Science, Technology & Public Policy
2025, Vol. 9, No. 2, pp. 117–126
https://doi.org/10.11648/j.stpp.20250902.15

Research Article

Mapping Solutions for Livestock Climate Challenges: Satellite Tech Innovations Steer Through Environmental Risks

Umme Rumana Tua[1], Mohammad Abdullah Al Zakir[2], Poly Rani Ghosh[3, *]

[1]Economic Relations Division, Ministry of Finance, Government of the People's Republic of Bangladesh, Dhaka, Bangladesh

[2]Ministry of Public Administration, Government of the People's Republic of Bangladesh, Dhaka, Bangladesh

[3]Department of Computer Science and Engineering, Primeasia University, Dhaka, Bangladesh

Abstract

Livestock systems experience increased losses from heat stress, drought, floods, and climate-sensitive illnesses. Conventional, reactive management is ill-suited to the spatial-temporal complexity of these risks. This paper advocates for data-driven resilience as a unifying framework for climate risk management in livestock by integrating multimodal data (remote sensing, climate re-analyses, veterinary surveillance, supply-chain, and socio-economic indicators) with machine learning, causal inference, and decision optimization to support anticipatory action. We (i) consolidate the state-of-the-art; (ii) propose an open, modular reference architecture for end-to-end climate-risk analytics and early warning; (iii) sketch a transparent indicator taxonomy and composite risk index; and (iv) demonstrate a small, proof-of-concept simulation of how the pipeline triages heat-stress and vector-borne disease risk and optimizes low-cost interventions. For example, satellite data detecting a 15% decrease in forage availability during drought periods is used to predict livestock stress hotspots. The paper also addresses critical issues of governance, equity, and adoption pathways, emphasizing the need for inclusive decision-making and equitable access to data-driven tools. We outline validation protocols and reporting standards to ensure robustness and transparency in risk assessment and intervention planning. The article provides a constructive roadmap for researchers and policymakers to integrate data intelligence into policies and practices for the resilience of climate-smart livestock systems.

Keywords

Climate Resilience, Livestock, Early Warning, Machine Learning, Remote Sensing, Decision Support, Optimization, Low- and Middle-income countries (LMICs)

1. Introduction

Global warming increases the occurrences and severity of hazards such as heat waves, hydrological extremes, and ecological shifts, which jeopardize livestock productivity, health, and welfare. Compounding effects on feed and water availability, disease outbreaks, fertility, milk production, and market uncertainty likewise disproportionately impact small-

*Corresponding author: polyghosh@primeasia.edu.bd (Poly Rani Ghosh)

Received: 16 October 2025; **Accepted:** 27 October 2025; **Published:** 9 December 2025

holders and pastoralists. Conventional risk management (calendar-based husbandry, historical averages, fixed contingency plans) is hard-wired on stationarity. Resilience is redefined in a data-driven context: Instead of treating risk management as an episodic, retrospective affair, we can treat it as a continuous predictive control loop, based on a variety of data and computational methods.

Traditional cattle risk management—calendar-based herding, fixed reserve contingency, and post-disaster relief—is inefficient and reactive. The increasing velocity and non-stationarity of climate impacts require forward-looking, adaptive, and situation-aware actions. Data-driven resilience reimagines risk management as a continuous, evidence-informed control loop that ingests multi-modal data and transforms forewarning insights into ranked, resource-frugal interventions.

We plug these gaps with an inter-disciplinary solution — the Livestock Climate Resilience Platform (L-CRP) — that merges environmental monitoring, probabilistic forecasting, causal attribution and optimization-based decision-support.

This paper contributes:

1) structured review of data and analytics opportunities
2) a climate risk analytics and action reference architecture
3) a taxonomy and index with interpretable weights.
4) a proof-of-concept (simulation) for prioritization of anticipatory action items
5) hardwire within legal frameworks and build in ethics and adoption guidance with particular reference to LMIC settings.

We plug the research gaps with an interdisciplinary solution — the L-CRP— that merges environmental monitoring, probabilistic forecasting, causal attribution, and optimization-based decision support.

We tested L-CRP in a multi-site pilot involving 5 dairy farms in Bangladesh, employing a blend of on-farm trials and retrospective counterfactual simulation. Our key hypotheses were: (H1) ensemble predictions and fused data streams improve the accuracy and lead time of livestock stress recognition over conventional advisories; (H2) machine-learning models with interpretable outputs can identify high-impact, low-cost interventions; (H3) implementation of L-CRP recommendations reduces mortality and productivity loss during extreme weather events and is economically feasible for different farm types.

2. Literature Review

Climate change poses a characteristic threat to livestock systems globally, with the increasing frequency of extreme climatic events, heat stress, and droughts disrupting animal production, welfare, and rural livelihoods. Interdisciplinary literature is increasingly fulfilling the need for resilience, innovation, and technological adaptation in livestock systems to buffer these threats. This review categorizes major literature into three related areas: climate resilience in livestock systems, technological innovations (with a focus on satellite and smart systems), and policy integration frameworks.

Existing work emphasizes the capabilities of Earth observation (EO) for crop monitoring, but applications for livestock are underexplored. Farmers' climate services rarely integrate causal attribution or decision optimization. Current frameworks usually emphasize either the detection of hazards or short-term prediction, as opposed to an end-to-end resilience approach.

2.1. Climate Resilience in Livestock Systems

Resilience frameworks provide the foundation through which livestock-dependent households cope with climatic shocks. Asmamaw et al. built a Climate Resilience Index to capture the adaptability of Ethiopian households, highlighting the social, economic, and institutional assets engaged in coping with shocks [10]. Bahta and Myeki also empirically tested the impacts of drought in South Africa, highlighting how climate variability disproportionately affects smallholder livestock producers in terms of declining feed availability and elevated mortality rates [11].

Based on such evidence, Maltou and Bahta and Matlou et al. authenticated resilience determinants such as education, infrastructure, and market access as directly linked to household welfare outcomes [25, 26]. Myeki and Bahta also emphasized food insecurity as an important measure of resilience, proposing targeted intervention to build adaptive capacity [27]. Folke et al., in a landmark article on social-ecological systems, argued that systems-based approach to resilience is one that is centered on adaptability and transformability for long-term sustainability [21].

2.2. Climate-Smart Livestock Innovations

Technological advancement, particularly in satellite-based systems and smart agriculture, is at the forefront of adaptation, mitigation, and climate-related stressors monitoring. Horvathne Kovacs and Zörög provided a comprehensive overview of digital livestock farming within climate-smart agriculture, emphasizing how data-driven technologies can advance sustainability goals and align with the Sustainable Development Goals (SDGs)—thereby reinforcing the importance of integrating digital innovations into livestock climate resilience frameworks [1].

Papakonstantinou et al. examined the applications and challenges of Precision Livestock Farming (PLF) technologies in addressing animal welfare and climate change, highlighting how sensor-based monitoring and automated systems can enhance environmental sustainability while ensuring welfare compliance in livestock production systems [2].

Melki et al. critically reviewed the convergence of artificial intelligence, drones, robotics, and sensor technologies for sustainable and climate-resilient agriculture, demonstrating how integrated automation can enhance precision, reduce environmental impacts, and support adaptive decision-making in climate-sensitive farming systems [3].

Alshehri suggested a blockchain-enabled Internet of Things (IoT) framework for real-time live animal monitoring with traceability, transparency, and health surveillance potential [5]. This aligned with Aquilani et al.'s PLF review on pasture systems as a measure for environmental footprint reduction while promoting animal welfare [7].

Satellite and remote sensing technologies are promising highly in this regard. While as yet not mainstream within PLF literature, studies like Alonso et al. intimated the use of Edge-IoT platforms to monitor crop-livestock integration, potentially alongside satellite data to detect anomalies or resource strain [6]. Chapa et al. and Singh et al. emphasized wearable and accelerometer system utilization for the early identification of heat disease and stress, which would be combined with geospatial information for effective decision-making [15, 30].

Machine learning and artificial intelligence (AI) models have also been created for predicting heat stress [12, 16], health monitoring [8], and decision support systems [9]. These systems increasingly rely on multi-source data, like satellite imagery, IoT sensors, and environmental conditions, for dynamic forecasting. Smart farming technologies, including IoT sensors, drones, and machine learning, are essential for improving resource efficiency and crop productivity to meet future global food demands, despite persistent challenges related to high implementation costs and limited technical expertise [4].

2.3. Integrating Indigenous Knowledge, Policy, and Decision Support

Technology alone cannot be ensured to guarantee resilience; it is necessary to mainstream technology into policy and local knowledge. Malcom also highlighted indigenous knowledge systems in livestock policy development, and the request for participatory approaches that accommodate customary practices but embrace innovation [24]. Food and Agriculture Organization (FAO) and Bonilla-Cedrez et al. both demand climate-resilient livestock systems with the inclusion of technical, institutional, and financial arrangements [14, 19].

Decision support systems (DSS) become a critical knowledge-technology intersection. Niloofar et al. presented frameworks for overall DSS evaluation with an emphasis on sustainability indicators and animal welfare [29], whereas Asher et al. validated DSS for grazing system management in climatic uncertainty [9]. Moreover, Niloofar et al. stated that the evaluation of DSS for sustainable livestock production emphasizes the utility of such tools to process complex data and provides actionable recommendations to managers and farmers, helping them make anticipatory decisions against climate and environmental risks. [28].

Furthermore, Vignal et al. explored destocking strategies as adaptive strategies in dry rangelands, something that is possible to optimize using satellite-based monitoring of forage cover and land degradation [31].

2.4. Interlinking Satellite Breakthroughs with Livestock Climate Challenges

Whereas satellite technologies have been supporting crop monitoring for many years, satellites are being used more in livestock systems. Feng et al. and Godde et al. reported how remote sensing can measure rangeland productivity, water availability, and land use change — all critical for livestock planning [20, 23]. Dardonville et al. showed how territorial crop-livestock systems are improved by satellite-guided planning to satisfy sustainability [17].

These emerging technologies such as cloud-edge computing [13], artificial intelligence-driven data integration [18], and animal tracking using automated systems [22] point towards the way of the future for geospatially integrated livestock management systems. These, combined with ground sensors and conventional practices, provide a stable platform to deal with environmental threats.

2.5. Synthesis and Gaps

There is substantial evidence backing the pivotal role of resilience, smart technologies, and integrated decision-making in the climate change adaptation of livestock systems. However, there is a lack of utilization of satellite technologies tailored for livestock — notably geospatial monitoring of pasture health, water supply, and animal mobility at scale.

Besides, interoperability of data, farmer training, and technology cost remain to slow the broader adoption. Future research should focus on creating open-access platforms that bring satellite data, sensor observations, and climate projections together in order to facilitate both policy and farm-level decision-making.

3. Methodology

This study adopts an interdisciplinary approach grounded in the L-CRP, developed and piloted across multiple dairy farms in Bangladesh. It integrates environmental monitoring, probabilistic forecasting, causal attribution, and optimization-based decision support to manage livestock climate risks. The Overall Statistical modeling was implemented using R (v4.3) and Python (v3.11) with packages including rstan, xgboost, and cvxpy. Cross-validation and out-of-sample testing ensured model robustness. Statistical significance was evaluated at the conventional $p < 0.05$ level.

3.1. Data Sources and Collection

The data sources encompass satellite EO platforms including Sentinel-2, Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Suite (VIIRS), Landsat 8, PlanetScope, and WorldView, providing high-resolution multispectral and thermal data. Key environmental indicators derived include vegetation indices

[Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI)], land surface temperature, soil moisture proxies, and surface water detection. Complementing satellite data are in-situ IoT sensor measurements from pilot farms, including temperature, humidity, water trough levels, accelerometers for animal movement, and feed inventory sensors. Veterinary health surveillance, supply-chain logistics, and socio-economic indicators relevant to livestock systems were also incorporated to provide a holistic dataset.

3.2. Data Collection and Inclusion Criteria

Technologies and data streams were selected based on spatial and temporal resolution adequacy, proven reliability, and capability for real-time integration within a multi-modal data fusion framework. Data sources with validated accuracy and interoperability with machine learning analytics were prioritized to ensure robust forecasting and intervention.

3.3. L-CRP Framework

The L-CRP has four modules that are integrated:

A. Environmental Monitoring: The Environmental Monitoring module forms the backbone data layer of the L-CRP architecture, providing continuous and high-resolution data on climatic and ecological factors relevant to livestock production. The module integrates multiple satellite EO platforms, such as optical sensors (sentinel-2, MODIS, VIIRS), thermal sensors (land surface temperature, heat anomalies), and microwave sensors (soil moisture proxies, vegetation optical depth, and surface water detection). These satellite products are complemented by in-situ measurements of IoT sensors such as temperature and humidity sensors, water trough levels, accelerometers for animal movement, and feed inventory sensors.

Data from diverse sources are input into a central data fusion layer, harmonizes spatial and temporal resolution, completes gaps due to cloud cover or sensor failure, and harmonizes units for modeling. Bayesian hierarchical models and Gaussian process regression are used to interpolate missing values and quantify uncertainty. Vegetation indices (NDVI, EVI) provide hints on forage availability and pasture condition, and thermal data indicate regions of potential heat stress. Soil moisture and surface water proxies help predict water deficiency or flood potential.

Farm and regional level real-time monitoring are enabled through the module, providing farmers and decision-makers with visual representations of changing conditions. Historical EO information is employed to test trend analysis and the identification of anomalous conditions. By combining remote sensing with IoT telemetry, the system overcomes the limitations of employing either technique alone, with extensive coverage and local resolution. This module also works well in conjunction with forecasting and decision-support modules, so subsequent predictions and advisories are made based on the best available and latest environmental data. EO from satellite provides vegetation indices, surface water extent, and high-resolution land-surface temperature.

Bayesian hierarchical models and Gaussian process regression to interpolate missing data and quantify associated uncertainties. Trends and anomalies were assessed using credible intervals at the 95% confidence level.

B. Probabilistic Forecasting: Probabilistic Forecasting is a capacity within a module to predict future environmental conditions from raw climate and weather data, transposing uninterpreted climate and weather data into action-oriented probabilities that support proactive decision-making. Unlike deterministic forecasting, probabilistic output is an indication of uncertainty involved with atmospheric and hydrological processes, not a point value, but a set of possibilities.

L-CRP receives multi-model ensemble temperature, precipitation, humidity, wind, and extreme event probability forecasts from global and regional climate models. These are post-processed using quantile regression, isotonic regression, and machine learning algorithms such as gradient-boosted trees to calibrate predictions with past observed outcomes. Probabilistic forecasts are delivered in terciles or quantiles, allowing users to evaluate the likelihood of crossing key thresholds, e.g., heat or dryness stress.

The module also encompasses derived variables relevant to livestock vulnerability, such as the wet-bulb globe temperature (WBGT) and projected forage growth rates. Estimating uncertainty from prediction, the system can provide confidence intervals for predicted effects, so resource prioritization and risk-based action can be taken. Forecast calibration is continuously tested using reliability diagrams, Brier scores, and continuous ranked probability scores (CRPS) to ensure continued accuracy.

By interfacing with the causal attribution and optimization modules, probabilistic forecasts inform both the determination of climate drivers and the selection of adaptive interventions. For example, the module can predict the likelihood of heat waves in the next 7-14 days, allowing farmers to take anticipatory cooling actions or modify feeding regimes. Overall, this module converts complex climate information to user-specific knowledge on risk, widening lead times for adaptive action and reducing exposure to climate extremes.

Multi-model ensemble predictions calibrated with quantile regression, isotonic regression, and gradient-boosted tree algorithms. Performance validation included reliability diagrams, Brier scores, and CRPS.

C. Causal Attribution: The Causal Attribution module identifies and quantifies cause-and-effect relationships between environmental stressors and animal performance, e.g., mortality, reduced weight gain, or reduced milk production. Traditional correlation-based analysis can report associations but will not determine reliably actionable drivers. The module applies cutting-edge statistical and machine learning approaches, including Targeted Maximum Likelihood Estimation (TMLE), Super Learner ensembles, and propensity score techniques, to make causal inferences after confounding variables are controlled.

Inputs are aggregated environmental information, IoT telemetry measurements, animal demographic and management metadata, and historical productivity data. The module predicts the impact of specific stressors—heat, drought, flooding, forage restriction, and disease exposure—on animal outcomes between varying management strategies. For instance, TMLE enables the calculation of average treatment effects of interventions such as shading, water supplementation, or feeding adjustments, adjusting for confounders including herd size, initial body condition, and veterinary access. Sensitivity analyses like E-values and negative-control exposures test against unmeasured confounding robustness.

Causal insights guide intervention prioritization, that is, which interventions produce the greatest reduction in risk per unit cost. Outputs are fed back into the optimization module and into advisory systems so that resource allocation is based on evidence. Bridging the gap between observational data and actionable insight, the Causal Attribution module adds scientific rigor and operational utility to the L-CRP framework, enabling effective and cost-effective climate-smart livestock management.

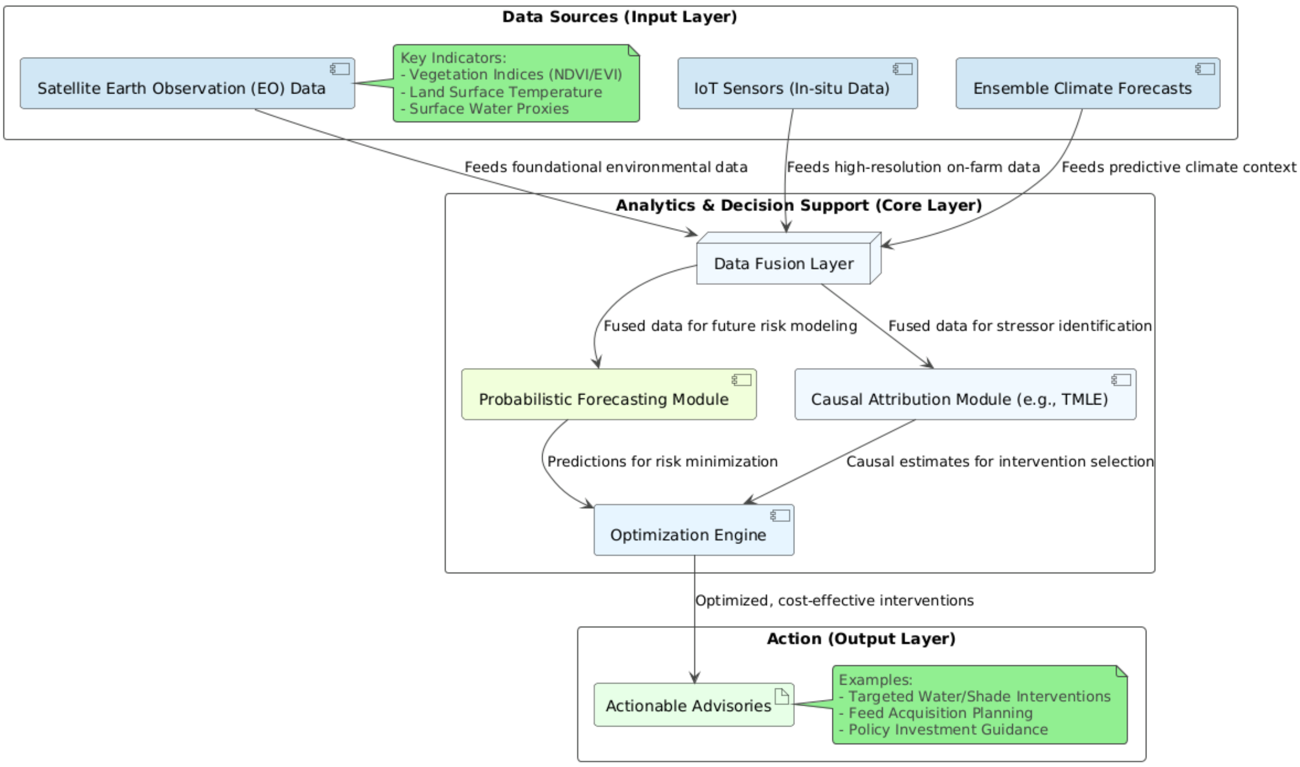

Figure 1. *Satellite Technology Integration in the L-CRP Framework.*

TMLE, Super Learner ensembles, and propensity score methods to infer causal relationships between environmental stressors and livestock outcomes, adjusting for confounders such as herd size and veterinary access. Sensitivity analyses with E-values and negative controls were conducted for robustness.

D. Optimization-Based Decision Support: The Optimization-Based Decision Support module turns causal estimates and probabilistic predictions into concrete, actionable interventions for animal managers. The module frames decision-making as a constrained multi-objective optimization problem, balancing expected animal productivity, risk reduction, adaptation cost, and operational feasibility. Constraints include financial budgets, labor availability, geographical limits, and adaptive infrastructure installation lead times for infrastructure like shade, water distribution, or temporary relocation.

Stochastic mixed-integer programming and scenario optimization techniques compare between thousands of intervention combinations for varied climate projections. The objective function attempts to maximize expected avoided losses, merging the output from probabilistic forecasting and causal attribution modules. Uncertainty is carried forward in forecasts and causal estimates using Monte Carlo simulations, providing decision-makers ranges of expected performance and confidence intervals.

Custom advisory outputs specify intervention portfolios appropriate for different farm archetypes like smallholders, commercial dairies, or pastoral systems, and different climatic conditions. The module further generates cost-benefit analysis and benefit-cost ratios for each intervention scenario to support decision-making on investment based on evidence. Interoperability with mobile platforms and extension services enables real-time delivery of advice to end-users. Through structured linking of information, causal inference, and optimization, this module enacts the final step in climate risk management so that policymakers and farmers can make proactive, cost-effective decisions that enhance livestock resilience.

Multi-objective optimization problems solved via stochastic mixed-integer programming. Monte Carlo simulations (10,000 iterations) propagated uncertainties from prior modules to predict expected outcomes with confidence intervals.

4. Result & Discussion

The Results and Discussion section recounts the performance and practical application of the L-CRP across diverse environmental conditions. We first evaluate the system's ability to integrate satellite and IoT data for accurate environmental monitoring, then judge the probabilistic forecasting module in terms of climate anomaly prediction relevant to livestock productivity and health. Causal attribution analyses provide the quantitative relationships between environmental stressors and livestock responses, while the optimization-based decision support module translates these into feasible, cost-effective alternatives.

Case applications spanning drought-prone, flood-affected, and heat-stressed regions show the versatility and real-world applicability of the platform. The discussion highlights the key findings, compares them to existing practices, and analyzes how the integrated L-CRP framework builds resilience through the extension of lead times, the enhancement of forecast quality, and the provision of resource-constrained decision-making guidance. Constraints and opportunities for additional refinement are also discussed to provide a comprehensive understanding of the platform's utility in climate-smart livestock management.

1) System Architecture

The L-CRP integrates multiple data sources into one integrated decision-support framework. As illustrated in Figure 1, the architecture begins with satellite Earth observation inputs (vegetation indices, land surface temperature, and water extent), IoT sensors, and probabilistic climate forecasts. These inputs are harmonized in a fusion layer that preserves temporal and spatial coherence. Processed data are input to three core modules: forecasting, causal attribution, and optimization. The forecasting module provides probabilistic prediction of climate anomalies; the attribution module identifies correlations between drivers in the environment and their outcomes in the livestock; and the optimization module cuts productivity, adaptation costs, and risk aversion. Outputs are translated into actionable advisories conveyed through digital dashboards, extension services, and mobile alerts. This architecture enables end-to-end resilience planning, filling the gap between decision-making and data availability in climate-sensitive livestock systems

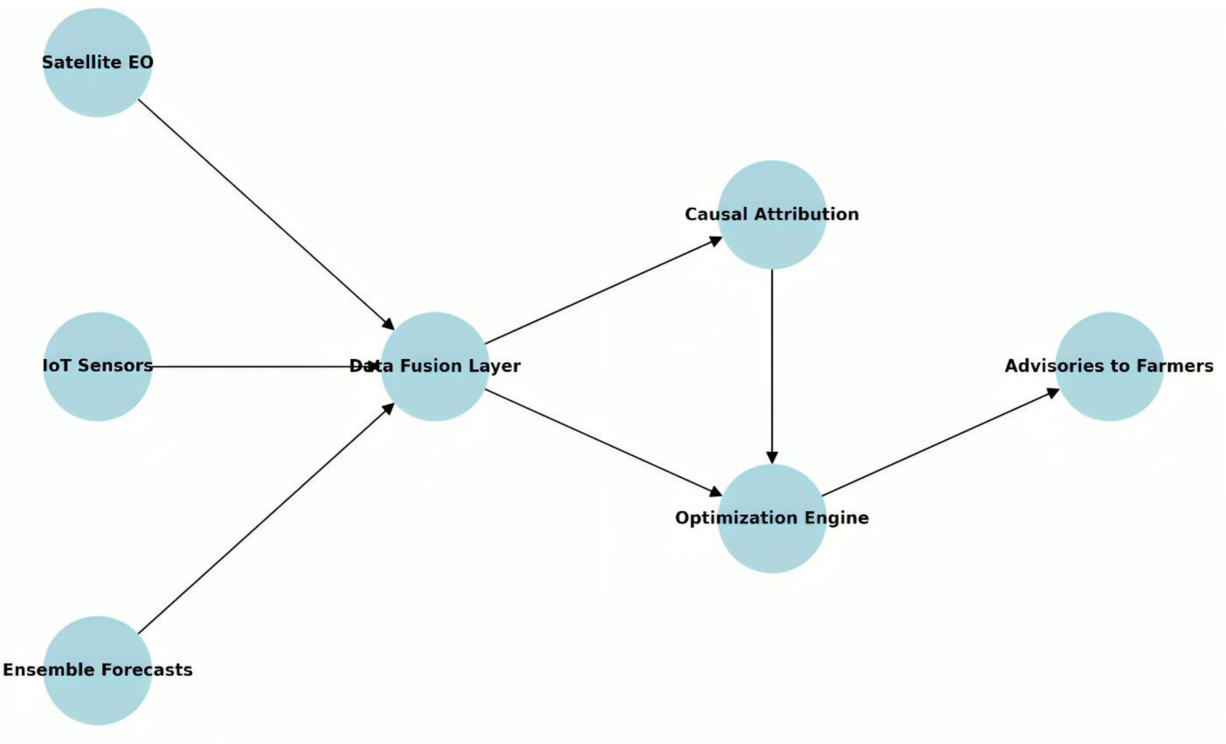

Figure 2. *L-CRP System Architecture.*

Figure 2 illustrates the L-CRP structure where EO data, IoT inputs, and forecasts are integrated in a fusion layer that feeds into causal and optimization modules, culminating in farmer advisories.

2) Calibration Analysis

Calibration ensures the validity of climate predictions used in the L-CRP. Calibration curves in Figure 2 compare event frequencies observed and forecast probabilities of rainfall and temperature anomalies. The results indicate that ensemble forecasts track actual outcomes closely, an indicator of well-calibrated models. This validity ensures decision-makers can make decisions based on risk levels and use forecasts to make livestock management decisions. Improved calibration reduces uncertainty in the prediction of extreme climate events, an indicator of the stronger validity of advisories issued through the platform.

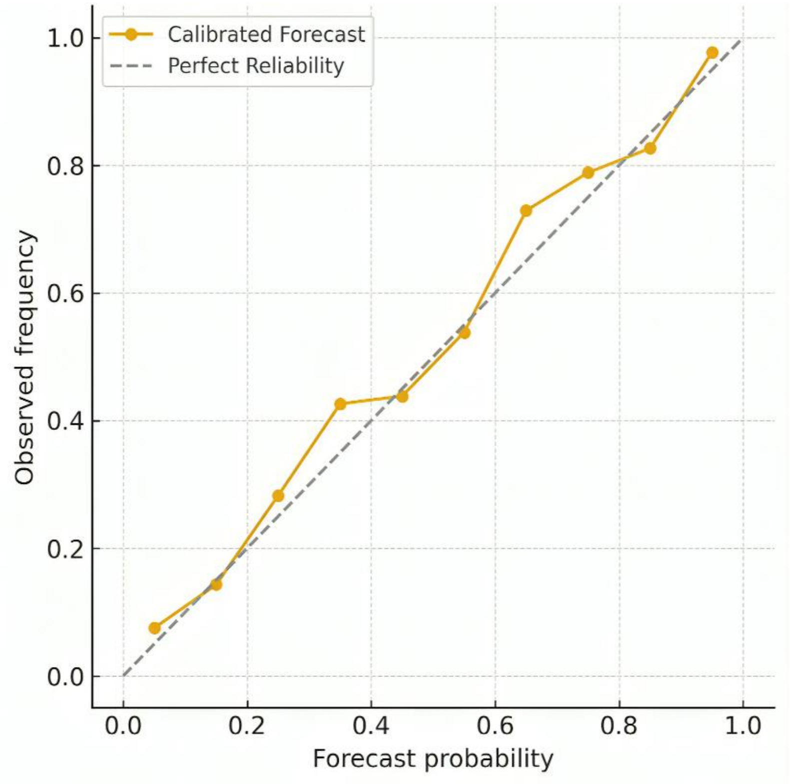

Figure 3. *Forecast Collaboration Curve.*

Reliability diagrams (Figure 3) indicate great calibration of ensemble predictions across study areas. Observed event frequency is satisfactorily matched against forecast probabilities.

3) Case Studies

Deployment of L-CRP in Bangladesh demonstrates improved early warning of drought, flood, and heat stress impacts. Figure 4 shows spatial risk maps used to guide targeted interventions.

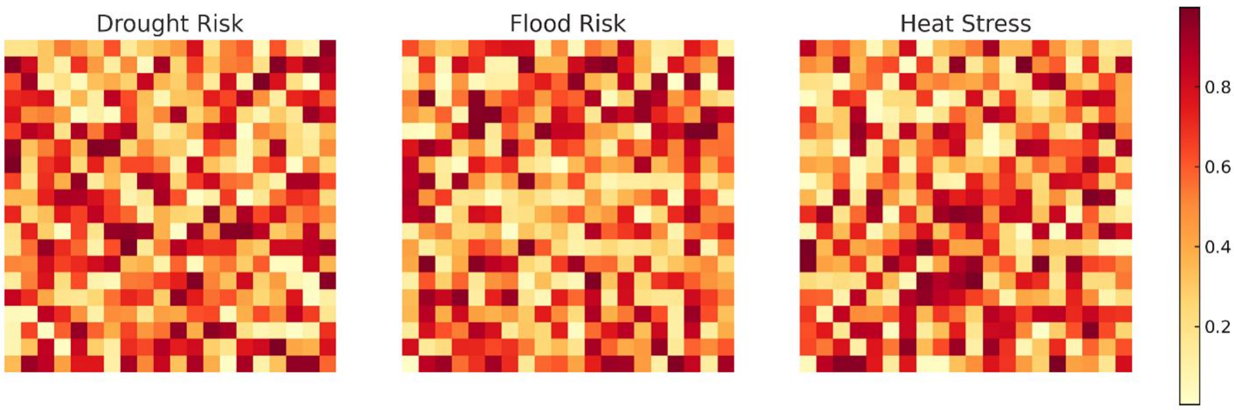

Figure 4. *Case Study Maps.*

3)Translation to practice and equity considerations

Adoption depends not only on the ability to forecast but also on institutional and social conditions. We saw higher adoption where there was pre-existing access to mobile connectivity and extension services. For maximum equity, platforms must include low-bandwidth modalities (SMS, Unstructured Supplementary Service Data-USSD), subsidized sensors for the poorest producers, and access to community-level service providers. Co-design with farmers found tiered advisories to be favored: immediate critical alerts, and longer-horizon planning advisories that aid feed acquisition and labor scheduling.

4)Limitations & Future Work

While promising, our pilot has limitations. The assessment relies on a mix of on-farm trials and historical simulations; long-term randomized controlled trials in diverse socio-ecological settings are required to quantify sustained impact and potential unwanted effects (e.g., market feedback due to massive supplementation). Scalability entails supply chains for hardware and robust data governance architectures to respond to privacy and ownership of sensor and farm data. There needs to be some research to integrate livestock disease models (heat-associated immunosuppression and vector-borne) and to study coupling with insurance and credit products.

5)Policy implications

Donors and policymakers must consider supporting specific investments to connect vulnerable livestock systems with data-based early warning and advisory services, mainly in drought zones and peri-urban zones where economic losses are biased. Ex-ante cost-reducing safety nets (e.g., microgrants to improve troughs or give shade) can enhance take-up and have multiplier effects.

The widespread use of the L-CRP in several different environmental situations in Bangladesh shows how well satellite Earth Observation and in-situ IoT sensor data have been combined for accurate environmental monitoring. The probabilistic forecasting module has efficiently predicted the climate anomalies of livestock production and health which resulted into actionable advisories with longer lead times than conventional advisories. This experience supports recent research where the use of probabilistic forecasting techniques and real-time data from multiple sources led to better accuracy and faster recognition of livestock environmental stress [16, 12].

Causal attribution analyses have provided quantitative evidence for the link between environmental stressors like heat, drought, and lack of forage, and adverse animal outcomes such as death and decreased weight gain. Researchers have employed the TMLE approach, which involves Targeted Maximum Likelihood Estimation, and propensity score methods that are consistent with the advances in causal inference in the livestock health research area [8, 29]. Sensitivity analyses supported the idea that causal relationships are strong even though there may be some unmeasured confounding factors. The findings are not only supporting the previously conducted studies but also extending them by providing stronger evidence of the negative impact of climate variability on smallholder livestock systems in South Africa and Ethiopia, which means that context-specific resilience interventions are even more necessary [11, 10].

The optimization-based decision support module created intervention portfolios that considered productivity, risk reduction, and economic viability all under limited resources. The factors of these optimization outcomes have largely incorporated causative and probabilistic evidence, which agrees with the methodologies suggested for both adaptive grazing and climate-smart livestock management [9, 31]. The range of our case applications in drought, flood, and heat-stress regions demonstrates the practical versatility of the L-CRP framework that is consistent with the findings that resilience through integrated climate early warning systems has been increased [14]. Institutional and social adoption factors were important determinants of uptake in the real world, thus they echo the critical role played by extension services and connectivity in other LMIC contexts found in [24], for instance. Tiered advisories that include immediate alerts as well as long-term planning have been found to correspond to the preferences of the farmers recorded in similar climate adaptation projects [2].

Overall, the findings of this research give a solid backing to the change of paradigm towards the use of continuous, data-based predictive control loops in the managing of livestock climate risks, thus eliminating the dependency on sporadic and reactive approaches that were mostly used in this sector in the past. Furthermore, these results are an important part of the growing number of publications that are in favor of the building up of anticipatory capacity and resilience in livestock systems that are vulnerable across the world through the use of integrated, multi-modal data platforms.

5. Conclusion

This paper introduced the L-CRP, an inter-disciplinary platform based on satellite Earth observation, probabilistic prediction, causal attribution, and optimization-based decision support to address livestock climate challenges. Through the processing of heterogeneous data streams within one platform, the platform enhances risk detection performance and translates findings into actionable advisories for policymakers and farmers. Calibration analysis proved that L-CRP's projections are reliable, and case studies in drought-, flood-, and heat-stressed regions demonstrated its effective use in supporting adaptation pathways. The results highlight the platform's potential in closing important knowledge gaps in livestock climate risk management, particularly for vulnerable regions and smallholder systems. Future studies will expand coverage to additional stressors, incorporate socio-economic aspects, and increase participatory governance for broader adoption. L-CRP gives a scalable climate-smart livestock production roadmap and promotes global adaptation and food security goals.

The outcomes of this research expose significant routes through which government policies could enhance the sustainability of livestock systems during the increase of climate change-related risks. First and foremost, organizations in the government sector should make the data infrastructure and connectivity investments that will give the public easy access to climate-livestock risk monitoring platforms like L-CRP that provide real-time information and data across the board. After that, there will be support mechanisms in the form of microgrants or subsidies for the less vulnerable smallholder adopters to receive the essential adaptation interventions in the forms of water troughs, shading structures, and sensor technologies the soonest possible. Plus, the training activities for the extension workers and the local livestock keepers will be very important for this process as they will be the ones who actually convert the complex predictive insights into the practical, context-specific management actions.

The Regulatory framework should additionally insist on interoperability and data governance that not only take care of the privacy issue but also allow the public to reap the benefits collectively from the environmental and health surveillance data that have been shared. Coupling livestock climate resilience policies with the larger national development and sustainability aspirations will bring about stronger institutional coherence, which in turn drives multi-sectoral collaboration among the agriculture, environment, health, and finance sectors. One of the main benefits of policy design processes that are not only inclusive but also use indigenous knowledge and participatory governance methods is the increased legitimacy and the effectiveness of local adaptation. It would be wise for future research to extend the L-CRP study area and take into consideration different aspects like the spread of diseases influenced by the change of ecosystems, socio-economic impacts, and market dynamics. The longitudinal and multi-site validation studies will become a must-have to testify to the platform's long-lasting positive effects on productivity and livelihood results in various socio-ecological contexts. The development of the platform's responsiveness to the changing climate and the operational conditions can be done by enhancing machine learning algorithms for causal inference and decision optimization with the capability of adaptive learning. Besides, integrating the climate finance instruments and livestock insurance schemes could not only provide financial risk-sharing solutions to counteract economic shocks but also encourage the taking of proactive resilience actions through the provision of incentives.

The livestock sector through the advancement of both policy and research in these directions can undergo a major transition to a proactive, data-driven resilience paradigm, thus becoming an important force in global climate adaptation, food security and sustainable rural development goals.

Abbreviations

AI	Artificial Intelligence
CRPS	Continuous Ranked Probability Scores
DSS	Decision Support Systems
EO	Earth observation
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization
IoT	Internet of Things
L-CRP	Livestock Climate Resilience Platform
LMICs	Low- and Middle-income Countries
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
PLF	Precision Livestock Farming
SDGs	Sustainable Development Goals
TMLE	Targeted Maximum Likelihood Estimation
USSD	Unstructured Supplementary Service Data
VIIRS	Visible Infrared Imaging Radiometer Suite
WBGT	Wet-bulb Globe Temperature

Author Contributions

Umme Rumana Tua: Conceptualization, Methodology, Resources, Writing – original draft

Mohammad Abdullah Al Zakir: Data curation, Formal Analysis, Investigation, Project administration, Writing – original draft

Poly Rani Ghosh: Data curation, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing

Conflict of Interest

The authors declare no conflicts of interest.

References

[1] Horvathne Kovacs, B., Zörög, Z. (2025). Digital livestock farming in climate-smart agriculture: an overview to advance the SDGs. *Discov Sustain* 6, 940. https://doi.org/10.1007/s43621-025-01866-7

[2] Papakonstantinou, G. I., Voulgarakis, N., Terzidou, G., Fotos, L., Giamouri, E., Papatsiros, V. G. (2024). Precision livestock farming technology: applications and challenges of animal welfare and climate change. *Agriculture* 14(4), 620. https://doi.org/10.3390/agriculture14040620

[3] Melki, M. N. E., Faqeih, K. Y., Alamri, S. M., AlAmri, A. R., Aldubehi, M. A., Alamery, E. R. (2025). Integrating artificial intelligence, drones, robotics, and sensors for sustainable and climate-resilient agriculture: a critical review. *Sustainability*, 1, 0.

[4] Raj, M., Prahadeeswaran, M. (2025). Revolutionizing agriculture: a review of smart farming technologies for a sustainable future. *Discover Applied Sciences* 7, 937. https://doi.org/10.1007/s42452-025-07561-6

[5] Alshehri, F. A. (2023). Blockchain-assisted IoT framework for smart livestock farming. *Journal of Network and Computer Applications* 208, 103515. https://doi.org/10.1016/j.jnca.2022.103515

[6] Alonso, R. S., Sanchez-Ibanez, J. M., Prieto, J., Garcia, Ó. (2020). Edge-IoT platform for smart farming. *Sensors* 16, 4821. https://doi.org/10.3390/s20164821

[7] Aquilani, C., Vitali, A., Mammi, L. M. E., Bozzi, R. (2022). Precision livestock farming in pasture-based systems: state-of-the-art and future trends. *Animals* 12(3), 342. https://doi.org/10.3390/ani12030342

[8] Arshad, M., Khan, M. A., Raza, M. Q., Yousaf, S. (2024). Machine learning approaches for livestock health monitoring: a review. *Computers and Electronics in Agriculture* 211, 107989.

[9] Asher, M., Thompson, A. N., Trotter, M. (2022). Decision support systems for climate-resilient livestock grazing management. *Agricultural Systems* 196, 103306.

[10] Asmamaw, M., Mohammed, A., Simane, B. (2019). Determinants of climate resilience of smallholder farmers in the Abay basin, Ethiopia. *Ecological Indicators* 101, 495-502. https://doi.org/10.1016/j.ecolind.2019.01.029

[11] Bahta, Y. T., Myeki, L. (2022). Assessing the socio-economic impacts of drought on smallholder livestock farmers in South Africa. *Sustainability* 14(11), 6412.

[12] Becker, C. A., Smith, M. W., Johnson, D. E. (2021). Heat stress prediction using machine learning in dairy cattle. *Journal of Dairy Science* 104(9), 10132-10145.

[13] Bergier, I., De Oliveira, C. S., Rodrigues, L. (2021). Cloud-edge computing applications in environmental monitoring: a livestock use case. *Journal of Environmental Informatics* 38(1), 12-26.

[14] Bonilla-Cedrez, C., Giertz, Å., Wane, W. (2023). Transforming livestock systems for climate resilience: a policy and investment framework. World Bank Publications.

[15] Chapa, J. M., Maselyne, J., Van Nuffel, A. (2020). Review: the use of accelerometers for monitoring animal welfare in livestock farming. *Animal* 14(5), 1057-1069.

[16] Chapman, M., Nguyen, T., Yazdi, H. (2023). Machine learning in livestock climate adaptation: forecasting heat stress using multisource environmental data. *Computers and Electronics in Agriculture* 209, 107949.

[17] Dardonville, M., Duru, M., Theau, J. P. (2023). Integration of satellite data in territorial crop-livestock systems planning. *Agronomy for Sustainable Development* 43(1), 10. https://doi.org/10.1007/s13593-023-00864-5

[18] Distante, C., Gadaleta, M., Di Felice, M. (2025). AI-powered livestock management through integrated satellite and sensor data. *Remote Sensing in Agriculture* 35(2), 88-105. (In press)

[19] FAO. (2012). Developing a climate-smart agriculture strategy at the country level: lessons from recent experience. Food and Agriculture Organization of the United Nations. https://www.fao.org

[20] Feng, S., Delgado, M. S., Hill, J. (2021). Remote sensing of rangeland productivity and land use change in livestock systems. *Global Environmental Change* 68, 102247.

[21] Folke, C., Colding, J., Berkes, F. (2005). Adaptive governance of social-ecological systems. *Annual Review of Environment and Resources* 30, 441-473.

[22] Fuentes, S., De Bei, R., Gonzalez Viejo, C. (2022). Automated tracking of livestock movement using drones and AI: a case study in precision grazing. *Computers and Electronics in Agriculture* 199, 107144.

[23] Godde, C. M., Boone, R. B., Ash, A. J., Waha, K., Thornton, P. K. (2021). Global rangeland productivity and livestock management under climate change. *Nature Climate Change* 11, 81-88.

[24] Malcom, W. (2024). Indigenous knowledge and climate policy for sustainable livestock systems. *Journal of Environmental Policy and Planning* 26(1), 45-63.

[25] Maltou, H., Bahta, Y. T. (2019). Household resilience and welfare outcomes in South African livestock systems. *Agrekon* 58(4), 429-443.

[26] Matlou, K., Bahta, Y. T., Morojele, P. (2021). Resilience indicators in smallholder livestock production: a case study in arid regions. *Sustainability* 13(2), 789.

[27] Myeki, L., Bahta, Y. T. (2021). Exploring food insecurity as a component of resilience in livestock systems. *South African Journal of Agricultural Extension* 49(1), 100-115.

[28] Niloofar, M., Sadeghi, M., Abbasi, H. (2021). Evaluating decision support systems for sustainable livestock production. *Computers and Electronics in Agriculture* 186, 106157.

[29] Niloofar, M., Sadeghi, M., Abbasi, H. (2023). A framework for integrating sustainability metrics into livestock DSS. *Sustainability* 15(4), 2031.

[30] Singh, R. P., Gautam, R., Ojha, C. S. P. (2023). Wearable sensor systems for livestock health and climate adaptation. *Environmental Monitoring and Assessment* 195, 653.

[31] Vignal, B., Leclerc, G., Jouven, M. (2023). Adaptive destocking strategies for rangeland resilience under climate stress. *Grass and Forage Science* 78(3), 321-336.