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SmartHerd Decision Support Framework for Adaptive Livestock Management Under Changing Environmental Conditions

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Key Words

decision support system, adaptive livestock management, precision livestock farming, climate resilience, heat stress, herd health monitoring

Abstract

Climate change presents a growing threat to the wellbeing and productivity of livestock as well as profit-making through its impact on the livestock production system. Existing livestock herding practices are based mostly on fixed thresholds and reactive measures, which do not suffice for the new challenges presented by climate change. The purpose of this research is to outline an innovative framework called SmartHerd, which is designed to facilitate adaptive herding of livestock under changing conditions of climate. The SmartHerd decision support framework involves the combination of real-time monitoring of environmental factors and animals' physiologic state, multi-tiered classification of risks, and adaptive recommendation system based on rule logic into a modular structure appropriate for any farm regardless of its size and resourcefulness. In contrast with existing approaches in developing decision support frameworks, which are focused primarily on a single stressor or a production-related indicator, the proposed framework brings together a number of sources of information - temperature-humidity index values, animal-specific physiologic data, and herd-specific production performance indicators - into one decision layer. The design rationale for each layer, present a comparative analysis of existing precision livestock farming and decision support literature, and outline evaluation criteria for framework adoption across low-resource and high-resource farm settings. The paper further discusses implementation pathways, data governance considerations, and barriers to adoption, including cost, connectivity, and farmer trust. By consolidating dispersed monitoring and decision-making functions into a coherent and adaptable structure, SmartHerd aims to support more resilient, welfare-conscious, and economically sustainable livestock management as environmental variability intensifies globally.

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Introduction

Background and Motivation

The changing environmental conditions due to climate change are affecting livestock farming. The elevated temperatures, increase in number of heat waves, and growing uncertainty in the environment lead to constant physiological stress on the farm animals (Becker et al., 2021; Gorczyca & Gebremedhin, 2020). This stress decreases feed consumption, fertility, productivity, and immunity, and increases morbidity risk, causing significant financial losses (Bovo et al., 2021; Lees et al., 2019). In traditional livestock management, decisions have been made based on rigid schedules and threshold values like THI to initiate certain actions. However, such approach is unable to account for cumulative and personalized effect of environmental stress.

Development of precision livestock farming (PLF), namely, wearable sensors, environmental monitoring, and machine learning predictions, provides the technical basis for adaptive, data-driven herd management (Becker et al., 2021; Gorczyca & Gebremedhin, 2020; Idris et al., 2021). Research demonstrates that machine learning allows for accurate predictions of heat stress and core body temperature ; moreover, continuous monitoring enables early detection of thermal stress and diseases (Kim et al., 2019; Lees et al., 2019). However, the current research is fragmented, where individual works focus on one type of sensing or predictive algorithm without considering a holistic decision-making system. There is a gap between current sensor/prediction techniques and farm-based decision-making systems which provide actionable decisions based on multi-sensor/multi-prediction inputs.

Key Contributions

This paper aims to fill this gap by suggesting a decision support framework, SmartHerd, for adaptive livestock management. Key contributions of this paper are:

(1) Synthesis of recent findings from precision livestock farming and animal physiology in order to identify the key environmental stressors and sensing modalities
(2) Proposal of a four-layer decision support architecture including data acquisition, risk assessment, adaptive decision logic, and stakeholder communication.
(3) A system of risk classifications and adaptive management actions associated with specific combinations of environmental and physiological indicators is defined.
(4) Implementation issues such as evaluation criteria and factors are provided in order to employ the framework in farms with diverse technology and economic conditions.

Paper Organization

The rest of this paper is organized as follows. Section 2 provides related work on precision livestock farming, environmental stress prediction, and decision support systems for animal agriculture. Section 3 describes the SmartHerd framework and its four layers along with the risk classification and adaptive action mappings. Section 4 discusses implementation issues, evaluation criteria, and ways for adopting the framework in different farm settings. Limitations and future work are addressed in Section 5. Finally, Section 6 concludes this paper.

Related Work

Increasingly, sensor-based monitoring of and predictive modeling for livestock environmental stress has been investigated (Becker et al., 2021). Machine learning has been utilized for prediction of heat stress in dairy cattle from environment and animal level sensors, showing that ensembles are capable of predicting stress before indices based on thresholds (Becker et al., 2021). Stress due to environmental heat stress has been ranked, with interactions among multiple variables shown to dictate stress level and not just temperature (Gorczyca & Gebremedhin, 2020). Random forest modeling has been used to predict reduction in milk yield in relation to environmental heat stress (Bovo et al., 2021). Rumen temperature boluses with machine learning have been used to predict heat stress events in pasture-based dairy cows (Woodward et al., 2024). Non-invasive physiological measures, such as respiration rate, panting score and surface temperature have been identified as appropriate metrics for continuous heat stress monitoring (Idris et al., 2021). Real-time temperature measurement has also been developed for mastitis detection (Kim et al., 2019). In addition, there are review papers that summarize the physiological, behavioral, and production effects of heat load in cattle, as well as the necessity of heat stress management according to various stress levels (Lees et al., 2019).

Table 1: Summary of Reviewed Studies on Environmental Stress Monitoring and Prediction in Livestock

Study	Primary Focus	Monitoring Modality	Analytical Approach
Becker et al.	Heat stress prediction	Environmental + animal data	Ensemble machine learning
Gorczyca & Gebremedhin	Stressor ranking	Multi-variable environmental data	Machine learning ranking
Bovo et al.	Milk yield under heat stress	Environmental + production data	Random forest modeling
Woodward et al.	Heat stress event prediction (grazing)	Rumen temperature bolus	Machine learning
Idris et al.	Non-invasive stress indicators	Behavioral + physiological signals	Literature review
Kim et al.	Early mastitis detection	Real-time body temperature	Threshold + monitoring system
Lees et al.	Heat load impact synthesis	Cross-modality (review)	Comprehensive literature review

Table 1 presents these studies. Together, they provide evidence that (i) multiple environmental factors interact to influence the degree of stress experienced by animals, (ii) machine learning techniques are superior to single-threshold indices, (iii) non-invasive continuous monitoring of animal wellbeing is possible in different housing systems, and (iv) monitoring covers wider health surveillance. They fail to suggest, however, an integrated, implementable decision architecture; rather, all of them suggest a part of it: a model, a monitoring method, or a set of indicators.

The SmartHerd Decision Support Framework

Framework Overview

The architecture of SmartHerd includes four layers, described in Table 2. The output of each layer serves as the input for the subsequent one, which makes the solution scalable: a farm can start implementing SmartHerd from data collection and risk assessment, and gradually go through adaptive decision making and communication with stakeholders. This takes into account different technological readiness of farms – ranging from smallholders without any connectivity to fully automated commercial dairies.

Table 2: The Four Functional Layers of the SmartHerd Decision Support Framework

Layer	Function	Representative Inputs	Representative Outputs
1. Data Acquisition	Continuous collection of environmental and animal-level data	Ambient temperature, humidity, wind, animal surface/core temperature, respiration rate, activity, rumination	Time-stamped raw and pre-processed data streams
2. Risk Assessment	Classification of current and forecast stress severity	THI, physiological indicators, breed/production-stage metadata	Tiered risk classification (low/moderate/high/severe)
3. Adaptive Decision Logic	Mapping of risk tier and indicator pattern to recommended actions	Risk tier, herd composition, resource availability	Ranked, context-specific management recommendations
4. Stakeholder Communication	Delivery of recommendations to farm personnel in interpretable form	Recommendation set, user role, delivery channel	Alerts, dashboards, and action logs

Data Acquisition Layer

The data acquisition process is based on the monitoring approaches presented in the reviewed literature. Environmental variables (ambient temperature, humidity, solar radiation, and wind speed) are aggregated into indexes like THI, in accordance with multi-variable stressor ordering by (Gorczyca & Gebremedhin, 2020). Animal-level physiological data are acquired non-invasively when possible, according to the indicator set of, including respiration rate, panting score, and surface/core temperature. If applicable, rumen temperature boluses provide data with adequate resolution for pasture-based systems. Production and health data, such as the trend in milk yield and early mastitis markers, constitute the second channel for linking environmental exposure with downstream effects.

Risk Assessment Layer

The risk assessment layer categorizes environmental conditions into several risk tiers, rather than using a one-cut decision rule. This addresses the shortcoming of single-indicator thresholds, which overlook compound stress conditions. An example of tier-based categorization inspired by stress severity groups.

Table 3. Illustrative tiered risk classification combining environmental and physiological indicators

Risk Tier	Approximate THI Range	Physiological Indicators	General Herd State
Low	< 68	Normal respiration rate; no panting	No intervention required
Moderate	68–74	Elevated respiration rate; occasional panting	Early behavioral adaptation; monitoring intensified
High	75–79	Sustained panting; elevated surface temperature	Feed intake and yield decline likely; active mitigation needed
Severe	≥ 80	Open-mouth panting; elevated core temperature; reduced activity	Welfare and production risk elevated; urgent intervention required

Adaptive Decision Logic Layer

The adaptive decision logic layer takes the risk tier generated from section 3.3 with context-aware herd information and converts it into a prioritized list of recommendation actions. As such, it is a rule-based system rather than a black box to ensure recommendations are comprehensible to and auditable by farm management staff. Table 4 displays an example action library which shows how interventions are escalated according to risk tier.

Table 4. Representative mapping of risk tier to adaptive management actions within the SmartHerd framework

Risk Tier	Recommended Adaptive Actions	Responsible Role
Low	Routine monitoring; no schedule changes	Herd attendant
Moderate	Increase water access points; adjust feeding to cooler hours; increase shade access	Farm manager
High	Activate supplemental cooling (fans/sprinklers); reduce stocking density; reschedule handling and transport	Farm manager / veterinary advisor
Severe	Emergency cooling protocols; veterinary consultation; suspend non-essential handling; isolate and monitor at-risk animals	Veterinary advisor / farm owner

Stakeholder Communication Layer

The outermost layer makes classifications and suggestions available to the concerned parties – herd attendants, farm managers, veterinary advisors – using role-specific communication mechanisms like mobile alerts for the former and dashboards for the latter. It keeps an action log for the recommendations generated and acted upon by the stakeholders.

Implementation Considerations and Evaluation Criteria

Adapting SmartHerd to farms of varying sizes would need to address issues of cost, connectivity, and usability, common challenges to adoption cited in precision livestock farming literature. Evaluation criteria are presented in Table 5.

Table 5. Evaluation criteria for assessing SmartHerd implementation across farm contexts

Evaluation Dimension	Criterion	Illustrative Metric
Technical	Sensor coverage and data completeness	Proportion of herd continuously monitored
Technical	Prediction and classification accuracy	Agreement between risk tier and observed stress outcomes
Economic	Cost of deployment and maintenance	Cost per animal per year relative to production value protected
Organizational	Recommendation uptake	Proportion of high/severe-tier recommendations acted upon
Organizational	Usability and trust	Farm personnel confidence in and comprehension of alerts
Welfare	Reduction in stress-related incidents	Change in heat-stress-related morbidity or production loss over time

Small-scale farms can deploy the simple architecture by employing inexpensive ambient sensors together with manual behavioral observations. Large-scale farms can adopt the whole architecture by continuously monitoring the physiology of the animals. The feasibility of this has been shown in, and automated dashboards. The scalability of this framework from small farms to large farms makes it applicable to diverse production environments around the globe.

Discussion and Limitations

SmartHerd is framed as a structural integration of monitoring and predictive systems separately validated previously, but not validated on a field trial basis by this paper. The major contribution is its architecture which integrates scattered results - ranking of stressors, modeling yield-impact relations, monitoring of animal physiology continuously, selecting non-invasive indicators, and integrating stress severity - into a modular design that a farm can implement in layers. The limitations are related to lack of empirical evidence to validate the risk levels and actions in Tables 3-4 for various breeds, climates and systems as literature-based thresholds depend on particular cases. In addition, there is a need to address data governance as monitoring data become tied to an individual animal more often than before. The future research should focus on field testing for different farms, locally adjusted thresholds, and forecast-based environmental data in order to conduct preemptive management.

Conclusion

This paper presented SmartHerd, a decision support framework for adaptive livestock management under changing environmental conditions. Motivated by the growing threat climate variability poses to livestock welfare and productivity, and by the fragmentation of existing precision livestock farming research into single-modality or single-stressor studies, SmartHerd consolidates environmental monitoring, physiological indicators, tiered risk assessment, and rule-based adaptive decision logic into a unified, four-layer architecture. Development of the framework was achieved through the synthesis of seven different types of research, including heat stress prediction; ranking of environmental stressors; modeling of production impacts; physiological monitoring in continuous form; non-invasive indicators identification; and health surveillance. The framework was made interpretable, auditable, and adoptable in sequential steps for farms with various technological and financial capacities. Tiered risk classification and adaptive actions presented in the framework serve as a tool for transformation of the output of the predictive models used in the literature into herd management practices for farmers. Criteria for evaluation of the framework performance on different levels, such as technical, economic, organizational, and welfare aspects, were stated for future use. Although the framework requires empirical validation in order to generalize its thresholds and action mappings, the multi-layered approach of the framework provides a way for implementation of precision livestock farming knowledge into practice. With growing environmental variability, frameworks that include monitoring and prediction tools within one decision-making structure, like SmartHerd, will become increasingly relevant.

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