reduced the clarity of object boundaries.

Second, the visual scenes were complex. Sheep regularly occurred in tightly clustered groups, leading to partial occlusion and overlapping bounding boxes. Individuals near fences, walkways or heat-reflective ground surfaces were particularly difficult to distinguish from background structures, and shadows sometimes produced signatures similar to true detections. In some instances, even manual interpretation could not determine the veracity of a detection, including when cross-checking with RGB imagery.

Third, annotation quality was challenged by these ambiguities. Border cases, such as animals partially outside the frame, occluded individuals or blurred outlines, required subjective judgement. Annotation was also time-consuming, and small inconsistencies in box placement may have influenced reported IoU despite representing reasonable detections.

Finally, model characteristics interact with these constraints. Although YOLOv8 uses an anchor-free detection head, it still performs best when objects occupy a moderate proportion of the image and the bounding box contains limited background. Very small thermal targets with variable posture therefore represent a particularly demanding use case.

### 4.4.5 Opportunities for improvement and future work

Several practical refinements could improve model performance in future deployments. Increasing dataset size would allow the model to learn a wider range of backgrounds, postures and environmental conditions, including variation arising from different weather conditions and ambient temperatures. Conducting additional flights across seasons and times of day may also improve robustness to variations in thermal contrast driven by atmospheric conditions and diurnal heating effects. Where regulations and safety permit, selecting flight altitudes that produce a slightly larger pixel footprint per animal would likely support better localisation performance without compromising operational feasibility. From a sensing perspective, integrating additional modalities such as visible-light or multispectral imagery could help distinguish vegetation and soil artefacts from true detections, either via image fusion or complementary detectors. Higher spatial resolution thermal payloads than the DJI Zenmuse XT2 used in this study are now available (e.g. the newer DJI Zenmuse H30T with 1280 × 1024 sensors), which could increase per-animal pixel coverage without altering flight altitude, albeit with additional cost and payload constraints. Collectively, these refinements would also support improved generalisability of the approach to different terrain and environmental settings beyond those represented in the present dataset.

Annotation consistency could be strengthened by introducing clearer labelling guidelines, double-checking a subset of images, or using assisted-labelling tools to reduce fatigue. In ambiguous situations (e.g. edge crops or heavily occluded animals), marking regions as “ignore” rather than forcing bounding boxes may yield more reliable training signals and evaluation metrics.

Although YOLO performed well overall, alternative architectures tailored for very small objects or segmentation-based approaches may warrant exploration, as they reduce reliance on precise bounding-box alignment when animals occupy only a few pixels.

Practical deployment would also require assessment of the resources needed to extend this approach to larger grazing areas or more frequent surveys. Additional flights would increase the volume of imagery requiring storage and processing, alongside the time needed to review uncertain detections. Survey coverage would depend on flight duration, battery availability, weather and access to a suitable operator. In this study, imagery was downloaded and processed after flights, so real-time operation was not demonstrated. Future evaluation should therefore measure the time and computing resources required from image collection through to usable animal-location information. Options for developing a real-time processing pipeline are discussed further in Section 5.4.3.2.

## 4.5 Conclusion

This study demonstrated that YOLOv8 can be trained to detect sheep in UAV-acquired TIR imagery, despite challenges posed by small object size, low contrast and frequent occlusion. Two candidate models (epochs 39 and 53) achieved comparable detection accuracy, with mAP50 values around 0.76 and mAP50–95 values near 0.30. While these scores reflect the difficulty of precise localisation in TIR imagery, they nonetheless indicate reliable detection performance for a newly developed dataset.

Comparison of checkpoints supported epoch 53 as the more appropriate model for operational use, where avoiding missed animals is prioritised. It achieved higher recall while maintaining acceptable precision and had the highest F1-score in the Ultralytics validation summary. Sensitivity analysis further demonstrated that post-processing thresholds influenced outcomes more than checkpoint choice, and that the confidence=0.25 and NMS IoU=0.4 gave the highest F1-score among the fixed-threshold combinations tested for both checkpoints.

The work also highlights several inherent limitations of thermal UAV datasets, including small pixel footprint, environmental artefacts and annotation ambiguity. Addressing these through expanded data collection, clearer labelling protocols, and potential integration of multispectral, hyperspectral or visible-light imagery could meaningfully improve model robustness. Expanding the dataset with further annotated imagery and evaluating the model across

multiple flights, times of day, seasons and environments would provide a more reliable estimate of real-world generalisation.

Overall, the findings confirm that deep-learning-based object detection is a viable approach for livestock monitoring using UAV TIR imagery. With continued dataset development and targeted architectural refinements, such systems have clear potential to support practical farm management and automated surveillance applications.

# 5 Discussion

## 5.1 Introduction

This thesis explores the feasibility of integrating remotely sensed technologies, specifically infra-red thermography, unmanned aerial vehicles, and machine learning, into existing veterinary surveillance frameworks as components of early warning systems for animal disease. Rather than proposing a deployable real-time system, the work clarifies the technical, methodological, and governance conditions under which such technologies could be responsibly developed and meaningfully utilised. As outlined in Chapter 1 animal health surveillance is shaped by interdependent technical, institutional, legal, and social factors, rather than by any single technological limitation. Accordingly, the thesis adopts a selective empirical focus, using thermography and UAV sensing, the latter underpinned by machine learning, as case studies through which broader surveillance data challenges are examined.

While real-time early warning systems for animal disease remain compelling aspirations, the results indicate that rapid data availability does not confer surveillance value *per se*. Without calibration discipline, transparent data pipelines, and clearly defined decision pathways, real-time data risks amplifying uncertainty rather than reducing it, as evidenced by the thermographic limitations discussed in Chapter 2, the surveillance integration challenges identified in Chapter 3, and the deployment constraints examined in Chapter 4. Viewed in this way, the challenge is not whether remotely sensed data can contribute to surveillance, but how it can be collected and managed to do so effectively. Taken together, the results from each chapter demonstrate that drone-acquired, remotely sensed data can contribute to animal health surveillance as an early warning and decision-support input, but only when embedded within robust technical, governance, and institutional frameworks. This discussion chapter moves from chapter-level results to their broader implications. Findings from the preceding chapters are first summarised and then synthesised to highlight key emergent themes, followed by an assessment of strengths, limitations, and future directions for related research. Table 5-1 summarises additional terminology used in this discussion.

**Table 5-1.** Key terms used in Chapter 5.

| Term | Meaning in this chapter |
|---|---|
| Socio-technical system | A system whose operation depends on interactions between technology, people, institutions and governance. |
| One Health | An integrated approach recognising the interconnections between human, animal and environmental health. |
| Vegetation indices | Numerical indicators combining reflectance measurements from different spectral bands to describe vegetation cover or condition. In aerial livestock imagery, they could help distinguish vegetation from other features in the scene. |
| Normalised Difference Vegetation Index (NDVI) | A vegetation index comparing near-infrared and red reflectance, calculated as their difference divided by their sum. Green vegetation typically reflects more near-infrared light and absorbs more red light, producing higher NDVI values. |
| Edge computing | Processing data at or close to the point of collection, reducing the need to transmit raw data to distant computing infrastructure. |
| Bandwidth | The amount of data a communication connection can carry per unit of time. For UAV monitoring, available bandwidth limits how quickly images or video can be transmitted for processing. |
| Latency | The delay between data capture and the availability of a processed result. In UAV monitoring, transmission and processing delays affect how quickly detections can inform an alert or flight-path adjustment. |

## 5.2 Summary of key findings

Chapter 2 identifies key parameters for accurate IRT usage and inconsistencies in their reporting for livestock disease detection research. It highlights IRT as an emerging tool for disease detection but finds that its usefulness will depend on carefully controlled parameters. High-quality cameras, environmental monitoring, interdisciplinarity, and trained operators are distinguished as essential components allowing further high-quality research in this area.

Chapter 3 identifies challenges that exist within the current veterinary surveillance landscape in Scotland and determines points of friction that are likely to arise when integrating novel surveillance data. Veterinary and epidemiological concerns, data and infrastructure concerns, and legal and

regulatory concerns emerge as the largest points of data friction. The chapter argues that future surveillance, driven by the IoT (Internet of Things) and sensor-derived data, will require mitigation strategies such as strong data governance, secure traceability, scalable storage, and trusted public-private data sharing to ensure novel data can be responsibly and effectively incorporated into veterinary surveillance systems.

Chapter 4 examines real-life deployment of UAVs, sensors, and machine learning analytics. This chapter illustrates that YOLO-based machine learning models can effectively detect livestock in thermal UAV imagery, under difficult real-world conditions. It also stresses that model choice and evaluation must be guided by operational needs, with appropriate emphasis placed on precision, recall, and F1-score, rather than solely relying on IoU-based metrics, again reinforcing the necessity of interdisciplinarity in the development of novel systems.

## 5.3 Themes

The synthesis of findings across the three research chapters reveals three cross-cutting themes that have broader implications for the design and governance of digital veterinary surveillance systems. First, that novel technology is inadequate without human input and oversight; second, that rigour and transparency are central to digital veterinary surveillance; and finally, that surveillance technologies are defined by the trade-offs inherent in their design. These are discussed in detail below.

### 5.3.1 Technology alone is insufficient: people, institutions and governance matter

Technologies that appear promising only become useful when embedded in supportive human and institutional contexts. This is evidenced across all three chapters, and indeed in the interdisciplinary nature of this thesis. In Chapter 3, stakeholders emphasised the need for tools that support rather than replace clinical and surveillance veterinary decisions, while Chapter 4 demonstrated that even sophisticated models require human oversight in threshold setting and interpretation. Recent work on participatory AI auditing further underscores that such oversight cannot be confined to technical experts alone. Di Campli San Vito *et al.* (2025) argue that AI systems should be subject to structured, participatory auditing processes involving diverse stakeholders, including domain experts, decision subjects, and regulators, throughout the system lifecycle, in order to

identify harms, define appropriate evaluation criteria, and ensure accountability. Additionally, the methodological issues identified in Chapter 2 arose not just from the cameras, but from their configuration and reporting by human operators. Future veterinary surveillance systems will require governance to ensure that the essential pillars of governance are satisfied: accountability, transparency, responsibility, fairness, and participation. Therefore, novel digital veterinary surveillance data must be appreciated in a socio-technical context, where technology, humans, regulatory systems and governance work together symbiotically. Technologies should not, and do not, operate in isolation. Their ability to be effective in any sphere depends greatly on human judgement, institutional regulation, and social acceptance.

The importance of stakeholder participation extends beyond developing useful and acceptable technologies to considering whose interests surveillance serves. The concerns about data control, access and subsequent use identified in Chapter 3 illustrate a tension between the collective benefits of surveillance and the interests of individual farmers whose data support it. In human public health surveillance, the World Health Organization (2024) emphasises balancing individual rights with collective interests, transparent decision-making and oversight of new uses of existing data. This offers a useful ethical perspective for veterinary surveillance: sharing data may improve disease monitoring, but decisions about access and reuse should also consider confidentiality, commercial sensitivities and potential consequences for those providing the data. The stakeholder participation discussed above therefore matters not only for designing useful systems, but also for enabling those affected to influence how benefits, risks and responsibilities are distributed.

These concerns also extend to the commercial use of agricultural data. Agri Stats (Agri Stats Inc., n.d.) is a US company providing data analysis and benchmarking services to meat processors. It collects commercially sensitive information on prices, production volumes and costs from processors' accounting systems, standardises these data and distributes detailed reports that allow participating companies to compare their operations with those of competitors. The US Department of Justice alleged that this exchange reduced competition and facilitated price increases. A final judgment entered on 10 September 2026 imposed restrictions on Agri Stats' information-sharing practices, requirements

for wider access to specified reports and independent compliance monitoring (United States District Court for the District of Minnesota, 2026). This case illustrates the sociotechnical nature of agricultural data sharing: its consequences depend not only on the technology used to collect and analyse data, but also on the commercial interests, organisational practices and governance arrangements shaping their use. It provides a concrete context for participants' concerns in Chapter 3 about who controls agricultural data and whose interests their subsequent use serves. For veterinary surveillance data, it highlights the need for governance arrangements that specify permitted uses, responsibilities and oversight when data move between farmers, commercial providers, and public bodies. The ethical and societal implications extend to how the benefits and risks of sharing are distributed, particularly where those supplying data have limited influence over their subsequent use. Building trust therefore requires both transparent agreements and meaningful opportunities for farmers and other affected groups to influence decisions about data use and share in the benefits generated, including potential financial returns where data are used commercially.

One way to put these governance principles into practice is through contractual agreements. The voluntary EU Code of Conduct on Agricultural Data Sharing by Contractual Agreement promotes clear contractual terms, transparency about intended uses and a leading role for data originators in controlling access to and use of their data (Copa and Cogeca et al., 2018). While the EU Code of Conduct provided a voluntary industry framework, the broader legal landscape has evolved since it was drafted. The EU Data Act, Regulation (EU) 2023/2854 (2023), generally applicable from 12 September 2025, introduces legally binding requirements for business-to-business and business-to-consumer data sharing involving connected products, including agricultural machinery and equipment. It gives users rights to access specified data generated through their use of these products and related services, and to request that these data be shared with third parties, subject to safeguards and exceptions. Although this is an EU legal development, it is relevant to the wider discussion of how governance arrangements can strengthen users' control over agricultural data. In the UK, Farm Data Principles Ltd, a not-for-profit organisation continuing the work of the British Farm Data Council, has developed an industry-informed set of data-

sharing principles and a voluntary self-declaration certification scheme for organisations collecting and using farm data. Its principles emphasise farmers' control over their data, permission for sharing and transparency about who benefits from their use (Farm Data Principles Ltd, n.d.).

These governance considerations also extend to the technologies that use agricultural data to inform decisions. In the context of AI and sensor technologies, Neethirajan (2024) emphasises that technological tools should support farmers' knowledge and decision-making, alongside attention to ethical and social implications. The author argues that AI and sensor technologies enhance animal welfare only when integrated into human decision-making processes and are subject to ethical oversight and institutional governance structures. This necessary incorporation of novel technologies within supportive governance structures is further reinforced by a recent US regulatory perspective on artificial intelligence in veterinary medicine (Duggirala *et al.*, 2025). The authors emphasise that AI and machine learning systems can only be deployed responsibly through human-led governance frameworks to ensure accountability, transparency, data quality, and continuous oversight. AI is framed as a decision-support tool, with its reliability and legitimacy depending on regulatory safeguards, institutional capacity, and human judgement throughout the system lifecycle. This socio-technical interpretation of veterinary surveillance is also supported by Fejzić *et al.* (2019) who argue that the increasing digitalisation of veterinary medicine, rather than diminishing the need for professional judgement, instead intensifies it. Despite rapid advances in emerging AI tools, the authors emphasise that veterinary medicine operates within biologically and socially complex contexts that are inherently resistant to full automation.

Ezanno *et al.* (2021) combine a review of animal health AI literature with stakeholder interviews to examine the applications and future development of AI in animal health. They also frame surveillance systems as socio-technical, arguing that analytical performance cannot be separated from human decision-making, operational constraints, and ethical considerations. Their analysis shows that surveillance outputs are primarily used as decision-support tools, with their practical value shaped by factors such as interpretability and user trust. In the context of this thesis, these considerations suggest that surveillance system

design must involve continual negotiation between sensitivity, usability, and organisational capacity, rather than treating performance optimisation as a purely technical problem. They further suggest that future AI-enabled surveillance systems should be developed iteratively with end users to ensure alignment with real-world practices and constraints.

Human healthcare provides a useful comparison for translating these governance principles into practice. Guidance jointly developed by the Medicines and Healthcare products Regulatory Agency (MHRA), the US Food and Drug Administration and Health Canada emphasises multidisciplinary expertise throughout the product lifecycle (Medicines and Healthcare products Regulatory Agency, 2021). This reinforces the conclusion in Chapter 2 that thermography research requires teams with physics expertise and practical experience of infrared equipment. The guidance also emphasises assessing how people and AI systems perform together, communicating limitations clearly and monitoring performance after deployment. These principles were subsequently developed further by the International Medical Device Regulators Forum (IMDRF, 2025), which explicitly considers users' understanding of model outputs, potential overreliance and user error within the intended working environment. Applied to veterinary surveillance, these principles suggest that responsibilities should extend beyond initial model development to reviewing alerts, investigating errors and reassessing performance when equipment, farm conditions or software change. This comparison offers practical lessons for oversight without assuming that medical-device regulatory arrangements can be transferred unchanged to livestock surveillance.

A complementary comparison comes from human public health surveillance. The World Health Organization's framework for collaborative surveillance emphasises collaboration across sectors and the integration of multiple data sources to address fragmented surveillance capacity (World Health Organization, 2023). This aligns with the findings of Chapter 3, where the usefulness of animal health data depended on its movement between organisations and the arrangements governing its interpretation and use.

These converging perspectives illustrate how, across the different empirical and methodological contexts examined in this thesis, veterinary surveillance systems consistently emerge as socio-technical in nature, requiring the co-ordination of

technology, human expertise, and governance to achieve operational effectiveness.

### 5.3.2 Rigour and transparency in digital veterinary surveillance

AI cannot compensate for weak measurement foundations. Reproducibility, parameter discipline and honest reporting are essential. The reliability of automated surveillance ultimately depends on the quality and transparency of its underlying measurements. Chapter 2 reveals widespread variation in parameter choices and poor reporting, making results difficult to interpret, compare or reproduce, while Chapter 4 shows how minor decisions, such as default model selection, IoU thresholds and annotation ambiguity, can materially change model performance. Stakeholders in Chapter 3 express reluctance to rely on systems that do not lend themselves to being understood or interrogated. These observations highlight that progress in AI-enabled surveillance requires equal investments in measurement standards, metadata, and reproducible practices.

This view is supported by current veterinary literature. In a perspective piece, Bruno (2025) shares an outlook into the incorporation of real-world data into future veterinary drug development. The author hypothesises that expanding digital data sources in veterinary medicine will not automatically yield reliable evidence, as regulatory acceptance of real-world data will be limited by measurement heterogeneity, poorly specified endpoints, and insufficient transparency. The paper hypothesises that even advanced sensing and analytics may fail in their role as decision support technology when data provenance, methodology, and bias controls are unclear. This reinforces the argument that automation cannot compensate for deficiencies in underlying data. This is supported by a 2021 review by Meyer et al. (2021), which provides empirical evidence that veterinary epidemiological research frequently falls short of the FAIR principles, particularly “findability” and “accessibility” (due to absent datasets), and “interoperability” (due to lack of standardised formats and vocabularies). Their systematic “FAIRness assessment” shows that most datasets were not available as distinct digital resources and that even available data often lacked the metadata and structural standardisation necessary for reuse. These findings directly support the claim that progress in digital surveillance

depends on disciplined data stewardship, transparent documentation, and structured data management practices.

In describing a comprehensive framework for the application of AI in veterinary medicine, Basran & Appleby (2024) note widespread professional reluctance to rely on veterinary AI systems that operate as opaque “black boxes”, particularly in the absence of regulatory oversight and clear documentation of data quality and model behaviour. Their emphasis on transparency, interpretability, and lifecycle governance aligns with stakeholder concerns in Chapter 3 and underscores that trust in automated surveillance depends on sound underlying measurements. Bök & Micucci (2024) analyse digital health platforms for human and animal health and show how reliability is shaped by choices made throughout complex sensing and data-processing pipelines. They highlight the fact that decisions concerning data acquisition, filtering, and interoperability can affect downstream analytics, reinforcing the argument that methodological choices play a critical role in reported system performance.

Together, these findings reinforce the contention that advances in AI for veterinary surveillance must be matched by equally rigorous standards of measurement, documentation, and governance, without which automated systems cannot be considered reliable.

### 5.3.3 Surveillance design: managing trade-offs and consequences

The design of animal surveillance systems will always involve choice, and those choices inevitably involve degrees of risk and cost (Hoinville *et al.*, 2013). Novel surveillance technologies are no different and are defined by the trade-offs built into their design. Chapter 2 shows that methodological decisions in thermography, such as emissivity settings and reporting practices, influence not only scientific validity but also downstream interpretation. Stakeholders in Chapter 3 describe the practical and ethical balances that must be negotiated: avoiding unnecessary disruption while still detecting disease as early as possible. The field experiment in Chapter 4 illustrates similar tensions, such as trading precision for recall, altitude for resolution, and automation for human verification. These examples demonstrate that surveillance systems do not simply succeed or fail. Rather, they encode value-laden decisions about what risks are tolerated, and what errors are deemed acceptable.

Whether a compromise is acceptable depends on the surveillance objective, the consequences of error and the capacity to investigate alerts. For early detection of an exotic disease incursion, high sensitivity may be prioritised because missing initial cases could delay recognition and allow further spread. Specificity nevertheless remains important: when disease prevalence is very low, false-positive alerts may substantially outnumber true positives, making timely investigation and confirmatory testing essential. For established endemic disease, surveillance may instead seek to monitor trends or evaluate control measures, requiring sufficiently consistent case detection to distinguish genuine changes in disease occurrence from changes in system performance. For production diseases such as mastitis or lameness, which may also be endemic, the balance between sensitivity and specificity should reflect the benefits of early intervention, the welfare consequences of missed cases and the costs of unnecessary investigation or treatment. These examples extend the disease-specific considerations discussed in Section 3.3.4.1.2: no single balance is appropriate for every application. A compromise may be acceptable when errors can be identified and managed through follow-up, but unacceptable when missed cases undermine the surveillance objective or false alerts overwhelm available resources. Performance criteria should therefore be agreed for the intended use rather than inferred from a model score alone.

Using a simulated model grounded in sensor-based veterinary health surveillance, Edwardes *et al.* (2024) examine how system design choices translate into economic and animal welfare outcomes. They analyse how human-assigned mobility scores for cattle could be simplified into system-level disease decisions, and how the choice of decision threshold affects rates of false alerts and delayed lameness detection. The model evaluates threshold-based decision rules in which graded mobility scores are mapped onto three disease states (no action, monitoring, or intervention), reflecting how sensor outputs may be utilised in practice. The modelling shows that economic outcomes are more sensitive to these threshold choices than animal welfare outcomes. This creates asymmetric trade-offs in which thresholds optimised for economic efficiency (lower intervention costs) tend to tolerate greater welfare impacts (delayed treatment). In this instance, a system that prioritises economic return permits greater welfare impacts, directly illustrating trade-offs in design.

While Edwardes *et al.* (2024) reveal how surveillance design trade-offs affect technical, economic, and animal welfare outcomes, similar tensions are also present at the level of system configuration and governance. MacLoughlin's (2025) master's thesis presents a narrative literature review of AI-based zoonotic disease surveillance within a One Health framework. The author examines how surveillance systems are designed, integrated, and governed across human, animal, and environmental health domains. The thesis analyses how choices around automation, data integration, and oversight involve trade-offs between efficiency and accountability, coordination and equity, and scalability and institutional control. These governance-level trade-offs echo many of those observed empirically in Chapter 3, particularly in how surveillance system configuration shapes data flows across institutional boundaries. Rather than attributing surveillance outcomes to algorithmic performance alone, MacLoughlin shows that system design decisions determine how action is triggered and coordinated, and how costs and benefits are distributed among stakeholders.

These findings demonstrate that surveillance technologies employing AI are likely to result in consequences that extend beyond detection into organisational, institutional, and ethical domains.

For industry, these findings suggest that development should focus on clearly defined tasks that support existing farm and veterinary practice. The animal-detection work in Chapter 4 provides a basis for investigating whether aerial imagery could help farmers locate livestock for subsequent inspection, although practical benefits would need to be evaluated. For veterinarians, any future temperature-based health alerts would require validation and an agreed route for follow-up assessment. For technology providers, the findings emphasise the need to report measurement limitations, evaluate performance under intended field conditions and consider compatibility with existing recording systems. The immediate contribution is therefore evidence to inform these activities, while applying this approach within automated disease surveillance remains a longer-term goal requiring further research, development, and validation.

These implications for industry also raise questions for surveillance policy, particularly about how new data sources should be assessed and incorporated into existing systems. The findings support establishing explicit criteria for

accepting such data for a specified surveillance purpose, covering measurement quality, evidence of performance, and arrangements for follow-up. Those criteria should distinguish technologies that support an individual stage, such as animal detection, from systems validated for disease surveillance. This would provide a basis for deciding where a technology can contribute and what further evidence is needed before its role is expanded.

Taken together, the three themes outlined above clarify the practical and institutional implications of integrating remote sensing technologies into veterinary surveillance systems.

## 5.4 Strengths, limitations and future directions

As with any research, this thesis has strengths and limitations, both of which are outlined below. This section aids interpretation of research findings and also lays the groundwork for identifying priorities for future research.

### 5.4.1 Strengths

This thesis demonstrates several strengths that contribute to both the scientific and practical application of digital surveillance within a veterinary context. Research approach and methodology are notable strengths. An interdisciplinary approach was adopted, integrating veterinary surveillance, machine learning, remote sensing, and a crucial assessment of related governance. Interdisciplinarity is increasingly recognised as critical for addressing complex challenges, enabling a deeper understanding of the complexities of animal health surveillance (Berezowski, Rüegg and Faverjon, 2019). A mixed methods design, combining a scoping review, qualitative stakeholder interviews and thematic analysis, and a real-world UAV field experiment, strengthens the credibility and transferability of findings (Scott *et al.*, 2024; Bhujel *et al.*, 2025). The methodology allows the results to provide a rich, nuanced account of how surveillance technologies operate and are perceived in practice.

Intentionally avoiding the adoption of a technology-enthusiastic stance, the empirical chapters aim for a critical appraisal of underlying technologies. This analytical stance is essential where hype about AI and sensing performance can obfuscate rigorous evaluation (Scott *et al.*, 2024), and it positions the thesis as a constructive narrative in response to overly optimistic attitudes. Chapter 2 systematically identifies methodological gaps, such as inconsistent parameter

reporting, calibration issues, and reproducibility concerns. Anchored in stakeholder-grounded perspectives, Chapter 3 centres farmers, veterinarians, and policy actors, revealing concerns about trust, social licence, data ownership, and thresholds for action. Including these voices aims to prevent biased, naïve, or purely technocentric conclusions. This emphasis aligns with broader trends in the livestock digitalisation literature that emphasise the importance of addressing adoption barriers, stakeholder concerns, and governance challenges *(*Neculai-Valeanu, Sanduleanu and Porosnicu*,* 2025*)*. The inclusion of real-world field testing in Chapter 4 is a significant strength. This work does not rely solely on simulations or controlled laboratory conditions but aims to evaluate drone-mounted thermal imaging under genuine farm constraints. Such field validation provides practice-relevant evidence of feasibility and limits, aligning with calls in precision livestock farming and UAV sensing literature for more *in situ* evaluation to understand performance under environmental variability and operational constraints (Araújo et al., 2025).

The discussion demonstrates transparency about trade-offs inherent in digital surveillance systems. Again, it aims not to oversell AI performance but to clearly articulate how choices such as threshold settings, evaluation metrics, and default model parameters influence outcomes. This aligns with Adam et al. (2025), who emphasise the importance of transparent performance evaluation, metric selection, and deployment-aware trade-offs in UAV-based livestock detection systems. By connecting empirical work to these broader field challenges, the thesis contributes not just data and results, but an understanding of how future surveillance systems must be designed and evaluated. Finally, the work makes an important conceptual contribution by framing surveillance as a socio-technical system.

### 5.4.2 Limitations

While this thesis makes substantive contributions, several limitations are acknowledged below to contextualise the findings.

First, the empirical work focuses on specific livestock systems and disease contexts. The extent to which these findings generalise to other species, climatic environments, diseases, or production systems remains unexplored. Thermal imaging and UAV deployments were constrained by the practical realities of sensor resolution and chosen altitudes, which impacted the

detectability of small objects and occlusion patterns. These constraints mirror real-world implementation environments and therefore provide valuable insights into operational feasibility, but they also mean that performance observed here may not translate directly to other settings. Additionally, the thermal datasets used in the experimental work were relatively modest in size, and annotation ambiguity (for instance, very small or partially occluded animals) introduced variability that challenges machine-learning evaluation. Similar gaps have been observed across *aerial and thermal* imaging research, where the availability of large, robust, well-annotated datasets remains limited and impedes broader model generalisation and benchmarking efforts (Adam et al., 2025; Ulmămei et al., 2025).

Stakeholder interviews, while diverse in perspective, were conducted with specific groups and within particular geographic and sectoral contexts. Other actors, such as regulators in different jurisdictions, and farmers in low-resource settings, might hold different priorities or experiences, limiting the transferability of governance insights. Additionally, although individual components of surveillance systems were examined in detail, the research did not evaluate complete surveillance pipelines from detection through decision-making and response. System-level outcomes, such as how alerts would translate into veterinary or policy action, were consequently beyond the scope of this thesis.

### 5.4.3 Future directions and implications for veterinary surveillance

Expanding on the limitations outlined above, a few approaches with regard to future research are discussed below.

#### 5.4.3.1 Extending spectral approaches: from incorporating vegetation indices to the development of "animal indices"

This thesis did not experimentally evaluate multimodal or multispectral approaches (e.g. vegetation indices, sensor fusion), which have previously been identified in agricultural remote-sensing and computer vision literature as promising ways to improve robustness and generalisation (Kamilaris and Prenafeta-Boldú, 2018; Liakos *et al.*, 2018). Future work could explore the integration of existing vegetation indices like the Normalised Difference Vegetation Index (NDVI) into works similar to Chapter 4. Vegetation indices are numerical indicators derived from satellite or UAV imagery that quantify

vegetation condition by combining reflectance values from different spectral bands, most commonly red and near-infrared (Huang *et al.*, 2020). They exploit the fact that healthy vegetation strongly reflects near-infrared light and absorbs red light. Use of multispectral sensors, which are available for the UAV used in chapter four, could be explored as an optional preprocessing step to identify and reduce the influence of vegetation-dominated areas within imagery. Such an approach has the potential to limit background variability in pasture environments and may support more focused analysis of livestock features.

Further development of this idea of "indices" could lead to new metrics specifically tailored to animals. While vegetation indices have proven effective for quantifying plant health, equivalent indicators for livestock or wildlife condition remain unexplored. Further utilising IRT or advancing into multispectral and hyperspectral imaging modalities, it may be possible to derive "animal indices" from which data can be extracted that indicate physiological stress, surface temperature variation, coat condition/skin lesions, or behavioural patterns. Developing and validating such indices would require controlled experiments, field-based image collection, and robust ground-truth data, such as veterinary assessments and body condition scores. Ultimately, these indices could provide non-invasive, scalable tools for monitoring health and welfare across large herds or populations.

#### 5.4.3.2 Building a real-time data pipeline

Another promising direction is the development of a real-time data pipeline for aerial sensing. In this thesis workflow, data were collected, downloaded from the drone, and processed offline. Transitioning to real-time deployment would involve transmitting data directly from the drone to an edge device, base station, or cloud platform where automated processing could occur immediately. Edge computing involves performing computational tasks at, or close to the data source, reducing the need to transmit raw data to distant cloud infrastructure. This would enable rapid decision-making, such as early detection alerts or adaptive flight planning. Key research challenges include bandwidth limitations, data compression strategies, latency management, and secure communication protocols. Evaluating different architectures (edge-only, hybrid edge–cloud, or cloud-first) will help determine where computation is best performed for both reliability and cost. While recent studies have demonstrated the feasibility of

edge (onboard UAV) (Tagarakis *et al.*, 2024) and near-edge computing (edge-devices on-farm) (Alonso et al., 2020) for agricultural monitoring, many existing systems adopt a single deployment rather than attempting to implement and test multiple alternatives. Toth et al., (2025) recently published a comparison of edge and cloud architectures for processing data from large scale poultry farming, finding that a hybrid approach was the best future strategy and it would be interesting to determine if this also holds true for UAV-acquired data. A systematic evaluation in which edge-only, hybrid edge–cloud, and cloud-first pipelines are all implemented and directly compared with respect to bandwidth usage and latency, under real-world operating conditions, remains an open area of research.

#### 5.4.3.3 Improving dataset availability and IRT temperature accuracy

Bhujel et al.'s (2025) systematic survey of publicly available livestock datasets highlights that data availability, quality, and contextual metadata remain bottlenecks for advancing AI applications in precision livestock farming. Future work should prioritise the creation of well-annotated, publicly available IRT datasets of livestock, both from static cameras and from UAVs. Improved metadata and standardisation will be necessary for benchmarking and translation across disciplinary boundaries. Thermography showed strong potential in this work, but future research should focus on exploring and improving absolute temperature calibration and validation. As outlined in Chapter 2, multiple factors can introduce bias into thermal measurements. Establishing standardised calibration procedures will improve measurement reliability. With more accurate absolute temperature data, thermal imaging can be more confidently applied to early disease detection and health monitoring.

# 6 Conclusion

Across the empirical components of this thesis, potential limitations in surveillance effectiveness arose from challenges related to calibration, parameter discipline, data interpretation, and governance. The central tenet of this thesis is to frame remotely-sensed animal health surveillance as a socio-technical endeavour, positioning machine-learning analysed data as a decision-support tool whose value greatly depends on human judgement and institutional support. In doing so, the thesis demonstrates that drone-acquired remote sensing can contribute to integrated early warning systems for animal disease, but only under clearly defined technical, methodological, and institutional conditions. This thesis argues that the future effectiveness of novel tools will depend not on the speed or scale of automation alone, but on the careful integration of sensing technologies, transparent analytics, and human-led governance of data, models, and decision pathways into systems designed to support trusted decision-making. By defining these constraints and trade-offs, this thesis provides a framework for evaluating future developments in digital veterinary surveillance without overstating technological readiness or underestimating socio-institutional complexity.

# Appendix 1

**Table A1-1.** Illustrative search combinations for Chapter 2

| Supplementary search element | Description |
|---|---|
| Purpose | To identify relevant studies not captured by the structured Web of Science search |
| Sources searched | Google Scholar; Scopus; reference lists of included articles |
| Thermography terms | “infrared thermography”; “infra-red thermography”; “thermal imaging”; IRT; IR; thermal |
| Animal terms | cattle; cow; calf; bovine; sheep; goat; pig; horse; equine; deer |
| Disease terms | disease; fever; mastitis; lameness; |
| Example supplementary searches | “infrared thermography” AND cattle AND mastitis; “thermal imaging” AND livestock AND disease; “infrared thermography” AND fever AND animals; “thermal imaging” AND lameness AND cattle |
| Citation chasing | Reference lists of included articles were screened for additional relevant studies |
| Limitation | No contemporaneous supplementary search log is available. The combinations shown are illustrative rather than verified historical search strings. Exact search dates, query sequences and numbers of results screened cannot be reconstructed, limiting reproducibility. |

This table summarises supplementary searches used to identify literature not captured by the structured Web of Science search, including sources searched, indicative search terms, citation chasing, and limitations of reproducibility.

# Appendix 2

**Supporting calculations for Table 2-7**

Emissivity formula: $E = \epsilon\sigma T^4$

Where,

E = energy flux (also called the radiant emittance),

ε = emissivity,

$\sigma$ = Stefan–Boltzmann constant (5.67x10-8 W m^-2 K^-4) and

T = Temperature (in kelvin).

or equivalently: $T = \left(\frac{E}{\epsilon\sigma}\right)^{\frac{1}{4}}$.

Error propagation formula: $\delta f = \left[\sum_i \left(\frac{\partial f}{\partial x_i}\delta x_i\right)^2\right]^{\frac{1}{2}}$,

applied to the temperature-emissivity equation:

$$\delta T = \sqrt{\left(\frac{\partial T}{\partial \epsilon}\,\delta\epsilon\right)^2 + \left(\frac{\partial T}{\partial E}\,\delta E\right)^2},$$

where:

$$\frac{\partial T}{\partial \epsilon} = -\frac{\epsilon^{-\frac{5}{4}}}{4} \times \left(\frac{E}{\sigma}\right)^{\frac{1}{4}}, and\ \frac{\partial T}{\partial E} = \frac{E^{-\frac{3}{4}}}{4\epsilon\sigma}.$$

Assuming $\delta E = 0$, i.e. ignoring the uncertaintity in the measured emission, we have:

$$\delta T = -\frac{\epsilon^{-\frac{5}{4}}}{4} \times \left(\frac{E}{\sigma}\right)^{\frac{1}{4}}.$$

For a given temperature, 308.15K (35°C), and considering the Stefan Boltzman constant $\sigma = 5.67\ 10^{-8} W/m^2K^4$, we can obtain the error in temperature for different choices of $\epsilon$. See Table 2-7.

# Appendix 3

Questions for Interviews

T1. Interviewee's understanding of precision farming/agritech:

- What is your current role?
- How long have you worked in your current role?
- What's your experience of new technology in farming/livestock agriculture?
- What do understand by the term sensor-derived data?
- What do you understand by the term precision agriculture?
- Have you seen that farms are starting to use drones to herd cattle etc? What do you think of it?
- Would you be in favour or against using on farm sensors to collect animal health (temperature, behaviour, weight, identify hotspots/lesions)? Why?

T2. Position on data use/access:

- What kinds/types of data do you currently work with?
- Where does it come from?
- How do you use it? What is it for?
- Do you think this data would be useful to you? How?
- Who do you think should have access to this data? Why?
- Should scientists have and use this data?
- Should an agricultural company have and use this data?
- Should the government have and use this data?
- Would you be happy for the government to have and use this data to make better informed decisions and plans around animal health and disease?
- Does it depend on who is in power (government) at the time?

T3. Position on data usage

- If data systems like this became available, what would encourage you to start using such a system?
- What would discourage you from using such a system?
- How do you think the data could/should be used?
- Do you think the data would be reliable enough to make decisions related to animal health? (these decisions could impact people's lives)

T4. Data storage and privacy implications

- How could such data be stored?
- Which entity (government, research institutes, companies etc) do you think should be responsible for storing and maintaining this data?
- What privacy implications would such types of data have? Would it affect GDPR?
- What are the legal risks of storing this data?

T5. Other Considerations

- Do you think this data could have unintended consequences?
- Who should bear the cost of such a system? Farmers? Government?
- Are there barriers to getting this type of data off the farm? (i.e. adequate ability to transfer data on-farm and off-farm)?

# Appendix 4

**Table A4-1.** Summary of the 107 studies included in the Chapter 2 scoping review of infrared thermography for disease detection in mammalian livestock, showing study aims, species, measurement approaches, key findings and identified gaps.

| Study | Study aim | Species | Measurement approach | Key findings | Identified gaps |
|---|---|---|---|---|---|
| Stumpf et al. (2021) | Compare udder-region analysis methods against rectal temperature. | Cattle | Still thermography of udder. Compared with eight analysis methods and rectal temperature. | Maximum temperature from a horizontal lateral-udder rectangle had the strongest correlation with rectal temperature (r = 0.897). | Correlation alone does not establish agreement or validated fever-detection thresholds. |
| Bleul, Hässig and Kluser (2021) | Evaluate smartphone thermal imaging for fever screening in cows. | Cattle | Still thermography of eye, muzzle, foot, udder, tail, flank. Compared with heated reference block and rectal temperature. | Sensitivity was relatively high, but specificity was very low at the tested sites, creating many false positives. | False-positive follow-up and environmental/ device effects limit mass-screening usefulness. |
| Machado et al. (2021a) | Detect subclinical mastitis in compost-barn cows. | Cattle | Still thermography of udder. Compared with quarter somatic cell counts. | Udder temperature was associated with somatic cell count; front-quarter views showed particularly strong relationships. | Routine use needs further processing and validation beyond the study setting. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Warner et al. (2021) | Compare analgesics after experimental lameness induction in cows. | Cattle | Still thermography of foot. Compared with placebo and sham controls with pain and gait measures. | Thermal differences detected induced inflammation, but the study did not establish consistent thermal discrimination between analgesic treatments. | A more reproducible model and validation against natural lameness are needed. |
| Velasco-Bolaños et al. (2021) | Evaluate thermal diagnosis of subclinical mastitis and intramammary infection. | Cattle | Still thermography of udder. Compared with cell counts, bacteriology and milking method. | Performance depended on case definition and milking method; screening for high cell counts was less sensitive than some infection definitions. | Diagnostic thresholds should be validated separately for the intended endpoint and milking context. |
| Anagnostopoulos et al. (2021) | Develop thermal models for active digital dermatitis detection. | Cattle | Still thermography of foot. Compared with clinical lesion status and cross-validated models. | Cross-validated models showed useful discrimination, but sensitivity and specificity varied by measurement occasion and model inputs. | Practical models require validation outside the development dataset and across management stages. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Cadaret et al. (2021) | Characterise physiological responses to endotoxin challenge in lambs. | Sheep | Still thermography of eye. Compared with rectal temperature and inflammatory measures after endotoxin. | Corneal and rectal temperatures rose, while inflammatory and metabolic changes followed different time courses. | A febrile response captures only part of the immune response and may miss continuing physiological disturbance. |
| Reppert et al. (2020) | Develop experimental lameness models in meat goats. | Goats | Still thermography of affected and contralateral feet. Compared with gait, pressure-mat and cortisol measures. | Induced lameness increased hoof temperatures alongside changes in gait, pressure and cortisol measures. | Experimental responses require comparison with naturally occurring disease before field application. |
| Bell et al. (2020a) | Assess thermal screening for fever in calves under farm conditions. | Cattle | Still thermography of eye. Compared with rectal temperature and environmental measures. | Eye and rectal temperatures were weakly correlated; adding environmental factors did not produce useful fever detection in the tested model. | Reliable field prediction requires more than a simple eye-temperature measure. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Teixeira, Boyle and Enríquez-Hidalgo (2020) | Relate pig skin temperature to tail-lesion severity. | Pigs | Still thermography of tail base and ear base. Compared with tail-lesion scores. | Tail-base and ear-base temperatures were higher in pigs with more substantial lesions. | The signal is not disease-specific; individual diagnostic performance requires validation. |
| Jorquera-Chavez et al. (2020) | Detect early physiological changes in experimentally infected pigs. | Pigs | Still thermography of eye and ear. Compared with clinical observations during respiratory challenge. | Thermal and heart-rate changes appeared several hours before technicians observed clinical illness. | Pilot challenge results require validation in larger, naturally infected farm populations. |
| dos Santos Sousa et al. (2020) | Compare non-invasive methods for induced laminitis detection. | Cattle | Still thermography of foot. Compared with hoof-testing, locomotion scoring and force plates. | Thermography had high sensitivity but lower specificity than locomotion scoring against hoof-testing in this experiment. | False positives and transfer from induced to natural disease require consideration. |
| Jia et al. (2020) | Predict pig body temperature using surface measures and environmental data. | Pigs | Still thermography of backside, ear root, eye, vulva. Compared with rectal temperature and environmental predictors. | Models incorporating ambient temperature and humidity outperformed models using surface temperature alone. | Performance requires external validation beyond the small study population and tested conditions. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Fabbri et al. (2020) | Locate digital and interdigital dermatitis using foot thermography. | Cattle | Still thermography of foot. Compared with clinical digital and interdigital dermatitis. | Central and interdigital regions were warmer in diseased cows than in healthy cows. | Cleaning, drying and anatomical region selection must be standardised before generalising results. |
| Scoley, Gordon and Morrison (2019) | Assess thermal measurement repeatability and its relationship with calf core temperature. | Cattle | Still thermography of eye, rectal area. Compared with core temperature and repeatability across operators and days. | Measurements were repeatable with a basic protocol, but correlations with core temperature were limited. | Repeatability does not establish accuracy as a substitute for core-temperature measurement. |
| M. Jorquera-Chavez et al. (2019) | Validate computer-vision estimates of cattle physiological measures. | Cattle | Computer vision using optical and thermal imagery of facial regions, compared with physiological reference measures. | Facial tracking and selected thermal and respiratory measures were promising, but performance varied by animal, camera position and measure. | Further automation and individual-level validation are needed. |

| Table A4-1 (continued) | | | | | |
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| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Giro et al. (2019) | Compare thermal and implanted-sensor measures with rectal temperature on pasture. | Cattle | Still thermography of eye and ear. Compared with rectal temperature, microchip readings and weather. | Ocular temperature correlated with rectal temperature more strongly than ear temperature; ear readings were more weather-sensitive. | Environmental dependence and modest correlations limit direct estimation of core temperature. |
| Macmillan, Colazo and Cook (2019) | Compare thermal and rectal measures for postpartum illness screening. | Cattle | Still thermography of eye and cheek. Compared with rectal temperature, clinical and blood indicators. | Some facial thermal measures performed as well as or better than rectal temperature, but discrimination remained limited. | Performance depended on the definition of illness; automation and validation remain necessary. |
| G. Lowe et al. (2019) | Measure calf respiration using thermal fluctuations at the nostrils. | Cattle | Thermal video of muzzle. Compared with video-observed flank movements. | Thermal breathing estimates closely tracked video observations of flank movements. | The small validation requires expansion and automated analysis before routine deployment. |

| Table A4-1 (continued) | | | | | |
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| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Kleinhenz et al. (2019) | Evaluate transdermal flunixin in experimentally induced cattle lameness. | Cattle | Still thermography of coronary bands of paired hind feet. Compared with placebo, sham induction and pain measures. | Treatment reduced the between-foot thermal difference alongside changes in cortisol and nociceptive responses. | Efficacy and thermal-response interpretation require validation in naturally occurring lameness. |
| G. L. Lowe et al. (2019) | Identify physiological and behavioural changes before calf disease. | Cattle | Still thermography of side, shoulder, back, eye, cheek. Compared with clinical signs, feeding and behaviour. | Side and shoulder temperatures and selected feeding and lying measures changed before clinical signs. | Disease in controls complicated the intended treatment comparison; indicators need prospective validation. |
| Tangorra et al. (2019) | Detect teat stress associated with machine milking. | Cattle | Still thermography of udder. Compared with teat-colour scores. | Thermal indicators had low sensitivity and specificity relative to the teat-colour assessment used. | Performance did not justify a dedicated monitoring device on this evidence alone. |

| Table A4-1 (continued) | | | | | |
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| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Watz et al. (2019) | Automate evaluation of udder thermograms during mastitis challenge. | Cattle | Still thermography of udder. Compared with manual image analysis during bacterial challenge. | Automatic and manual measures were strongly correlated and both detected clinical mastitis; absolute values differed by region selection. | Automated thresholds require validation with consistent regions and naturally occurring disease. |
| Deak et al. (2019) | Assess physiological -stage and seasonal influences on cattle thermograms . | Cattle | Still thermography of eye, muzzle, pelvis, abdomen, thorax, perineum, udder. Compared with rectal temperature, season and reproductive stage. | Anatomical temperatures varied with season and reproductive stage, with only limited correlations with rectal temperature at some sites. | Physiological and seasonal variation must be separated from disease-related change. |
| Byrne et al. (2019) | Develop and validate thermal screening for sheep hoof infection. | Sheep | Still thermography of foot. Compared with hoof infection status and flock baseline. | A flock-relative threshold performed well during development but less well in the validation dataset. | Performance loss during validation highlights the need for independent flock testing. |

| Table A4-1 (continued) | | | | | |
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| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Juozaitiene et al. (2019) | Relate teat-end hyperkeratosis, thermal patterns and mastitis status. | Cattle | Still thermography of udder. Compared with hyperkeratosis, cell counts and mastitis classification. | Teat temperature and cell counts varied with mastitis classification and hyperkeratosis severity. | Teat condition may influence thermal interpretation and needs inclusion in diagnostic validation. |
| Jaddoa et al. (2019) | Automate identification of facial thermal hot spots in cattle. | Cattle | Thermal video of face. Compared with automated face detection, thresholding and region refinement. | A preliminary algorithm located facial hot regions and extracted temperature measurements. | Region localisation requires further validation before it can support reliable clinical disease detection. |
| Lu et al. (2018) | Automate piglet ear-base temperature extraction. | Pigs | Still thermography of ear base in overhead images. Compared with manual temperature extraction. | The algorithm closely reproduced manual temperature extraction in most test images. | Accurate region extraction is a prerequisite, not direct validation of disease detection. |
| Schaefer, Genho, et al. (2018) | Automate thermal identification of fever and dark-cutting risk at processing. | Cattle | Automated orbital thermography linked to RFID at a commercial processing line. | The report described line-speed acquisition and thermal differences associated with fever and dark-cutting outcomes. | Operational performance requires independent validation with clearly reported diagnostic metrics. |

| Table A4-1 (continued) | | | | | |
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| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Murphy et al. (2018) | Assess effects of housing floor type on bull hoof health. | Cattle | Still thermography of foot. Compared with floor type, hoof lesions and locomotion. | Hoof temperature differed across some flooring conditions, but lower temperatures did not necessarily indicate improved hoof health. | Thermal differences cannot be interpreted as health improvements without corroborating outcomes. |
| Arican et al. (2018) | Compare imaging techniques for bovine laminitis assessment. | Cattle | Still thermography of foot. Compared with anatomical imaging and histopathology. | Thermography showed potential alongside anatomical imaging, but application during acute disease remained unresolved. | Validation in live animals during the initial disease phase is required. |
| Byrne et al. (2018) | Assess whether udder thermography identifies high somatic cell counts. | Cattle | Still thermography of udder. Compared with quarter cell counts and environmental covariates. | Thermal measures and environmentally adjusted residuals correlated too weakly with cell counts for useful stand-alone detection. | Thermography alone was insufficient for automated high-cell-count detection in this pasture system. |

| Table A4-1 (continued) | | | | | |
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| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Harris-Bridge et al. (2018) | Compare foot regions and thermal descriptors for digital dermatitis detection. | Cattle | Still thermography of foot. Compared with lesion status and alternative thermal descriptors. | Heel imaging and maximum temperature provided the strongest discrimination among the measures assessed. | Performance remained imperfect; contamination and region choice require consideration. |
| Sathiyabarathi, Jeyakumar, Manimaran, Pushpadass, Kumaresan, et al. (2018) | Compare thermal patterns in healthy and mastitic crossbred-cow quarters. | Cattle | Still thermography of eye and udder. Compared with cell counts, conductivity and mastitis tests. | Subclinical and clinical mastitis quarters were warmer than unaffected quarters and temperature rose with cell count. | Diagnostic thresholds require independent validation under different herd conditions. |
| Yang et al. (2018) | Assess udder-temperature variation before and after milking. | Cattle | Still thermography of udder. Compared with milk yield and pre/post-milking timing. | Milk yield influenced post-milking temperature; pre-milking imaging was proposed to reduce this source of variation. | The preferred sampling time requires validation against actual mastitis-detection performance. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Zaninelli et al. (2018) | Evaluate udder thermography under commercial-farm conditions. | Cattle | Still thermography of udder. Compared with cell-count-based classifications. | Automated indices achieved moderate sensitivity and specificity against somatic-cell-count classifications. | Image processing and indicator performance require improvement for routine automated screening. |
| Bobić et al. (2018) | Assess parity and lactation-stage influences on hoof temperature. | Cattle | Still thermography of foot. Compared with lesion status, parity and lactation stage. | Lactation stage influenced coronary-band temperature more strongly than parity. | Physiological stage should be considered when developing lameness-screening thresholds. |
| de Moura et al. (2018) | Assess urinary infection, reproductive outcomes and mammary temperature in sows. | Pigs | Still thermography of udder. Compared with urine tests and reproductive measures. | Urinary infection was associated with postpartum discharge but not mammary-system temperature. | Mammary thermography was not supported as a proxy for urinary infection. |
| Cook et al. (2018) | Automate assessment of piglet clustering during immune challenge. | Pigs | Still thermography of surface. Compared with manual clustering assessment and vaccination. | Thermal images captured both huddling and temperature changes; clustering itself affected measured group temperature. | Behaviour and ambient conditions must be considered jointly when interpreting group-level signals. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Gianesella et al. (2018) | Assess thermography for inflammatory foot disease. | Cattle | Still thermography of foot. | Affected cows had warmer feet across the evaluated regions; central and interdigital areas differed from claw surfaces. | Lesion-specific discrimination and reproducible anatomical sampling need further evaluation. |
| Shecaira et al. (2018) | Evaluate thermography as an aid to calf omphalitis diagnosis. | Cattle | Still thermography of umbilicus and abdomen. Compared with clinical omphalitis status. | Maximum lateral umbilical temperature was higher in affected calves, whereas the abdominal view did not distinguish groups. | Performance depends on anatomical view; diagnostic thresholds need wider validation. |
| Sathiyabarathi, Jeyakumar, Manimaran, Pushpadass, Sivaram, et al. (2018) | Assess thermal detection of subclinical mastitis in Deoni cows. | Cattle | Still thermography of eye and udder. Compared with ocular temperature, cell counts and conductivity. | Affected quarters were warmer; differences between ocular and udder surface temperatures showed screening potential. | Breed-specific results and derived cut-offs require external validation. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Schaefer, Von Gaza, et al. (2018) | Assess automated thermal measures of metabolic efficiency in pigs. | Pigs | Automated thermal index compared with feed-efficiency measures; ROI not specified in the extraction. | Thermal indices correlated with efficiency measures and identified some abnormal thermal profiles not apparent from feed data. | Efficiency associations do not establish validated fever or disease-detection performance. |
| Golzarian et al. (2017) | Evaluate thermal-image processing for mastitis detection. | Cattle | Still thermography of udder. Compared with cell counts and mastitis tests. | Detection accuracy was limited; hair, lighting, skin lesions and contact with nearby tissues affected interpretation. | Acquisition conditions and non-mastitis surface influences need better control. |
| Petry et al. (2017) | Compare pig eye and ear thermography with core and rectal temperature. | Pigs | Still thermography of eye and ear. Compared with rectal and internal temperature after immune challenge. | Eye temperature tracked the induced febrile response, whereas ear temperature did not show the same response. | Results from controlled immune challenge need validation under routine production conditions. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Stewart et al. (2017) | Evaluate remote respiration and movement monitoring in dairy cows. | Cattle | Thermal video of nostrils. Compared with observed respiration and accelerometer measures. | Thermal respiration estimates agreed with observed breathing; accelerometers captured selected leg-movement responses. | Automated recording and interpretation require further development for routine farm use. |
| Byrne et al. (2017) | Assess temporal, anatomical and operator repeatability of cattle thermography. | Cattle | Still thermography of eye, udder, foot. Compared with repeat images across days and operators. | Repeatability depended on anatomical region and temperature descriptor; replicate images and a common protocol improved precision. | High repeatability does not by itself establish disease-detection accuracy. |
| Jiao et al. (2016) | Correct viewing-angle effects using thermal and depth images. | Pigs | Still thermography of a pig specimen's flank, combined with depth imagery for viewing-angle compensation. | Depth-based compensation reduced temperature differences caused by oblique viewing angles. | Residual errors and performance with freely moving animals require evaluation. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Sathiyabarathi et al. (2016) | Evaluate udder-temperature differences as mastitis indicators. | Cattle | Still thermography of eye and udder. Compared with milk cell counts, conductivity and mastitis tests. | Mastitic quarters were warmer and temperature correlated with somatic cell count and electrical conductivity. | Thresholds require validation across herds, breeds and environmental conditions. |
| Digiovani et al. (2016) | Evaluate thermography against California Mastitis Test results. | Cattle | Still thermography of eye and udder. Compared with California Mastitis Test. | Temperature differences were found in front quarters but not rear quarters when comparing test-positive and test-negative animals. | A standardised protocol is needed to account for anatomical differences. |
| Michelotto, Rocha and Michelotto (2016) | Monitor developing dorsal metacarpal or metatarsal disease in racehorses. | Horses | Still thermography of metacarpal and metatarsal regions. Compared with training and subsequent clinical assessment. | Thermal increases accompanied early abnormalities in a small number of horses undergoing training. | Exercise-related changes and the small case count limit predictive generalisation. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Hoffmann, Schmidt and Ammon (2016) | Refine thermal-video monitoring of calf body temperature. | Cattle | Thermal video of head and body. Compared with rectal temperature. | Whole-animal maximum temperature closely resembled head maximum temperature and rose with rectal temperature. | Further validation is needed for continuous monitoring and fever detection beyond the small study group. |
| Rodríguez et al. (2016) | Assess hoof thermograms across mobility scores. | Cattle | Still thermography of foot. Compared with mobility scores. | Severely lame cows differed from sound cows, but intermediate mobility scores were not distinguished reliably. | The findings did not support practical early detection of mild lameness. |
| Pamparie ne et al. (2016) | Compare teat thermograph y with the California Mastitis Test. | Cattle | Still thermography of udder. Compared with California Mastitis Test. | The study reported agreement between thermographic inflammation patterns and test results across its ambient conditions. | Independent diagnostic validation is needed before generalising the reported agreement. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Orman and Endres (2016) | Assess thermal detection of different bovine foot lesions. | Cattle | Still thermography of foot. Compared with lesion type and locomotion score. | Results supported sole-ulcer detection more strongly than detection of white-line disease or digital dermatitis. | Performance depends on lesion type and the anatomical temperature measure used. |
| Talukder, Gabai and Celi (2015) | Evaluate thermography and oxidative-stress markers for sheep foot lesions. | Sheep | Still thermography of foot. Compared with foot-lesion scores and oxidative-stress markers. | Affected rams had warmer interdigital regions and altered oxidative-stress indicators. | The small comparison requires larger diagnostic-validation studies. |
| Alsaaod et al. (2015) | Assess how routine claw trimming changes claw temperature. | Cattle | Still thermography of foot. | Temperature differences between paired hind claws tended to decrease after trimming; ambient temperature and infection also influenced claw temperature. | Management-related changes must be separated from disease-related changes. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Menzel et al. (2015) | Identify anatomically appropriate thoracic regions for pig thermography. | Pigs | Still thermography of thorax. Compared with computed tomography and tissue anatomy. | Thoracic wall, lung thickness and ribs influenced surface-temperature differences and region selection. | Anatomical variation must be accounted for before applying lung-disease thresholds. |
| Wilhelm, Wilhelm and Fürll (2015) | Assess whether claw temperatures predict later sole haemorrhages. | Cattle | Still thermography of foot. Compared with subsequent sole haemorrhages. | Temperature distributions differed between claws, but post-calving temperature did not clearly predict lesions eight weeks later. | Contemporaneo-us thermal differences do not establish prospective early-detection ability. |
| Cook et al. (2014) | Assess group-level thermal responses to piglet vaccination. | Pigs | Still thermography of surface. Compared with vaccination, sham and untreated groups. | Group temperature and clustering changed after vaccination; thermal responses were detectable when fewer than 10% of pigs were vaccinated. | Further development and testing of a diagnostic index combining thermal measurements and clustering behaviour. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Bortolami et al. (2015) | Compare thermography with cell counts and bacteriology in subclinical mastitis. | Cattle | Still thermography of udder. Compared with bacteriology and somatic cell score. | Thermal measures correlated with somatic cell score but did not distinguish bacteriologically positive and negative cows. | Inflammatory temperature patterns did not provide pathogen-specific diagnostic discrimination. |
| Karakuş et al. (2015) | Predict ear-tag-associated infection in lambs. | Sheep | Still thermography of ear. Compared with subsequent ear-tag lesions and infection. | Early ear-temperature responses differed between ears that subsequently became infected and those that did not. | Predictive thresholds require validation across tag types and husbandry conditions. |
| Islam et al. (2015) | Detect thermal responses to bacterial challenge in piglets. | Pigs | Still thermography of head, body, tail. Compared with bacterial challenge and control groups. | Salmonella challenge increased temperature, whereas the E. coli group showed lower temperatures than controls. | Different disease processes can produce opposing thermal responses, limiting a universal fever-only rule. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Montanholi et al. (2015) | Quantify technical, environmental and biological influences on cattle thermograms. | Cattle | Still thermography of multiple body regions. | Distance, wind, debris, sunlight, exercise and pharmacological interventions altered thermal measurements. | Standardised acquisition and context-specific interpretation are essential for surveillance use. |
| Menzel et al. (2014) | Detect lung alterations following experimental respiratory infection. | Pigs | Still thermography of thorax. Compared with infection status and lung assessment. | Thoracic temperatures showed diagnostic potential, particularly during acute infection, but sensitivity depended on the measure used. | External and internal influences restrict transfer to routine field screening. |
| Oikonomou et al. (2014) | Relate digital-cushion thickness to sole temperature. | Cattle | Still thermography of foot. Compared with digital-cushion thickness and locomotion score. | Sole temperature increased with locomotion score and decreased with cushion thickness after environmental adjustment. | Anatomical and ambient influences complicate interpretation of temperature as inflammation alone. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Amezcua et al. (2014) | Evaluate thermography as an aid to sow-lameness detection. | Pigs | Still thermography of leg. Compared with gait-based lameness assessment. | Mean temperatures in selected hind-limb regions differed between lame and non-lame sows. Temperature differences between the affected and sound legs did not distinguish gait-score groups. | Individual and environmental influences require consideration; lesion-specific diagnostic validation remains necessary. |
| Caldara et al. (2014) | Relate birth weight to neonatal surface-temperature changes. | Pigs | Still thermography of surface. | Surface temperature fell soon after birth; low birth weight was associated with poorer thermal recovery and delayed colostrum intake. | Timing after birth and environmental conditions constrain generalisation of thermal thresholds. |
| Castro-Costa et al. (2014) | Assess udder thermography during lactation and endotoxin challenge. | Sheep | Still thermography of udder. Compared with vaginal temperature and milk measures during challenge. | Udder temperature changed after challenge but did not reliably distinguish healthy from infected udder halves. | Good camera precision alone did not yield useful mastitis discrimination. |

| Table A4-1 (continued) | | | | | |
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| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Samara, Ayadi and Aljumaah (2014) | Evaluate thermal screening for subclinical mastitis in dairy camels. | Camels | Still thermography of udder. Compared with cell counts and California Mastitis Test. | Udder temperature showed strong screening performance against somatic-cell-count and California Mastitis Test classifications. | Thresholds require independent validation in other herds and environmental conditions. |
| Alsaaod et al. (2014a) | Screen dairy cattle for digital dermatitis. | Cattle | Still thermography of foot. Compared with clinical lesion classification. | Affected feet were warmer; a relative front-to-rear temperature measure showed useful sensitivity but moderate specificity. | False positives and environmental influences limit stand-alone diagnosis. |
| Alejandro et al. (2014) | Assess teat-tissue changes associated with machine milking in goats. | Goats | Still thermography of udder. Compared with teat-wall ultrasound and milking-related changes. | Milking increased teat temperature and wall thickness, but relationships varied by site and gland condition. | A threshold indicating damaging rather than physiological change remains to be established. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Fraser et al. (2014) | Assess physical and blood indicators of experimental calf pneumonia. | Cattle | Still thermography of eye and muzzle. Compared with lung consolidation and blood indicators. | Nasal surface temperature differed with pneumonia severity, but the evaluated measures had limited diagnostic value overall. | A temperature association alone did not establish useful respiratory-disease screening. |
| McCoard et al. (2014) | Assess neonatal lamb thermal responses to cold exposure. | Sheep | Thermal video of surface. Compared with cold exposure, recovery and rectal temperature. | Surface thermal patterns changed rapidly during cooling and recovery, reflecting peripheral responses to cold. | Surface heat-loss patterns should not be treated as direct substitutes for core temperature. |
| Metzner et al. (2014a) | Compare udder-image analysis methods and their relation to rectal temperature. | Cattle | Still thermography of udder. Compared with different image-analysis regions and rectal temperature. | Maximum temperatures from polygon regions provided repeatable measurements and discriminated challenged from healthy observations. | Automated monitoring needs consistent region selection and validation beyond the challenge setting. |

| Table A4-1 (continued) | | | | | |
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| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Ajuda, Vieira and Stilwell (2014) | Assess claw deformation and thermal changes after trimming in goats. | Goats | Still thermography of foot. Compared with claw deformation before and after trimming. | Deformed claws were warmer before trimming; group differences were absent fifteen days afterwards. | Temperature changes indicate a response but do not independently quantify pain or establish lesion-specific diagnosis. |
| Church et al. (2014a) | Quantify environmental and acquisition effects on cattle eye temperature. | Cattle | Still thermography of eye. Compared with controlled distance, wind, sunlight and setting changes. | Wind lowered measured eye temperature and direct sunlight increased it; distance and camera settings also required consideration. | Reproducible screening needs control or correction of environmental influences. |
| Hoffmann et al. (2013) | Identify practical thermal-video sites for body-temperature monitoring. | Cattle | Thermal video of multiple body regions, then eye and ear base. Compared with rectal and vaginal temperatures. | The eye and back of the ear were practical monitoring sites; maximum surface temperatures generally rose with rectal temperature. | Agreement across the clinically relevant temperature range requires checking before fever screening. |

| Table A4-1 (continued) | | | | | |
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| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Kammers gaard, Malmkvist and Pedersen (2013) | Evaluate full-body thermograms for neonatal thermal-status assessment. | Pigs | Still thermography of surface. Compared with rectal temperature and time after birth. | Maximum surface temperature indicated hypothermia, but agreement with rectal temperature varied with time after birth. | Surface measurements were not interchangeable with rectal temperature, especially immediately after birth. |
| Soroko et al. (2013) | Detect subclinical equine limb inflammation through repeated imaging. | Horses | Still thermography of leg. Compared with serial clinical, radiographic and ultrasonographic assessment. | A between-limb temperature difference identified subclinical inflammatory changes during longitudinal monitoring. | The derived threshold requires independent validation in other horse populations and conditions. |
| Schmidt et al. (2013) | Compare infrared measuremen t methods and anatomical sites in sows. | Pigs | Thermal video of eye, the back of the ear, the mammary gland, and the vulva. Compared with rectal temperature and spot infrared thermometry. | Eye and ear-base sites were practical; differences from rectal temperature favoured monitoring changes over absolute substitution. | Infrared and rectal measurements cannot be assumed interchangeable . |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Martins et al. (2013) | Assess udder thermography for mastitis detection in sheep. | Sheep | Still thermography of udder. Compared with milk cell counts and mastitis classification. | Udder temperatures helped distinguish mastitis groups, particularly subclinical cases. | Classification requires validation in additional flocks and against consistent diagnostic definitions. |
| Pérez de Diego et al. (2013) | Detect fever during experimental bluetongue infection. | Sheep | Still thermography of eye. Compared with rectal temperature during viral challenge. | Eye thermography distinguished febrile sheep with 85% sensitivity and 97% specificity under experimental conditions. | Performance under field conditions remains to be established. |
| Poikalainen et al. (2012) | Explore body-temperature patterns for automated cattle health monitoring. | Cattle | Still thermography of multiple body regions. | Udder, limb and skin-injury patterns showed monitoring potential; surface cleanliness affected measurements. | Clinical discrimination and automated implementation require validation beyond descriptive thermal patterns. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Schaefer et al. (2012) | Automate bovine respiratory disease monitoring at a water station. | Cattle | Still thermography of eye. Compared with RFID-linked acquisition and conventional clinical indicators. | Affected calves had higher peak thermal values; an RFID-linked system enabled automatic acquisition. | Diagnostic definitions and station attendance may affect transfer to other settings. |
| Stokes et al. (2012) | Assess thermal screening for bovine foot lesions. | Cattle | Still thermography of foot. Compared with clinical foot-lesion assessment. | Elevated temperatures distinguished feet with lesions, but did not reliably distinguish digital dermatitis from other lesion types. | Lesion-specific diagnosis and prospective early-intervention thresholds remain unresolved. |
| Alsaaod and Büscher (2012) | Detect hoof lesions using coronary-band and skin temperatures. | Cattle | Still thermography of foot. Compared with hoof-lesion assessment before and after trimming. | Affected limbs were warmer; discrimination changed with trimming, lactation stage and ambient temperature. | Thresholds require standardised acquisition and adjustment for management and environmental conditions. |
| Çetinkaya and Demirutku (2012) | Compare thermal imaging with other methods for equine lameness assessment. | Horses | Still thermography of leg. Compared with clinical, radiographic and ultrasonographic examination. | Thermography was useful as an adjunct to clinical, radiographic and ultrasonographic evaluation. | Artefacts and limited lesion specificity prevent replacement of other diagnostic methods. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Gloster et al. (2011) | Characterise normal thermal variation relevant to foot-and-mouth disease screening. | Cattle | Still thermography of eye,foot. Compared with ambient conditions and activity. | Healthy hoof temperatures varied markedly with ambient conditions and activity, limiting a universal diagnostic threshold. | Normal environmental variation must be distinguished from disease-related warming. |
| Johnson et al. (2011) | Assess eye thermography as a fever-screening measure in ponies. | Horses | Still thermography of eye. Compared with rectal temperature and acquisition conditions. | Maximum eye temperature showed useful screening performance, influenced by sunlight and camera distance. | Positive screens still require confirmatory measurement; acquisition conditions must be controlled. |
| Pezeshki et al. (2011) | Characterise inflammatory responses to experimentall-y induced mastitis. | Cattle | Still thermography of udder. Compared with rectal temperature, inflammatory markers and clinical signs. | Udder skin warmed after challenge, but its peak followed rectal temperature and local signs. | Thermal changes were detectable but did not provide a convincing early-warning advantage. |
| Polat et al. (2010) | Evaluate diagnostic performance for bovine subclinical mastitis. | Cattle | Still thermography of udder. Compared with cell counts and California Mastitis Test. | Udder thermography showed high sensitivity and specificity against the study's mastitis classification. | Reliability across different cows and environmental conditions remained unresolved. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Westin and Rydberg (2010) | Identify sows at risk of shoulder lesions before clinical diagnosis. | Pigs | Still thermography of shoulder. Compared with subsequent clinical shoulder lesions. | Single mean temperatures were insufficient; local hot spots appeared more informative for subsequent lesions. | Individual variation and prospective predictive performance require further assessment. |
| Holzer, Rijkenhuizen and Simhofer (2010) | Assess thermal asymmetry for equine sinonasal disease. | Horses | Still thermography of head/maxillarysinuses. Compared with clinical, endoscopic and radiographic findings. | Thermal findings did not correlate significantly with the clinical findings or final diagnosis. | The evidence did not support reliable stand-alone sinonasal diagnosis. |
| Dunbar et al. (2009) | Assess thermal changes during experimental foot-and-mouth disease infection. | Mule deer | Still thermography of eye, mouth and foot. Compared with internal temperature and lesion development. | Eye temperature reflected internal temperature in well-focused images; foot temperatures increased around lesion development. | Experimental infection findings require field validation and confirmatory pathogen testing. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Rainwater-Lovett et al. (2009) | Screen cattle for foot-and-mouth disease using thermal measurements. | Cattle | Still thermography of eye, foot. Compared with experimental infection and clinical lesion development. | A foot-temperature threshold identified some infections before visible vesicles, with moderate sensitivity and higher specificity. | Mild and subclinical infection, vaccination status and field conditions require further evaluation. |
| Krogbeumker et al. (2009) | Evaluate thermography as an adjunct for equine head disease. | Horses | Still thermography of head. | Preliminary comparisons suggested thermal asymmetry could complement diagnosis of inflammatory and neoplastic conditions. | Small, heterogeneous clinical groups do not establish disease-specific diagnostic performance. |
| Friendship, Poljak and McIntosh (2009) | Assess pen-level thermography during a respiratory-disease mortality outbreak. | Pigs | Still thermography of groups of pigs at pen level. Compared with pen-level mortality during an outbreak. | Pens with mortality had higher maximum temperatures on the day of death and up to two days beforehand. | The single-barn observational association requires prospective validation and disease confirmation. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Hovinen et al. (2008) | Detect experimentally induced clinical mastitis through udder temperature. | Cattle | Still thermography of udder. Compared with rectal temperature and clinical and milk indicators. | Udder temperature increased with rectal temperature, but local clinical signs appeared before the thermal rise. | Detection of inflammation does not establish earlier detection than clinical examination. |
| Colak et al. (2008) | Compare udder surface temperature with California Mastitis Test scores. | Cattle | Still thermography of udder. Compared with California Mastitis Test scores. | Surface temperature increased with test score, whereas rectal temperature changed relatively little. | A screening association needs validation against microbiological diagnosis and external conditions. |
| Schaefer et al. (2007) | Evaluate thermography for early bovine respiratory disease detection. | Cattle | Still thermography of eye. Compared with clinical respiratory-disease assessment. | Thermal indicators identified some affected calves before clinical signs and outperformed clinical scoring on selected measures. | Predictive performance must be tested across populations with different disease prevalence and management. |
| Ciutacu, Miclaus and Tanase (2007) | Assess thermography alongside clinical examination in sport horses. | Horses | Still thermography of leg. | Thermal patterns helped localise musculoskeletal abnormalities in a small clinical series. | Heterogeneous conditions and limited diagnostic-validation data restrict generalisation. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Nikkhah et al. (2005) | Assess hoof temperature and visible lesions across lactation stages. | Cattle | Still frames extracted from thermal video of the feet. Compared with visual hoof examination and lactation stage. | Earlier-lactation cows had warmer coronary bands and more sole haemorrhages; heel lesions followed a different pattern. | Lactation stage and lesion type complicate interpretation of a single hoof-temperature threshold. |
| Schaefer et al. (2004) | Evaluate early thermal indications of experimental viral infection. | Cattle | Still thermography of eye. Compared with clinical, blood and saliva indicators during viral challenge. | Facial temperatures increased before conventional clinical and acute-phase indicators in infected calves. | Experimental infection results need independent validation in routine surveillance populations. |
| Berry et al. (2003) | Characterise normal daily udder-temperature variation. | Cattle | Still frames extracted from thermal video of the udder. Compared with daily baseline and environmental measures. | Exercise, circadian rhythm and environmental conditions affected udder temperature; prior measurements helped predict expected values. | Normal-baseline modelling needs validation in mastitic animals before diagnostic use. |

| Table A4-1 (continued) | | | | | |
|---|---|---|---|---|---|
| **Study** | **Study aim** | **Species** | **Measurement approach** | **Key findings** | **Identified gaps** |
| Loughmiller et al. (2001) | Separate ambient-temperature effects from pig febrile responses. | Pigs | Still thermography of surface. Compared with ambient and rectal temperatures during challenge. | Ambient temperature influenced surface temperature; adjusted measurements detected febrile changes but later than rectal measurements. | Environmental correction and detection timing constrain early-warning use. |
| Barth (2000) | Explore highly sensitive thermography for udder inflammation. | Cattle | Individual udder thermograms. Compared with cell counts, viewing direction and clinical observations. | Teat temperatures varied by location and viewing direction; one clinical case showed a potentially useful pattern. | Limited clinical cases and strong perspective effects prevent firm diagnostic conclusions. |

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