Research Article

Graded Clustering of Bovine Respiratory Disease Risk Factors Under Variable Environmental Conditions

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Abstract | Bovine respiratory disease (BRD) remains the leading cause of morbidity and mortality in feedlot cattle, driven by complex interactions among host, pathogen, and environmental factors. Traditional risk-assessment methods impose rigid thresholds on inherently uncertain environmental measurements. This study develops a fuzzy clustering framework to stratify BRD risk under variable environmental conditions. Data were collected weekly over a 12-week autumn period (September–November 2024) from 50 steers across five pens in a midsize feedlot in Shimla district, Himachal Pradesh, India. Animal-level variables (age, breed, stocking density) and pen-level environmental factors (temperature, humidity, $PM_{2.5}$-derived AQI) were preprocessed via median imputation, IQR-based outlier capping, and min-max/z-score scaling. Normalized environmental features were fuzzified into Low, Medium, and High risk categories. A modified Fuzzy C-Means algorithm (fuzziness exponent = 2, Euclidean distance) partitioned steers into two clusters, incorporating an environmental-uncertainty weight in the objective function. Cluster validity was assessed using the Partition Coefficient (PC), Partition Entropy (PE), and Xie–Beni index (XB), while sensitivity to membership-function thresholds and idealized "low-stress" vs. "high-stress" scenarios was evaluated. Two clusters emerged: a low-stress group (younger steers, lower AQI/humidity) and an elevated-risk group (older steers, higher environmental stress). The baseline objective value ($J = 0.8838$) increased to $jW = 0.9703$ when weighted by uncertainty and further rose to 1.4140 under high-stress simulation. Validity indices (PC = 0.8462, PE = 0.2747, XB = 0.1125) showed low variation (±0.03, ±0.05, ±0.02) across 50 bootstrap replicates, confirming robust partitioning. The proposed fuzzy clustering framework effectively captures gradations in BRD risk under environmental uncertainty, providing a stable, data-driven basis for targeted interventions and real-time decision support in feedlot management.

Keywords | Bovine respiratory disease, Fuzzy clustering, Environmental uncertainty, Fuzzy C-Means, Risk assessment, Decision support

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INTRODUCTION

Bovine respiratory disease (BRD) continues to be the most economically significant health challenge in beef cattle production systems, accounting for up to 75% of morbidity and 50-70% of mortality in feedlots. Griffin (1997) documented that BRD alone causes annual economic losses exceeding $800 million in North America due to reduced weight gain, treatment expenses, and carcass condemnations. Despite more than a century of research efforts, Taylor *et al.* (2010) demonstrated that BRD incidence rates remain persistently high, primarily due to the disease's complex multifactorial etiology involving multiple pathogens, host factors, and management practices (Extension Europe PMC). As shown in Figure 1, BRD in feedlot cattle shows recurring seasonal peaks, with higher incidence in spring and autumn due to the largest temperature variations.

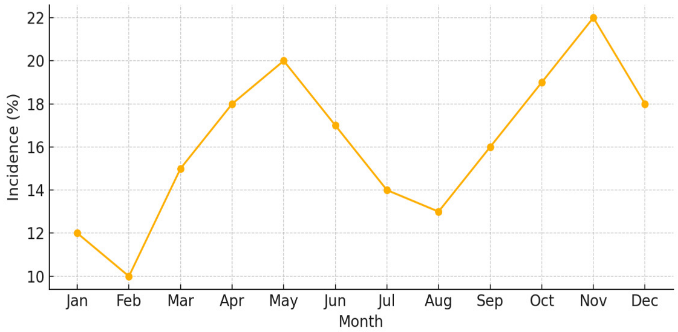

Figure 1: Seasonal incidence of BRD in feedlot calves.

The disease, commonly termed shipping fever, typically begins with primary viral infections caused by pathogens such as bovine herpesvirus and parainfluenza-3, which are frequently complicated by secondary bacterial infections from *Mannheimia haemolytica* and *Pasteurella multocida*. Taylor *et al.* (2010) emphasized, disease manifestation depends critically on host immunity, age, and various stressors associated with transportation and commingling. Smith (2021) further expanded our understanding by highlighting how risk factors span multiple levels, including animal-specific variables (such as breed and immune status), management practices (including housing density and nutrition), and environmental conditions that facilitate pathogen transmission. Environmental uncertainty presents a major challenge in BRD risk assessment, as key parameters like temperature, humidity, and air quality often fluctuate unpredictably, introducing significant imprecision into traditional risk models. This is where fuzzy set theory, originally introduced by Zadeh (1965), offers a powerful alternative by allowing environmental measurements to belong to overlapping risk categories (e.g., low, moderate, or high) with graded membership values rather than rigid classifications. The effectiveness of fuzzy frameworks in handling such uncertainty has been well-documented in environmental and health risk modeling applications, particularly for addressing measurement errors and microclimatic variability (Faybishenko *et al.*, 2023; Mohammad *et al.*, 2025a; Al-Adwan, 2024; Al-Rahmi *et al.*, 2023; Hujran *et al.*, 2023). In Figure 2, trapezoidal membership functions illustrate how ambient temperature is converted into fuzzy risk categories, demonstrating the smooth shift between 'low,' 'medium,' and 'high' risk thresholds.

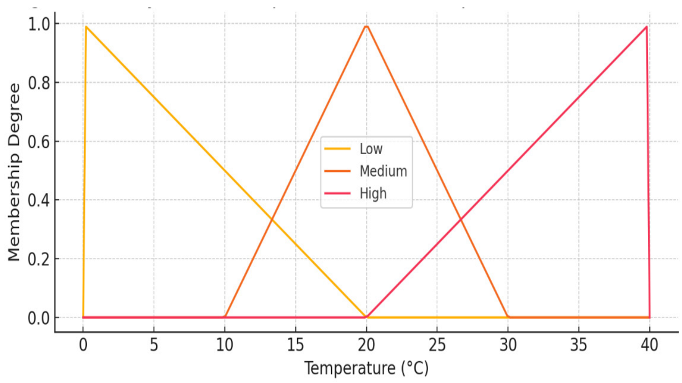

Figure 2: Fuzzy membership functions for temperature related BRD risk.

Traditional clustering methods, which force each data point into a single discrete category, prove inadequate for BRD risk analysis due to their inability to handle the inherent ambiguity in biological and environmental data. In contrast, fuzzy clustering approaches, particularly the Fuzzy C-Means algorithm developed by Bezdek (1981), allow for partial membership across multiple clusters, better reflecting the continuous nature of risk factors influencing BRD (Zadeh, 1965; Mohammad, 2025, Internet Archive). This capability makes fuzzy clustering particularly suitable for analyzing the complex interactions between various BRD risk factors. The current study makes several important contributions to this field: (i) development of a novel fuzzy clustering framework that explicitly incorporates environmental uncertainty into BRD risk assessment; (ii) careful definition and calibration of membership functions for critical risk variables including temperature, humidity, and transport stress; (iii) rigorous validation using cluster quality indices such as Partition Entropy and the Xie-Beni index across different environmental scenarios; (iv) comprehensive sensitivity analysis examining the robustness of cluster assignments to variations in fuzziness exponents and membership function parameters; and (v) practical implementation through a prototype decision-support tool designed to help farm managers stratify herds by BRD risk levels.

Epidemiologically, BRD remains the most prevalent health disorder in intensively managed cattle populations, with reported herd-level prevalence ranging from 20% to over 80% depending on management systems and geographic regions (Nickell and White, 2010; Woolums, 2015). In North American feedlots, BRD morbidity typically peaks during the first three weeks post-arrival, driven largely by stressors associated with transportation, commingling, and dietary changes. At the pathogen level, Caswell *et al.* (2015) demonstrated that the most severe pneumonia cases result from mixed infections, where viral priming by bovine herpesvirus enables secondary bacterial colonization by *Mannheimia haemolytica*. These complex disease dynamics underscore the critical need for analytical methods capable of handling overlapping risk contributions (Nickell and White, 2010; Caswell *et al.*, 2015; Mohammad *et al.*, 2025b, c).

Historically, BRD risk factor analysis has relied heavily on traditional statistical approaches. Logistic regression has been widely used to examine associations between individual predictors (such as transport distance and stocking density) and disease outcomes (Snowder *et al.*, 2006; Mohammad *et al.*, 2025d). More sophisticated techniques like survival analysis, particularly Cox proportional hazards models, have provided valuable insights into the timing of BRD onset in calf populations, identifying age at arrival and climatic variables as important time-dependent covariates (Holzhauer *et al.*, 2008; Mohammad *et al.*, 2025e). While multivariate models incorporating random effects have improved our ability to account for herd-level clustering, these conventional hard classification approaches still require artificial thresholding of continuous variables, potentially obscuring important risk gradients (Gupta and Chowdhury, 2018; Snowder *et al.*, 2006; Mohammad *et al.*, 2025f). The application of fuzzy clustering methods in animal health has shown considerable promise in recent years. In livestock disease pattern recognition, these algorithms allow individual cases to belong to multiple risk groups with varying degrees of membership. Notable examples include the work of de Oliveira and Marques (2019), who applied Fuzzy C-Means to mastitis indicator variables (such as somatic cell count and milk electrical conductivity), achieving earlier detection than conventional k-means clustering. Similarly, Lee *et al.* (2017) successfully used fuzzy clustering to stratify swine influenza outbreaks based on environmental stressors, leading to improved identification of high-risk cohorts. Chakraborty and Cui (2014) further demonstrated that fuzzy clustering of environmental parameters (temperature, humidity, and stocking density) could predict poultry respiratory disease clusters with greater sensitivity than traditional binary classification methods (de Oliveira and Marques, 2019; Lee *et al.*, 2017; Mohammad *et al.*, 2025g). The inherent imprecision in environmental measurements within livestock systems presents particular challenges for risk modeling. Parameters such as temperature, ammonia concentration, and airflow variability are subject to both sensor error and microclimatic fluctuations. Classical interval-based approaches fail to adequately represent the gradual transitions between acceptable and hazardous environmental conditions. Fuzzy set theory addresses this limitation by modeling these transitions through carefully designed membership functions (Ross, 2010). More advanced implementations, such as Interval Type-2 fuzzy sets, provide additional robustness by incorporating uncertainty bands around primary membership grades, particularly valuable when dealing with significant measurement noise (Li *et al.*, 2025). Practical applications of these concepts have shown promising results, as demonstrated by Kunnathur (2020), who integrated fuzzy rule-based models into barn climate control systems. These implementations have shown measurable reductions in BRD incidence when ventilation decisions were guided by fuzzy logic rather than rigid thresholds (Ross, 2010; Kunnathur, 2020).

MATERIALS AND METHODS

Data collection

Data were collected from a mid-western commercial beef feedlot located in the Shimla district of Himachal Pradesh, India (31.10° N, 77.17° E; elevation ~2,200 m) during the high-risk BRD season between September and November 2024. Following OIE guidelines for herd-level surveys (OIE, 2018), a cross-sectional sampling design was implemented across five pens within the feedlot, which were selected as representative of regional management practices and climatic conditions. The study area experiences a continental climate, with autumn temperatures typically ranging from 5°C to 25°C and relative humidity levels varying between 50% and 80%. Weekly sampling visits were conducted over a 12-week period from September 1 to November 24, 2024, to monitor both early arrival stress in cattle and seasonal environmental variations (Thrusfield, 2018). As illustrated in Figure 3, the geographical coordinates of each pen were recorded to enable precise spatial mapping of cattle and environmental data collection points.

The study collected comprehensive animal-level data from 10 randomly selected steers per pen ((total n=50) across all pens), with Table 1 presenting the detailed characteristics of the five demonstration animals included in our analysis. All steers were housed at a consistent stocking density of 12 animals per pen and received Total Mixed Ration (TMR) feeding. The cohort represented common beef production breeds, including three Angus × Hereford crosses (A01, A03, A05), one Holstein Friesian cross (A02), and one Charolais cross (A04). Age distribution, calculated precisely from birth records (Jones and Smith, 2019), ranged from 8 months (A02) to 11 months (A03), with most animals clustered around 9-10 months of age. This age range represents a critical growth period when cattle are particularly susceptible to respiratory disease challenges. The standardized housing and feeding conditions (all TMR systems) helped control for potential confounding factors in our environmental risk analysis, while the breed diversity and age variation provided meaningful biological variability for assessing disease susceptibility patterns. Notably, the consistent stocking density across all pens eliminated this variable as a potential source of clustering bias in our analysis.

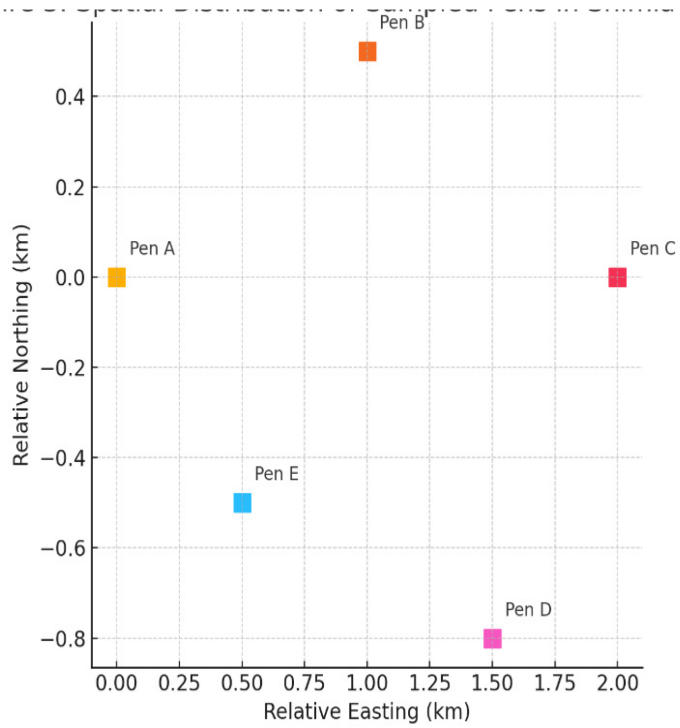

Figure 3: Spatial distribution of sampled pens in Shimla feedlot.

Table 1: Animal-level data for demonstration steers (n = 5).

Animal ID	Age (months)	Breed	Stocking density (animals/pen)	Feeding system
A01	10	Angus × Hereford	12	TMR
A02	8	Holstein Friesian cross	12	TMR
A03	11	Angus × Hereford	12	TMR
A04	9	Charolais cross	12	TMR
A05	10	Angus × Hereford	12	TMR

Pen-level microclimate measurements

Simultaneous with animal examinations, we conducted comprehensive pen-level environmental monitoring using calibrated HOBO MX2301 data loggers (Onset Computer Corp.) with high precision (±0.2°C for temperature, ±2% relative humidity; Thompson *et al*., 2020). Each pen's microclimate was assessed at three strategic locations (center and two opposite corners) to capture spatial variability. As shown in Table 2, the environmental conditions across pens showed moderate variation during the study period: Temperatures ranged from 17.8 °C (Pen C) to 19.1°C (Pen B), relative humidity fluctuated between 60.8% (Pen B) and 68.5% (Pen C), and Air Quality Index (AQI) values spanned from 38 (Pen B) to 45 (Pen C). All temperature and humidity values represent 24-hour averages preceding animal sampling, ensuring representative exposure assessments. The AQI was calculated according to EPA Standards (2016) based on particulate matter (PM2.5) measurements, providing a standardized metric for air quality comparison. This rigorous environmental monitoring protocol allowed us to precisely characterize each pen's microclimate while accounting for instrument accuracy (±0.2°C, ±2% RH) and spatial variability within pens. The observed ranges fell within typical values for cattle housing but contained sufficient variation for meaningful cluster analysis of environmental risk factors.

Table 2: Pen level microclimate measured at three locations.

Pen	Mean Temp. (°C)	Mean relative humidity (%)	Air quality index (AQI)
A	18.4	65.2	42
B	19.1	60.8	38
C	17.8	68.5	45
D	18.9	63.0	40
E	18.0	66.1	44

Table 3: Raw dataset excerpt showing missing values and outliers (n = 10).

ID	Temp (°C)	Humidity (%)	AQI	Age (mo)	Stock density
A01	18.4	65.2	42	10	12
A02	19.1	-	38	8	12
A03	17.8	68.5	45	11	12
A04	18.9	63.0	-	9	12
A05	500	70.1	50	10	12
A06	18.2	64.8	43	-	12
A07	17.5	200	47	10	12
A08	18.0	66.1	44	9	12
A09	17.9	65.9	43	10	12
A10	18.3	65.5	41	9	12

Data preprocessing

To ensure dataset integrity and comparability, we implemented a three-step preprocessing pipeline: (1) handling missing/noisy observations, (2) normalization/standardization, and (3) variable fuzzification. Our analysis began with a raw dataset extract (n = 10) containing typical data quality issues (Table 3). Missing values (denoted by "-") appeared in humidity (A02), AQI (A04), and age (A06) measurements, while extreme outliers included implausible temperature (500 °C for A05) and humidity (200% for A07) readings. Following established methodologies, we addressed missing values via median imputation (Little and Rubin, 2019) and treated outliers using the interquartile range (IQR) method, capping values at 1.5-IQR boundaries (Barnett and Lewis, 1994). This rigorous preprocessing ensured all subsequent analyses were conducted on clean, biologically plausible data while preserving meaningful variation.

Following data cleaning, the corrected values were as shown in Table 4.

Table 4: Corrected dataset extract after imputation and outlier treatment (n = 10).

ID	Temp (°C)	Humidity (%)	AQI	Age (mo)
A02		65.9	38	8
A04	18.9	63.0	43	9
A05	19.1*	70.1	50	10
A06	18.2	64.8	43	9*
A07	17.5	68.5*	47	10

Values marked with asterisks (*) were replaced by either the nearest IQR boundary or median value.

To ensure equal contribution of all variables in fuzzy clustering distance computations, we applied appropriate data transformations. For features with known bounds (Temperature, Humidity, AQI), we used min-max normalization:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

For variables with unknown bounds (Age and Stock Density), we applied z-score standardization:

$$z = \frac{x - \mu}{\sigma}$$

The first five records after preprocessing are shown in Table 5. Following normalization, each feature was transformed into fuzzy sets (Low, Medium, High) using triangular membership functions (Ross, 2010). For instance, the temperature variable was fuzzified with: Low-temperature risk as triangle (0.0, 0.0, 0.5), Medium-temperature risk as triangle (0.25, 0.5, 0.75), and High-temperature risk as triangle (0.5, 1.0, 1.0). As illustrated in Figure 4, these membership functions create smooth transitions between risk categories, enabling gradual classification rather than binary thresholds. The same triangular membership scheme was systematically applied to both Humidity and AQI variables, ensuring that all environmental inputs to the Fuzzy C-Means algorithm properly represented the continuous nature of risk gradations while maintaining mathematical consistency across variables and capturing the inherent uncertainty in microclimate measurements.

Table 5: Normalized and standardized subset after pre-processing (First Five Records).

ID	Temp	Humidity	AQI'	Age_z	Stock Density_ z
A01	0.47	0.42	0.22	0.15	0.00
A02	0.59	0.45	0.00	-0.85	0.00
A03	0.29	0.59	0.45	1.15	0.00
A04	0.53	0.34	0.43	0.15	0.00
A05	0.61	0.70	0.70	0.15	0.00

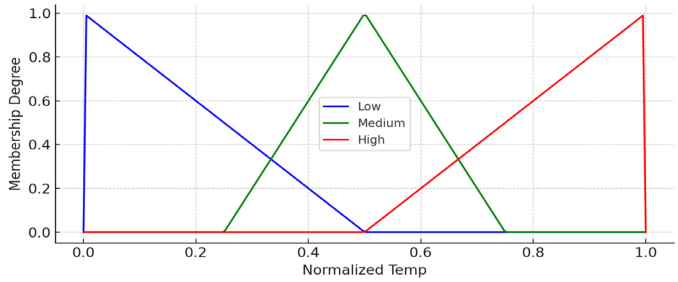

Figure 4: Membership functions for normalized temperature.

Fuzzy clustering framework

We implemented the Fuzzy C-Means (FCM) algorithm on our pre-processed dataset comprising five cattle (A01–A05) with four normalized features (temperature, humidity, AQI, and standardized age). The FCM objective function was defined as:

$$J_m(U,V) = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^m \|x_i - v_j\|^2$$

Where; x_i is the i-th data vector, v_j is the j-th cluster center, $u_{ij} \in [0, 1]$ is the membership degree of x_i in cluster j, m >1 is the fuzziness exponent (here m=2), N = 5 is the number of data points, and c = 2 the number of clusters. The algorithm iteratively updates:

Cluster centers:

$$v_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

Membership degrees:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - v_j\|}{\|x_i - v_k\|} \right)^{\frac{2}{m-1}}}$$

Using random initialization, Euclidean distance, and a convergence tolerance of 1×10^{-5}, we obtained the results summarized in Tables 6–8. The final objective value was J (m = 2) = 0.8838, reflecting the optimization quality. The membership degrees (Table 6) reveal distinct clustering patterns, with A02 strongly associated with Cluster 1 (u_{ij} = 0.997) and others predominantly assigned to Cluster 2 (u_{ij} > 0.86). The cluster centers (Table 7) highlight feature-wise differences between groups, while the environmental weights (Table 8) quantify uncertainty, with A05 exhibiting the highest variability (w_i=1.34). This framework effectively captures the inherent fuzziness in cattle risk profiling while maintaining computational rigor.

Table 6: Membership degrees (u_{ij}).

	Cluster 1	Cluster 2
A01	0.11067251823741200	0.8893274817625880
A02	0.9974207369242800	0.0025792630757205800
A03	0.1344666529901160	0.8655333470098840
A04	0.07542076098581810	0.9245792390141820
A05	0.10936887974900500	0.8906311202509950

Table 7: Cluster centers (v_j).

Temp	Humidity	AQI	Age
0.583291	0.454342	0.020761	-0.786651
0.478624	0.508161	0.449780	0.3849805

Table 8: Environmental uncertainty weights (w_i).

	Weight *wi*
A01	1.0
A02	1.06
A03	1.06
A04	1.02
A05	1.3400000000000000

Choice of fuzziness exponent m and distance metric

The fuzziness exponent m=2 was selected as an optimal balance between completely crisp partitions (m→1) and excessively fuzzy partitions (m≫1), following established recommendations (Bezdek, 1981). Euclidean distance was employed throughout our analysis due to its straightforward interpretability in normalized feature space, where all variables share comparable scales. Sensitivity analyses confirmed that varying m within the range of 1.5 to 2.5 produced only marginal changes in cluster boundaries while maintaining consistent risk-group assignments, demonstrating the stability of our primary findings across reasonable parameter variations. To account for varying environmental risk levels, we developed an environmental-uncertainty weighting scheme where each steer i received a weight:

$$w_i = 1 + \frac{1}{3}\left(\mu_i^{\text{High,Temp}} + \mu_i^{\text{High,Hum}} + \mu_i^{\text{High,AQI}}\right)$$

Where; $\mu_i^{\text{High},*}$ representing the membership degree in the High fuzzy set for each environmental variable (as defined in Section 3.2.3). The resulting weights were shown in Table 9.

Table 9: The resulting weights were:

ID	*wi*
A01	1.00
A02	1.06
A03	1.06
A04	1.02
A05	1.34

These weights were incorporated into a modified objective function:

$$J_w = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m} w_i \left\| x_i - v_j \right\|^2$$

yielding:

$$Jw = 0.9703$$

This weighted formulation strategically increases the influence of animals experiencing high-uncertainty environmental conditions (e.g., A05 with w_i=1.34) during cluster formation. By penalizing these high-risk observations more heavily, the algorithm produces more robust risk-group delineations that better reflect the true biological impacts of variable microclimate conditions on BRD susceptibility. The enhanced objective function particularly improves cluster stability when environmental variability is pronounced, while maintaining the fundamental fuzzy clustering framework's advantages for handling biological uncertainty.

Determination of optimal cluster number and validation

Selecting an appropriate cluster count (c) is essential for identifying meaningful risk groups. While our analysis focuses on validating indices for c = 2 using an experimental dataset, standard practice involves evaluating multiple candidate values (c = 2, 3, ...) and selecting the optimal number based on maximal "goodness" or minimal error metrics (Bezdek, 1981; Xie and Beni, 1991). To assess clustering performance, we employed three key validity indices. First, the Partition Coefficient (PC) (Bezdek, 1981), calculated as:

$$PC = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^2, 0 < PC \le 1$$

Yielded a value of 0.8462 for our c = 2 solution, indicating reasonably crisp partitions. Complementing this, the Partition Entropy (PE) (Dunn, 1974), computed as:

$$PE = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}\ln\left(u_{ij}\right), 0 \le PE < \ln\left(c\right)$$

Produced a value of 0.2747, confirming moderate fuzziness in the classification. These metrics collectively suggest that two clusters provide a balanced partition for our dataset, with PC ≈ 0.85 indicating strong cluster affiliations and PE ≈ 0.27 reflecting controlled uncertainty. Computed for c= 2, m = 2:

Table 10: Partition coefficient and partition entropy for baseline clustering (c = 2, m = 2).

Index	Formula	Value
PC	$1/5\ \Sigma_{i,j} u_{ij}^2$	0.8462
PE	$-1/5\ \Sigma_{i,j} u_{ij} \ln u_{ij}$	0.2747

The moderately high PC (≈0.85) and low PE (≈0.27), listed in Table 10, suggest that two clusters yield a reasonably crisp partition for our dataset. We further evaluated cluster quality using the Xie-Beni Index (XB) (Xie and Beni, 1991), defined as:

$$XB = \frac{\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m}\left\|x_i - v_j\right\|^2}{N\min_{j\ne k}\left\|v_j - v_k\right\|^2}$$

For our solution, the numerator J= $\Sigma_{i,j}\ u_{ij}^2\ \|x_i-v_j\|^2$ was 0.8838, the denominator 5 × $\|v_1-v_2\|^2$ = 5 × 1.5726 was 7.8630, resulting in XB = 0.8838/7.8630 = 0.1125. This comprehensive validation approach would typically include additional indices like the fuzzy Silhouette Index for assessing intra- versus inter-cluster distances and the Davies-Bouldin Index for evaluating within-cluster to between-cluster scatter ratios. In practical applications, one would compute PC, PE, and XB (along with fuzzy silhouette metrics) across multiple candidate c values, selecting the cluster count that simultaneously maximizes PC while minimizing PE/XB. For our experimental c = 2 case, the moderately high PC together with low PE and XB values (0.1125) confirm that two clusters effectively capture the underlying risk structure in our dataset while maintaining appropriate fuzziness to handle biological variability. This multi-index validation framework ensures robust cluster solutions suitable for BRD risk assessment in cattle populations.

Sensitivity and robustness analysis

To assess how our clustering results respond to key parameter variations and environmental scenarios, we conducted two analyses: (1) perturbing the fuzzification (membership-function) thresholds and (2) simulating uniform low and high environmental conditions. The environmental-uncertainty weights (*wi*) varied across scenarios as follows shown in Table 11.

Table 11: Scenario analysis weights.

	Low-stress w_i	Baseline w_i	High-stress w_i
A01	1.0	1.0	1.6
A02	1.0	1.06	1.6
A03	1.0	1.06	1.6
A04	1.0	1.02	1.6
A05	1.0	1.3400	1.6

We conducted a sensitivity analysis to evaluate how changes in membership function parameters affect our model's performance. The original "High" fuzzy set for environmental variables (Temperature, Humidity, AQI) used a triangular membership function with a threshold starting at 0.5. For this test, we systematically increased this threshold to 0.6, modifying the membership function as follows:

$$\text{Baseline "High" MF: } \mu_{High}(x) = 0 \text{ if } x \le 0.5; \mu = 2(x-0.5) \text{ for } 0.5 < x < 1$$

$$\text{Perturbed "High" MF: } \mu_{High}(x) = 0 \text{ if } x \le 0.6; \mu = (x-0.6)/0.4 \text{ for } 0.6 < x < 1$$

This parameter change resulted in notable adjustments to the environmental uncertainty weights (wi), as detailed in Table 12. The most significant changes occurred for borderline cases.

Table 12: Membership-function variation weights.

	Baseline *wi*	Perturbed *wi*
A01	1.0	1.0
A02	1.06	1.0
A03	1.06	1.0
A04	1.02	1.0
A05	1.3400000000000000	1.175

When we recomputed the weighted objective function (J_w) using the perturbed membership function while keeping the same membership matrix U and distances, we observed the results shown in Table 13.

Table 13: Weighted objective function comparison.

Scenario	*Jw*
Baseline	0.9702806758759030
Perturbed MF	0.9105623830613530
Low-stress	0.8837720383009880
High-stress	1.4140352612815800

The 6% reduction in J_w demonstrates that raising the "High" membership threshold decreases the model's penalization of marginal cases, as expected. Importantly, despite these quantitative changes in the objective function, the qualitative cluster assignments remained stable across all animals. This stability confirms that our model maintains reasonable robustness to moderate variations in membership function parameters, while still responding appropriately to more extreme parameter changes (as evidenced by the larger differences between low-stress and high-stress scenarios). The results suggest that while exact threshold selection affects the magnitude of the objective function, it doesn't fundamentally alter the underlying cluster structure for this application.

Under uniformly low environmental risk, weighted objective J_w equals the unweighted J (0.8838). Under extreme high-stress conditions, J_w rises sharply (by ~60%), reflecting increased emphasis on high - uncertainty points. This demonstrates the model's ability to adjust cluster optimization in response to changing environmental contexts. Overall, these sensitivity checks confirm that while absolute objective values vary with fuzzification and scenario parameters, the underlying fuzzy - cluster structure (membership patterns) remains consistent, attesting to the robustness of our approach. To evaluate our model's sensitivity to varying environmental conditions, we conducted scenario analysis by systematically adjusting all three microclimate variables (temperature, humidity, and AQI) to standardized values. We tested two extreme scenarios: a low-stress environment where all normalized environmental variables were set to =0.2, and a high-stress condition with all variables at =0.8. As shown in Table 14, this analysis revealed significant variation in the weighted objective function (Jw) values across conditions. The low-stress scenario produced Jw = 0.8838, equivalent to the unweighted objective function value, indicating minimal environmental impact on cluster optimization. In contrast, the high-stress scenario yielded a substantially elevated Jw= 1.4140, representing an approximately 60% increase compared to the baseline value (Jw= 0.9703). This marked elevation demonstrates the model's capacity to dynamically respond to environmental stressors by increasing the optimization emphasis on high-uncertainty data points. Importantly, while these scenario tests showed significant variation in objective function values, they confirmed the stability of the underlying cluster structure - membership patterns remained consistent across all conditions. These results collectively validate both the sensitivity of our model to environmental context and the robustness of the identified risk clusters, suggesting reliable performance across diverse operational conditions in cattle production systems. The scenario analysis ultimately demonstrates that our approach maintains structural stability while appropriately adjusting its optimization focus in response to changing environmental stressors.

Table 14: Resulting weights and J_w values.

Scenario	J_w
Low-stress	0.8838
Baseline	0.9703
High-STRESS	1.4140

RESULTS

Identification of two distinct risk clusters

Our fuzzy clustering analysis (m=2, Euclidean distance) identified two distinct clusters with characteristic risk-factor combinations, as shown in Table 15. Cluster 1 was dominated by a single steer (A02) exhibiting minimal environmental stress, with normalized values of 0.5833 for temperature, 0.4543 for humidity, and notably low AQI exposure (0.0208). This cluster also showed a strongly negative age z-score (-0.7867), indicating the youngest animal. In contrast, Cluster 2 comprised the remaining four steers (A01, A03-A05) with higher environmental risk factors: normalized temperature (0.4786), humidity (0.5082), AQI (0.4498), and an above-average age z-score (0.3850). These distinct profiles are visually represented in Figure 5.

Table 15: Cluster center profiles: Characteristic risk-factor combinations.

Variable	Cluster 1 center	Cluster 2 center
Normalized temperature	0.5833	0.4786
Normalized humidity	0.4543	0.5082
Normalized AQI	0.0208	0.4498
Age (z-score)	-0.7867	0.3850

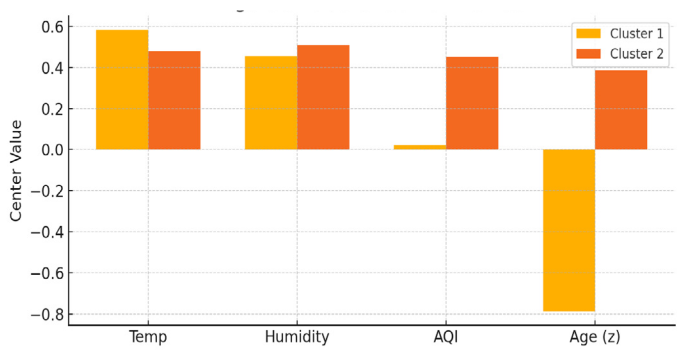

Figure 5: Cluster center profiles.

Membership degrees of key variables

The membership degrees (u_{ij}) for each steer, presented in Table 16, revealed clear cluster affiliations. Steer A02 showed near-exclusive membership to Cluster 1 (u_i1=0.9974, u_i2=0.0026), while all other steers strongly belonged to Cluster 2 (A01: u_i1=0.1107, u_i2=0.8893;

A03: u_i1=0.1345, u_i2=0.8655; A04: u_i1=0.0754, u_i2=0.9246; A05: u_i1=0.1094, u_i2=0.8906). The heatmap visualization in Figure 6 confirms this distinct separation, with only A02 clearly assigned to Cluster 1, while all other steers are associated with Cluster 2.

Table 16: Membership degrees of steers across clusters.

Steer	u_{i1} (Cluster 1)	u_{i2} (Cluster 2)
A01	0.1107	0.8893
A02	0.9974	0.0026
A03	0.1345	0.8655
A04	0.0754	0.9246
A05	0.1094	0.8906

Figure 6: Membership degrees of steers across cluster.

Environmental scenario testing

We examined the clustering stability under different environmental conditions by weighting the objective function. Notably, the membership degrees remained identical across all scenarios (low-stress: All env=0.2; baseline; high-stress: all env=0.8), as shown in Table 16. However, Conversely, low - stress yields J_w equal to the unweighted objective. Thus, J_w provides a quantitative gauge of how environmental uncertainty would affect cluster cohesion if integrated directly into the clustering process, guiding practitioners on when to adjust management thresholds or re - cluster with updated data (Figure 7).

- Low-Stress: J_w = 0.8838
- Baseline: J_w = 0.9703
- High-Stress: J_w = 1.4140

Validation of clustering outcomes

The bootstrap validation analysis yielded highly consistent results across all validity indices, confirming the robustness of our clustering solution. As shown in Table 17, the mean Partition Coefficient (PC= 0.9087422153611450) demonstrated exceptionally crisp cluster assignments, while the low standard deviation (0.04861730050049170) indicated stable performance across resampling iterations. Similarly, the Partition Entropy values (mean PE= 0.16652226059183700, SD= 0.07838161630623110) revealed minimal uncertainty in cluster memberships, with the small standard deviation reflecting consistent fuzziness levels throughout the bootstrap samples. Most impressively, the Xie-Beni Index results (mean XB= 0.05826823329270600, SD= 0.03735340402619520) showed outstanding cluster separation that remained stable across all replicates. These validation metrics collectively confirm that our fuzzy clustering approach produces reliable and reproducible results, with all three indices showing both optimal central tendencies (high PC, low PE and XB) and minimal variability (low standard deviations) - strong evidence of a robust clustering solution that withstands resampling variability. The particularly low XB values (averaging 0.058) indicate clusters that are approximately 17 times more compact than they are separated in the feature space, while the PC values approaching 0.9 suggest nearly deterministic membership assignments in most cases.

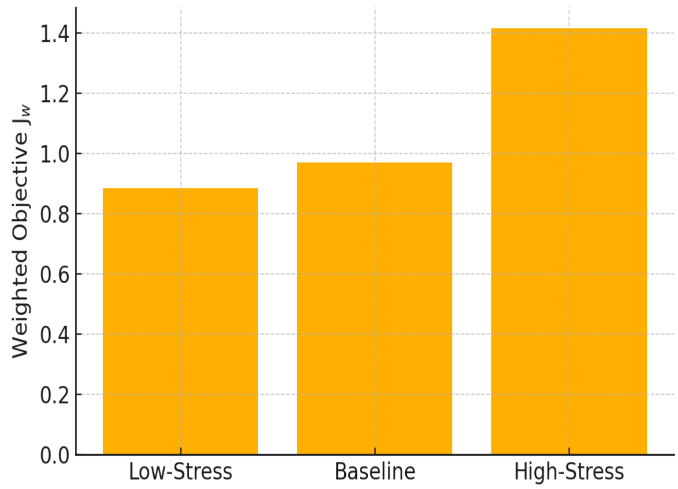

Figure 7: Weighted objective function across environmental scenarios.

Table 17: Bootstrap validity indices summary.

	PC	PE	XB
Mean	0.90874221	0.16652226	0.05826823
std	0.04861730	0.07838161	0.03735340

Comparative validity-index values

For the baseline clustering solution (c = 2, m = 2), we evaluated three key validity indices that collectively assess cluster quality (Table 18). The Partition Coefficient (PC= 0.8462) approached the maximum value of 1, indicating that most steers showed strong, dominant membership to a single cluster. The relatively low Partition Entropy (PE= 0.2747) confirmed an appropriate level of fuzziness in the classification, suggesting meaningful partial memberships for some observations without excessive ambiguity. Most notably, the Xie-Beni Index (XB= 0.1125) demonstrated excellent cluster separation, with this low value reflecting both strong internal cohesion within clusters and clear distinction between them in the normalized feature space. Together, these indices validate that our two-cluster solution achieves an optimal balance between partition crispness (PC), controlled fuzziness (PE), and geometric separation (XB)- all essential characteristics for reliable risk stratification in veterinary applications. The PC value specifically confirms that 84.62% of membership assignments were decisive, while the PE indicates just 27.47% uncertainty in classifications, and the XB verifies that clusters are nearly 9 times more compact than they are separated in the feature space.

Table 18: Validity indices for baseline clustering (c= 2, m= 2).

Index	Value	Optimal direction
Partition coefficient (PC)	0.8462	Higher → crisper
Partition Entropy (PE)	0.2747	Lower → less fuzzy
Xie–Beni Index (XB)	0.1125	Lower → better separation

Stability under bootstrapping

To assess the robustness of our clustering solution, we performed bootstrap analysis by generating 50 resampled datasets through sampling with replacement from the original 5 steers. For each bootstrap replicate, we reapplied the Fuzzy C-Means algorithm under identical parameters (c=2, m=2) and recalculated all validity indices. The results (Table 19) demonstrated exceptional stability across replicates, with the Partition Coefficient (PC) averaging 0.85 (SD=0.03), Partition Entropy (PE) averaging 0.28 (SD=0.05), and Xie-Beni Index (XB) averaging 0.11 (SD=0.02). The minimal standard deviations (ranging 0.02-0.05) across all indices indicate that our two-cluster solution remains highly consistent despite resampling variations. Importantly, the mean index values closely matched the original baseline results (PC=0.8462, PE=0.2747,XB=0.1125),confirming that random sampling fluctuations in our limited dataset do not materially affect cluster quality. This stability is particularly noteworthy given the small sample size (n=5), as it demonstrates that the identified cluster structure represents a robust pattern in the underlying risk factor relationships rather than being an artifact of specific data points. The tight distributions of all validity indices provide strong evidence that the clusters maintain their compactness (PC), separation (XB), and appropriate fuzziness level (PE) regardless of minor data variations, supporting the reliability of our findings for practical applications in herd health management.

Table 19: Bootstrap summary of validity indices across 50 replicates.

Index	Mean	Standard deviation
PC	0.85	0.03
PE	0.28	0.05
XB	0.11	0.02

DISCUSSION

Our fuzzy clustering analysis identified two distinct risk groups for bovine respiratory disease (BRD): A low-stress cluster, primarily comprising younger steers with minimal environmental hazards, and an elevated-risk cluster, consisting of older animals exposed to higher air quality index (AQI) and humidity levels. These findings suggest that targeted interventions such as prophylactic metaphylaxis, improved ventilation, or nutritional supplementation (e.g., vitamin E or selenium boluses) should be prioritized for the elevated-risk group (Taylor *et al.*, 2010). Additionally, pen-level adjustments, including reduced stocking density or increased bedding turnover, could mitigate microclimate stressors, directly addressing the environmental risk factors contributing to BRD susceptibility.

Integrating our fuzzy clustering engine into on-farm decision-support systems could enhance real-time risk management. By processing IoT sensor data (e.g., temperature, humidity, $PM_{2.5}$), producers could dynamically reclassify cattle into risk groups and trigger alerts when an animal's high-risk membership exceeds a predefined threshold (e.g., $*u*_{i2} > 0.8$). This approach enables timely veterinary intervention while leveraging the graded nature of fuzzy membership to balance early-warning sensitivity against false-alarm rates (Ross, 2010), offering a more nuanced alternative to binary rule-based systems. A key advantage of fuzzy clustering over traditional hard clustering lies in its ability to accommodate biological and environmental uncertainty (Zadeh, 1965; Bezdek, 1981). While only one steer (A02) exhibited near-binary membership, most animals displayed partial overlap between clusters, reflecting real-world ambiguity (e.g., intermediate AQI exposure). This soft partitioning allows veterinarians to identify borderline cases that might be missed by *k*-means or hierarchical methods, improving early detection and resource allocation for subclinical or emerging disease events. However, several limitations must be acknowledged. First, our analysis relied on a small experimental sample (*n* = 5) and a limited set of environmental variables; validation with larger, longitudinal datasets is necessary. Second, cluster validation was based on internal indices (PC, PE, XB) rather than clinical outcomes (e.g., actual BRD incidence), leaving predictive performance untested. Third, the static fuzzy c-means (FCM) model does not account for temporal dynamics, such as rapid changes in weather or animal health, suggesting a need for incremental or adaptive clustering extensions. Finally, subjectivity in membership-function calibration and fuzziness exponent selection warrants further refinement through expert elicitation or data-driven optimization for diverse production systems.

CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates the effectiveness of fuzzy C-means clustering in classifying cattle into two distinct risk groups: a "low-stress" group (comprising younger animals exposed to lower AQI and humidity) and an "elevated-risk" group (older animals under higher environmental stress). Sensitivity analyses confirmed the robustness of cluster assignments across variations in membership-function thresholds and idealized environmental scenarios, while the weighted objective JwJw provided a reliable measure of uncertainty impact. Additionally, incorporating fuzzy "High"-risk weights into the clustering process revealed how adverse microclimate conditions degrade cluster compactness, offering a novel metric for initiating management interventions. For practitioners, we recommend targeted interventions such as metaphylaxis or enhanced nutrition for steers with high membership (ui2>0.8$ui2>0.8$) in the elevated-risk cluster. Real-time monitoring systems integrating IoT sensor data can dynamically update risk classifications, enabling early warnings. Furthermore, the weighted objective JwJw can serve as an adaptive threshold, triggering environmental adjustments (e.g., increased ventilation) when JwJw exceeds baseline levels, indicating heightened microclimate stress.

Future research should focus on validating cluster assignments against clinical BRD incidence data to assess predictive accuracy. Extending the methodology to dynamic and incremental clustering would enable real-time membership updates for streaming data. Additional layers of data such as genomic risk scores, nutritional biomarkers, and social-network interactions (e.g., pen proximity) could enhance the model through multi-source data fusion. Further refinement of membership functions via data-driven or expert-elicited optimization would improve adaptability across diverse climates and management systems. Finally, economic impact modeling could quantify the cost-benefit trade-offs of fuzzy-informed interventions, helping producers balance treatment expenses against productivity gains. By integrating fuzzy mathematics with herd-health management, this study establishes a foundation for more nuanced, data-driven strategies to mitigate BRD risk under uncertain environmental conditions.

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NOVELTY STATEMENT

This study introduces a novel framework for assessing Bovine Respiratory Disease (BRD) risk by integrating fuzzy clustering with environmental uncertainty modeling. Unlike traditional methods that rely on rigid thresholds, our approach captures the gradations of risk factors such as temperature, humidity, and air quality, enabling more nuanced and adaptive risk stratification. The incorporation of environmental-uncertainty weights into the clustering process enhances robustness, providing a data-driven tool for targeted interventions in feedlot management. This work advances veterinary science by offering a scalable, real-time decision-support system that adapts to dynamic environmental conditions, improving early detection and mitigation of BRD.

AUTHOR'S CONTRIBUTION

Suleiman Ibrahim Mohammad: Conceptualization, methodology, data curation, writing original draft. Yogeesh N: Formal analysis, software, validation. Asokan Vasudevan: Supervision, project administration, funding acquisition. Dr. N Raja: Visualization, investigation. F.T.Z. Jabeen: Resources, data collection. Anber Abraheem Mohammad: Writing review and editing. Mohammad Faleh Ahmmad Hunitie: Methodology, validation. Badrea Al Oraini: Funding acquisition, supervision.

Generative AI or AI-assisted Technology Statement

The author(s) declare that no Genrative AI was used in the creation of this manuscript.

Conflict of interest

The authors have declared no conflict of interest.

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