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Integration of Drone Imaging and GIS Tools for Livestock Population Monitoring in Pastoral Systems

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ABSTRACT

Background: The sustainable administration of livestock is a challenge in pastoral systems, particularly in semi-arid regions, due to variable climatic conditions and inadequate monitoring methods.

Methods: This research investigates the use of Geographic Information System (GIS) technologies and drone imagery to monitor cattle populations in the Kachchh region of Gujarat, India. GIS techniques were employed to analyze cattle distribution and its correlation with environmental factors such as plant health and water availability.

Result: The drone-based approach achieved a detection accuracy with an F1-score of 92.5%. Spatial analysis revealed a strong correlation between cattle density, vegetation health and proximity to water sources, particularly during the dry season. The study highlights the potential of drone imaging and GIS integration as scalable and effective tools for sustainable pastoral management.

Key words: Drone imaging, Gis (Geographic information system), Livestock management, Livestock population monitoring, Unmanned aerial vehicles (Uavs).

INTRODUCTION

Significance of livestock monitoring

The livestock sector is a cornerstone of global agriculture, contributing significantly to food production, rural livelihoods and economic development. As herd sizes increase and farms expand, traditional methods of livestock monitoring become inadequate and labor-intensive. To address these limitations, modern farmers are turning to remote monitoring systems that integrate sensors, GPS and wireless communication technologies (Slimani *et al*., 2023). These systems enable real-time tracking of animal movement, health status and location, ensuring better control over herd management. Integrated sensor data also support data-driven decision-making, allowing timely interventions. For example, alerts can notify farmers of abnormal behavior, signs of illness, or potential theft, enabling early action. Overall, remote livestock monitoring systems reduce labor costs, enhance operational efficiency and improve animal welfare.

Role of drone mapping in agriculture

Drone mapping has transformed agricultural monitoring by offering detailed insights into field conditions. Equipped with high-resolution cameras, drones can capture aerial images that are processed into maps showing vegetation health, crop boundaries and areas affected by waterlogging or nutrient deficiencies (Mao *et al*., 2023; Phang *et al*., 2023). These detailed visuals help farmers make informed decisions on fertilizer application, irrigation scheduling and crop rotation (Guo *et al*., 2018). Unlike satellite imagery, drone data is more frequent, localized and adaptable to specific needs. Over time, this technology also supports historical comparisons for long-term planning and land use optimization.

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Drone technology for livestock monitoring

Unmanned Aerial Vehicles (UAVs) vary in design and sensor capability, including optical, thermal and multispectral options. These drones gather valuable data on herd distribution, grazing patterns and pasture conditions. For instance, 3D terrain models created from drone images help locate animals and assess accessibility (Lei *et al*., 2020). Compared to manual tracking or stationary cameras, drones offer wider coverage and greater accuracy. When integrated with Geographic Information Systems (GIS), UAV data enables trend analysis and spatial planning (Sandlana *et al*., 2022), helping farmers make decisions on rotational grazing or herd relocation.

Environmental and ecological context

Grasslands face increasing pressure due to human encroachment, overgrazing and climate change. These stresses contribute to land degradation, biodiversity loss and reduced carbon sequestration. To maintain ecological balance, grazing practices must be carefully managed. While controlled grazing trials in northeast China have shown positive outcomes, real-world adoption remains difficult due to the absence of scalable and practical monitoring systems (Porto *et al*., 2021). Traditional methods using vegetation indices or time-lapse photography often lack precision, highlighting the need for advanced technologies to assess pasture health effectively.

Challenges in grazing and biodiversity

Free-ranging livestock tend to overgraze specific zones, leading to uneven resource use and soil degradation. Vegetation heterogeneity across the landscape further complicates grazing management. UAVs address these issues by providing spatial data that show animal movement patterns and pasture usage (Mendoza *et al*., 2021). With frequent drone flights, farmers can adjust grazing schedules to prevent overuse of vulnerable areas and promote even distribution, which benefits both biodiversity and long-term productivity.

Applications of UAVs in wildlife and livestock

Unmanned aerial systems (UASs) comprise drones, sensors and control units designed for animal tracking and surveillance. They have been successfully used to monitor various species, including deer, elephants and cattle. Some systems now include AI-based models that recognize animal species with high accuracy. For example, drones have achieved over 98% accuracy in identifying Holstein Friesian cattle from aerial images (Neethirajan, 2016; Alanezi *et al*., 2022). However, factors such as weather, dense vegetation and fast animal movement can hinder detection. This requires continuous refinement of deep learning algorithms to function in diverse environments.

Importance of pastoral systems

Pastoralism is a centuries-old livelihood system that supports over one billion people globally. It relies on seasonal livestock movement and traditional ecological knowledge to sustainably manage rangelands. Pastoral communities contribute significantly to biodiversity and climate resilience by preserving native species and ecosystems. Despite their ecological importance, pastoralists are often marginalized in policy-making and face issues such as land tenure conflicts and loss of grazing rights (Estevez *et al*., 2023; Wang *et al*., 2024; Papadopoulos *et al*., 2025). Strengthening their resilience requires integrating modern monitoring tools with traditional practices.

Challenges in pastoral systems

Pastoral regions often face multiple challenges that hinder effective livestock monitoring, including erratic rainfall, sparse vegetation and limited water sources. Traditional methods for livestock tracking are time-consuming, lack spatial precision and often fail in remote areas with poor infrastructure. Additionally, land use conflicts, disease risks and limited access to veterinary services further complicate herd management (López-I-Gelats *et al*., 2016; Radoglou-Grammatikis *et al*., 2020). These constraints underscore the need for innovative technologies like UAVs integrated with GIS to enhance monitoring efficiency and resource planning.

Benefits and barriers of drone-based monitoring

Drones enhance livestock monitoring by reducing manual labor, increasing surveillance range and improving animal welfare. Thermal cameras can detect early signs of illness, while imaging tools measure pasture biomass and monitor water points (Mücher *et al*., 2022; Singh *et al*., 2024). These features support precision grazing and early disease management. Despite the benefits, adoption is slowed by high costs, regulatory hurdles, battery limitations and the need for technical training. Privacy concerns and adverse weather also pose operational challenges. However, ongoing advancements are making drones more user-friendly and affordable for small and medium-scale farmers.

Global use cases and technology trends

The integration of drones into GIS applications is gaining significant momentum and is emerging as a key focus for future research. The global GIS-drone mapping market is projected to reach USD 349.5 million in 2023 and is expected to grow at a compound annual growth rate (CAGR) of 16.5%, potentially reaching USD 1,609.6 million over the next decade. Drone applications in livestock management are expanding globally (Mohsan *et al*., 2023; Nex *et al*., 2022). In Australia, drones are used to track cattle over expansive ranches. In the United States, they help monitor pasture conditions and detect herd health issues. In South Africa, drones serve dual roles in both agriculture and wildlife protection. These real-world examples highlight the growing acceptance of drone technology in livestock systems. As equipment becomes more accessible, more farmers are expected to adopt drone-based monitoring to boost efficiency, sustainability and resilience.

Problem statement

Pastoral systems, particularly in semi-arid regions like the Kachchh district of Gujarat, India, have significant challenges regarding the sustainable management of cattle. Traditional monitoring techniques are labor-intensive, time-consuming and sometimes imprecise, despite the critical importance of livestock populations to the livelihoods of local people. Furthermore, environmental variables, such as plant vitality and water accessibility, vary regularly, hence complicating livestock management. The lack of efficient, scalable and precise tools for monitoring cattle populations and their environmental interactions hinders informed decision-making for sustainable pastoral practices.

Emerging technologies, such as those that use drones for photography and tools that are part of Geographic Information Systems (GIS), provide solutions that show promise. On the other hand, their incorporation and implementation in pastoral systems that are found in the actual world are yet underexplored. This research aims to close this gap by monitoring cow herds and assessing their spatial behavior within the framework of certain environmental circumstances by developing a strategy using drone imagery and geographic information system (GIS) capabilities.

Research objectives

The primary objectives of this research are:

1. Construct and execute a system that amalgamates drone photography and GIS technologies for the surveillance of livestock populations in pastoral systems.
2. Assess the precision of drone-assisted livestock identification and population estimate in comparison to conventional ground survey techniques.
3. Assess the geographical distribution of animals and their relationships with environmental factors, including plant health and water availability.
4. Produce high-resolution maps and data outputs to facilitate sustainable pastoral management and informed decision-making.
5. Investigate the feasibility of extending the suggested technique to other pastoral areas with analogous issues.

Literature review

Technological innovations and UAV adoption in livestock monitoring Alanezi *et al*. (2022) emphasized the growing adoption of UAVs in livestock agriculture, attributing it to their operational ease, evolving sensor technology and integration with AI, IoT and machine learning. Their study provides a broad overview of how drone-based monitoring systems can address economic, environmental and logistical challenges in livestock systems. Similarly, Aquilani (2021) described Precision Livestock Farming (PLF) as an evolving system integrating UAVs, GPS, accelerometers and RFID tags for real-time animal monitoring. These technologies help track animal behavior, health and pasture usage efficiently.

Critique

Although these studies demonstrate the technological potential of UAVs, they often provide general overviews without delving into implementation constraints in resource-poor or rugged pastoral environments. Furthermore, many proposed systems remain in experimental or early development phases, limiting their applicability in real-world conditions where terrain and weather play significant roles.

Machine learning and behavioral monitoring

AlZubi (2023) explored how combining drone imagery with Support Vector Machines (SVMs) can improve the monitoring of cattle movement patterns across large grazing areas. The use of machine learning allowed for a relatively high true positive rate (70-85%), though at the expense of poor classification accuracy (10-25%), depending on image resolution and quality. Ji *et al*. (2023) applied UAVs to assess grazing density and herding proximity of yak herds on the Qinghai-Tibetan Plateau, uncovering seasonal changes in spatial distribution and grazing behavior.

Critique

While AlZubi's study offers a promising ML-based monitoring approach, the relatively low overall classification accuracy suggests the model may not generalize well without further refinement. Ji *et al*. (2023) present valuable ecological insights, yet their work is limited to specific geographies and livestock types, raising questions about the transferability of methods across ecosystems or species.

Comparative technology assessment and integration frameworks

Montalván *et al*. (2024) reviewed literature from 2017 onward to evaluate livestock monitoring tools, collars, drones, cameras and identified key trade-offs in cost, invasiveness and data resolution. Their study presents a decision framework for adopting technology based on user needs and operational contexts.

Critique

Although the comparative analysis is informative, there is limited focus on data interoperability and long-term system maintenance, especially in low-income or semi-nomadic pastoral communities. Moreover, socio-cultural acceptance of new technologies, particularly those requiring animal tagging or frequent drone flights, is rarely addressed.

Research gaps and future opportunities

Despite growing interest in integrating UAVs, machine learning and GIS for livestock monitoring, few studies have examined the combined use of these technologies in challenging pastoral landscapes like those in arid or semi-arid regions of India. Additionally, while behavioral and ecological assessments are gaining traction, there remainsa lack of robust validation using ground-truth data and

limited discussion on the scalability and cost-effectiveness of these systems for large herds over time.

MATERIALS AND METHODS

This section outlines the methodology and technologies employed to integrate drone imagery with Geographic Information System (GIS) tools for monitoring cattle populations in pastoral systems. It includes the research area, data collection process, GIS integration, analytical techniques and validation methods.

Overview of approach

This study employs a combined remote sensing and drone-based monitoring approach for livestock management. Unmanned Aerial Vehicles (UAVs) were chosen over traditional ground-based methods due to their efficiency, spatial precision and wide coverage capacity. UAVs equipped with thermal, optical and multispectral sensors are capable of detecting livestock locations, analyzing behavioral patterns, assessing pasture health and identifying water sources, all with minimal human intervention.

Justification for method selection

UAV technology was selected due to its multiple advantages over conventional monitoring techniques. One key benefit is real-time data collection, which enables timely tracking of livestock movement and pasture health. UAVs also offer high-resolution imagery, capturing detailed visuals even under cloudy conditions, an area where satellite images often fall short. Another strength is cost-efficiency. After initial deployment, drones significantly reduce the need for repeated manual field visits, saving both time and labor. Their flexibility and scalability also make them suitable for diverse landscapes and adaptable to various livestock species and grazing systems (Radoglou-Grammatikis *et al*., 2020; Kim and AlZubi, 2024; Min *et al*., 2024). Most importantly, UAV data can be seamlessly integrated with GIS tools, providing layered spatial insights that enhance grazing zone management and resource planning (Maes and Steppe, 2018). These combined features make UAV-based monitoring particularly suitable for remote, large, or infrastructure-deficient regions where quick and accurate environmental assessments are essential.

Study area description

The study was carried out in the Kachchh area of Gujarat, India, which is noted for its sparse vegetation, undulating terrain and considerable temperature fluctuations (Fig 1). Mixed herds of cattle, goats and sheep identified within the study area, approximately 10,000 square kilometres, are overseen by local pastoral groups, including the Rabari tribe. This region is suitable for this study as it is a dynamic pastoral system since seasonal variations in rainfall affect the vegetation and the availability of water. A total of 500 high-resolution images were collected during 10 UAV flights conducted over semi-arid grazing areas in Kachchh.

Climate addition

The climate in Kachchh is arid to semi-arid, with extreme temperatures ranging from 4°C in winter to 45°C in summer. The region receives an average annual rainfall of around 350-400 mm, concentrated mostly during the monsoon season (June-September), which significantly influences forage availability and livestock movement (MoEF, 2018).

Livestock contribution

Livestock production plays a significant role in the local economy. Kachchh contributes notably to Gujarat's livestock sector, with over 2 million livestock recorded in the district, according to the 20th Livestock Census (Department of Animal Husbandry and Dairying, 2019). It is a key livelihood source for pastoral communities, especially in drought-prone areas, generating income through dairy, meat, wool and manure. This economic

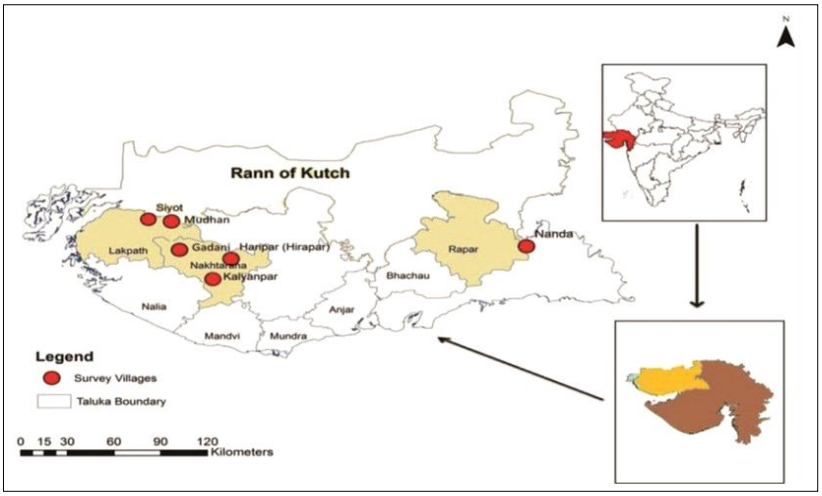


Fig 1: Map of the Kachchh district of Gujarat, India, showing the study area characterized by sparse vegetation, undulating terrain and seasonal water bodies.

dependency underscores the importance of monitoring and managing livestock using efficient tools such as UAVs.

Data collection

To ensure effective livestock monitoring in the selected pastoral region, this study employed a combination of aerial imagery and ground-truthing methods. Unmanned Aerial Vehicles (UAVs) provided systematic coverage and high-resolution visuals of grazing zones, while manual field observations validated the accuracy of the imagery. Integrating these approaches enabled reliable data interpretation for analyzing livestock distribution, movement and environmental conditions. The drone-based data collection setup included parameters such as flight altitude, speed, sensor type and image overlap, optimized to ensure complete and detailed coverage of each survey area (Table 1).

Field data collection

Field-based data collection was essential for validating the results obtained from UAV imagery. Manual livestock counts and environmental observations served as reference data, helping to enhance the accuracy of automated detection methods. These ground-truth datasets were used to assess the spatial distribution of livestock and to interpret ecological variables. The tools and methods used for field data collection, including GPS devices and binoculars, are summarized in Table 2.

Ground surveys were conducted simultaneously with UAV operations to validate drone-derived data. During drone flights, trained observers conducted farm-level visits and observations at communal grazing points, where livestock naturally congregate, such as water sources or shaded areas. Using binoculars and GPS devices, they manually counted animals and recorded environmental attributes including vegetation type, terrain condition and proximity to water bodies. This dual approach, UAV and on-ground monitoring, ensured consistency between aerial observations and actual field conditions, improving the reliability of livestock detection and behavioral analysis.

GIS Integration

Software and tools

To enhance spatial understanding of livestock and environmental interactions, UAV data were integrated with Geographic Information System (GIS) tools. The QGIS 3.28 platform was used for data processing and analysis due to its open-source nature, flexibility and wide range of geospatial functions. The Semi-Automatic Classification Plugin (SCP) was selected for its efficiency in extracting vegetation indices and classifying land cover types from remote sensing images. Additionally, Python libraries such as OpenCV were used for object detection and image processing tasks because of their high-performance computer vision capabilities. Pix4D Mapper was chosen to generate georeferenced orthomosaics due to its precision and ease of integration with UAV imagery workflows. The workflow shown in Table 3 summarizes the key data processing steps.

Analytical techniques

Population estimation

A combination of automatic item identification and manual validation was used in order to arrive at approximate estimates of livestock numbers. Accuracy was ensured by comparing the results to the data that was collected from the ground.

Movement and behavior analysis

Grazing patterns and clustering behavior were able to be identified via the use of time-lapse imagery, which was used to track the movements of cattle. With the use of geographic information system (GIS) technologies, we were able to determine the distances to vital supplies like water and shelter.

Environmental interaction

Through the use of spatial analysis, the distributions of cattle were connected with environmental factors. Examples of such comparisons are maps showing seasonal water availability, indices of vegetation health and livestock density.

Table 1: Drone setup parameters used for aerial data collection.

Parameter	Details
Drone model	DJI phantom 4 Pro
Sensor type	RGB, 20 MP
Flight altitude	120 meters
Flight speed	5 m/s
Coverage area	1 km^2 per flight
Overlap	80%
Data types	RGB imagery, NDVI from multispectral sensors

Table 2: Field parameters used for manual livestock validation and environmental monitoring.

Field parameter	Details
Validation method	Manual livestock counting
Tools used	Binoculars, GPS devices
Environmental data	Vegetation type, water sources, weather

Table 3: GIS data processing workflow for drone imagery.

Step	Description
Image preprocessing	Drone images stitched into orthomosaics using Pix4D Mapper; georeferenced to WGS 84.
Livestock detection	YOLOv5 algorithm for object detection; manual verification ensured accuracy.
Spatial data integration	Livestock positions overlaid onto vegetation indices (*e.g.*, NDVI) and water source maps.

Table 4: Validation metrics for drone-based livestock detection.

Metric	Description
Accuracy measures	Comparison of livestock counts from drone imagery and manual surveys.
Statistical analysis	Precision, recall and F1-score calculated to evaluate detection performance.

Table 5: Performance metrics for livestock detection using UAV-based automated object detection.

Metric	Value (%)
Precision	94
Recall	91
F1-Score	92.5

Validation and accuracy assessment

To ensure the reliability of UAV-derived results, validation procedures were implemented using ground-truth data and statistical performance metrics.

Validation approach

Manual livestock counts conducted during drone flights served as the reference standard. These observations were used to validate automated livestock detections and estimate classification performance.

Accuracy metrics

Quantitative measures, precision, recall and F1-score, were calculated to evaluate the effectiveness of the object detection model. These metrics provided insight into both false positives and false negatives, ensuring the system's robustness. Table 4 summarizes the validation metrics used in this study.

RESULTS AND DISCUSSION

Livestock detection and population estimation

The utilization of UAV imagery enabled precise identification and enumeration of livestock, yielding a high F1 score of 92.5%, with precision and recall values of 94% and 91%, respectively (Table 5). These outcomes demonstrate the robustness and efficiency of automated object detection using aerial imagery in semi-arid pastoral settings when compared with traditional ground-based counts.

The performance of the detection algorithm in this study aligns with and, in some cases, surpasses results reported in recent UAV-based ecological assessments. Retallack *et al*. (2022) achieved F1 scores of approximately 75% in detecting *Maireana sedifolia*, a dominant arid shrub species, using various convolutional neural network (CNN) architectures and ultra-high-resolution UAV imagery. While their focus was on vegetation, their study confirms the applicability of UAV-based deep learning models for fine-scale monitoring in rangelands. Similarly, Sankey *et al*. (2017) reported classification accuracies of 84-89% (kappa = 0.80-0.86) in identifying plant species using a fusion of UAV-mounted LiDAR and hyperspectral sensors. Notably, the present study achieved comparable or better results using only RGB imagery, highlighting the practicality and cost-effectiveness of such an approach in livestock detection. In contrast, Kariminejad *et al*. (2023) applied deep learning segmentation models (U-Net and Attention Deep Supervision Multi-Scale U-Net) to UAV data for detecting sinkholes and landslides, achieving a lower F1 score of 69%. This difference can be attributed to the increased complexity and variability of geomorphological features compared to the more distinguishable visual profiles of livestock.

Spatial distribution analysis

Spatial analysis indicated that livestock were more densely concentrated in areas with higher vegetation indices (NDVI > 0.4) and closer proximity to water sources (Table 6). During the dry season, animal density reached 120 animals/km^2 within 150 meters of water, while in the wet season, the density decreased to 80 animals/km^2 with a wider average distance of 500 meters from water sources.

These findings are consistent with UAV-based vegetation monitoring studies. Daryaei *et al*. (2020) also used object-based classification of UAV imagery, combined with Sentinel-2 data, to detect sparse riparian forests in semi-arid mountainous areas, where NDVI and water proximity were critical for accurate vegetation mapping. The congruence between the spatial patterns of livestock and vegetation distribution reinforces the ecological dependence of pastoral systems on resource availability and environmental gradients.

Environmental interaction

The analysis revealed a strong positive correlation (r = 0.78) between livestock density and NDVI, indicating that healthier vegetative cover attracted higher livestock presence. A moderate negative correlation (r = -0.65) was also observed between distance to water sources and livestock density, emphasizing the critical role of water availability, particularly during the dry season.

This environmental interaction aligns with previous findings in UAV-based ecological studies. Sankey *et al*. (2017) demonstrated that UAV-derived hyperspectral and LiDAR data captured fine-scale vegetation patterns that were strongly correlated with ecological conditions in arid and semi-arid regions. In addition, the shrub AGB mapping study highlighted the effectiveness of UAV data in predicting vegetation biomass and spatial distribution, reaffirming NDVI's utility as an indicator of ecological productivity across both plant and animal domains. Joshi *et al*. (2024) further emphasized the potential of machine learning and deep learning in arid environments for identifying resilient plant species and monitoring agro-biodiversity. Although their study focused on underutilized desert flora and bioactive

Table 6: Seasonal variation in livestock distribution relative to distance from water sources and NDVI range.

Season	Average distance to water (meters)	NDVI range	Livestock density (animals/km^2)
Dry season	150	0.4-0.6	120
Wet season	500	0.5-0.8	80

Table 7: Correlation between environmental variables and livestock density.

Variable	Correlation coefficient (r)
Livestock density and NDVI	0.78
Distance to water and density	-0.65

discovery, the emphasis on technology-driven monitoring in harsh ecosystems parallels the objectives of the present study. The relationships between environmental variables and livestock density are summarized in Table 7.

The present study confirms that the integration of drone photography and Geographic Information System (GIS) tools offers a reliable, accurate and scalable approach to livestock monitoring in semi-arid pastoral environments. The high F1-score (92.5%) and accuracy (94%) obtained for automated livestock detection strongly support the effectiveness of UAV-based models over traditional manual counting methods, which are often labor-intensive, time-consuming and susceptible to human error. The results align with prior work by Retallack *et al*. (2022), who demonstrated the applicability of CNN-based object detectors for ecological monitoring in rangelands using UAV imagery. Similarly, Sankey *et al*. (2017) reported accuracies up to 89% using a fusion of UAV-mounted LiDAR and hyperspectral data, further validating the potential of UAVs for high-precision field assessments.

Compared to conventional livestock census techniques, such as visual ground surveys or satellite image interpretation, UAV-based methods offer significant operational advantages. Ground-based techniques, although widely used, often require extensive manpower and can be logistically challenging in remote or expansive rangelands like those of Kachchh. In contrast, UAV systems can survey large areas quickly, repeat measurements frequently and produce high-resolution imagery capable of detecting individual animals. Moreover, while satellite imagery suffers from limitations in spatial resolution and cloud cover interference, UAVs operate at much finer resolutions and on-demand schedules.

The study also revealed a strong ecological link between livestock distribution and environmental variables, such as vegetation cover (NDVI > 0.4) and proximity to water sources. These findings corroborate with results from Daryaei *et al*. (2020) and the Shrub Dominance Study (2025), where NDVI was a major determinant of vegetation types and biomass in semi-arid landscapes. The observed correlations-positive between livestock density and NDVI (r = 0.78) and negative with distance to water (r = -0.65)-highlight the dependence of livestock on localized resource availability. This suggests that spatially-informed pastoral planning, especially in dry seasons, can enhance both animal welfare and rangeland sustainability.

However, the technology is not without limitations. One challenge is the misclassification of cattle breeds with similar visual profiles or animals partially concealed by trees or structures. Kariminejad *et al*. (2023) similarly noted reduced model performance when topographic complexity increased. To address such issues, future enhancements might include the use of thermal or multispectral sensors to detect livestock under canopy cover and the application of advanced machine learning algorithms such as attention-based object detectors or transformer models for improved feature extraction.

Affordability remains a concern for smallholder pastoralists. While high-end UAVs with multispectral or LiDAR sensors can be expensive, the promising results of this study using standard RGB cameras point to a cost-effective alternative. As Joshi *et al*. (2024) emphasized, machine learning and UAV technologies, when adapted for local conditions and supported by government or community initiatives, can offer economically viable solutions even in resource-constrained settings. The potential for collective ownership, drone-as-a-service models, or institutional support could further reduce entry barriers for small-scale users.

In conclusion, the integration of drone and GIS technologies presents a transformative tool for sustainable livestock management. The method is highly adaptable to the semi-arid conditions of Kachchh and holds potential for replication across similar ecosystems globally. By enabling accurate livestock monitoring and ecological assessment, these tools can support data-driven pastoral strategies that enhance productivity, conserve natural resources and reduce vulnerability to climate variability.

CONCLUSION

This study has explored the application of unmanned aerial vehicles (UAVs) in livestock monitoring, emphasizing their utility in tasks such as animal detection, counting, classification, tracking, health assessment, behavior analysis and herd dispersal measurement. UAVs offer a valuable aerial perspective that enhances the efficiency and accuracy of livestock management, particularly in remote or extensive grazing areas. Key findings demonstrate that integrating UAV technology with machine learning and IoT systems can significantly improve real-time monitoring, animal welfare and decision-making in precision livestock farming. The research also identifies persistent challenges, including regulatory restrictions, weather dependency and high initial costs. However, advancements in drone

hardware, intuitive control software and improved connectivity make UAV systems increasingly accessible and scalable for practical use. For local farmers and policymakers, the adoption of UAV-based systems presents a promising opportunity to modernize animal husbandry practices. These technologies can assist in optimizing resource use, reducing labor costs and enabling timely responses to animal health and environmental changes. Policymakers can support these efforts through subsidies, training programs and the development of UAV-operating guidelines tailored to rural and pastoral settings. Future research should explore the integration of UAVs with thermal imaging to enhance health monitoring, particularly for early disease detection or identifying animals in distress. Additionally, mobile application interfaces that allow farmers to interact with UAV systems in real time could improve usability and field-level adoption. Expanding studies to include drone swarm coordination and edge computing will further support the development of autonomous, intelligent livestock surveillance systems.

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Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all the aspects of this work.

Data availability

The data analysed/generated in the present study will be made available from corresponding authors upon reasonable request.

Availability of data and materials

Not applicable.

Use of Artificial Intelligence

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare no conflict of interest.

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