

A data-driven, reduced-input environmental screening framework for dairy heat-risk management

Janyelle do Nascimento Silva

Universidade Federal de Sergipe

Mariana Dias Meneses

`dias.meneses@unesp.br`

UNESP: Universidade Estadual Paulista Julio de Mesquita Filho <https://orcid.org/0000-0002-2043-7483>

Bruno Rafael Almeida Moreira

The University of Queensland - Saint Lucia Campus: The University of Queensland

Patrícia de Azevedo Castelo Branco do Vale

Universidade Federal de Sergipe

Glauco de Souza Rolim

UNESP: Universidade Estadual Paulista Julio de Mesquita Filho

Wellington Gonzaga do Vale

Universidade Federal de Sergipe

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Abstract

Heat stress is a central determinant of dairy welfare, milk production, and management stability in warm regions, yet barn decisions still rely on multi-factor environmental indices, such as the temperature-humidity index (THI), black globe humidity index (BGHI), and comfort enthalpy index (CEI). Precision livestock farming increasingly couples environmental monitoring with imaging, physiology, and machine learning, but routine barn control still depends on a small set of robust signals. We therefore asked whether conventional environmental heat-stress classes can be recovered from only dry-bulb temperature and relative humidity in a compost-barn dairy. We analyzed 6,624 environmental observations collected every 10 minutes over 46 days in Sergipe, Brazil. Each observation was classified as suitable, alert, danger, or emergency according to thresholds for THI, BGHI, and CEI. Decision tree (DT) and artificial neural network (ANN) models were trained under full-input and reduced-input scenarios. The barn was dominated by actionable heat-risk states, with mean THI, BGHI, and CEI values of 76.6, 77.2, and 70.6, respectively. ANN consistently preserved class structure under reduced inputs, achieving accuracies of 0.97 for THI, 0.92 for BGHI, and 0.94 for CEI using dry-bulb temperature and relative humidity alone. Corresponding DT accuracies were 0.87, 0.86, and 0.75. Remaining ANN errors were concentrated at adjacent class boundaries. These results establish a reduced-input environmental classification framework that recovers conventional heat-stress classes with high fidelity in a tropical compost barn. The study identifies dry-bulb temperature and relative humidity as a compact operational core for environmental screening and rapid management response to rising heat load.

Introduction

Among the management constraints that most directly determine whether dairy systems convert feed into stable milk production, heat stress is one of the most consequential. It acts through the cow and through the barn at the same time. As air temperature rises and humidity constrains evaporative cooling, cows reduce intake, alter respiratory and postural behavior, mobilize nutrients differently, and divert physiological capacity away from milk synthesis and composition (Dalcin et al. 2016; Florio et al. 2022; Fuentes et al. 2022; Giannone et al. 2023; Hammami et al. 2015; Tao et al. 2020; Zeng et al. 2023). In housed systems, these responses accumulate through the microclimate that the building produces around the animal. Heat-risk assessment is therefore a core measurement problem and part of the operating logic of dairy production.

That logic becomes more pressing in tropical and subtropical settings, where high daytime temperatures, rapid morning transitions, and persistent humidity can compress the margin between acceptable and harmful conditions. Compost-barn systems intensify the relevance of this problem because they combine animal heat production, bedding fermentation, ventilation schedules, water points, and feeding activity within one enclosed thermal environment. The result is a dynamic microclimate that changes across the day and that directly shapes the conditions under which cows eat, rest, and dissipate heat (Alvares et al. 2013; Kamal et al. 2018; Marchesini et al. 2018; Reuscher et al. 2023; Santos et al. 2022; Shiao et al. 2011). A barn-level signal that identifies when this microclimate

crosses from manageable load to actionable risk has immediate value for ventilation, cooling, inspection, and labor allocation.

Environmental heat-stress indices have long provided that signal. The temperature-humidity index (THI), black globe humidity index (BGHI), and enthalpy-based indices convert combinations of temperature, humidity, and radiant conditions into operational thresholds that can be used in routine management (Berman et al. 2016; Castro Júnior and Silva 2021; Furlan and Folegatti 2002; Thom 1959; Yan et al. 2022). Their strength lies in compression. A complex barn environment can be translated into a small number of classes that convey whether the herd is in a suitable, alert, danger, or emergency condition. That clarity explains why these indices remain deeply embedded in dairy practice and in precision livestock farming workflows (Lovarelli et al. 2020; Oliveira Júnior et al. 2019; Yan et al. 2022).

At the same time, the scientific literature has moved well beyond simple index application. Recent studies predict heat strain from respiration rate, rectal or vaginal temperature, rumen temperature, thermal-image signatures, milk responses, video-derived breathing patterns, and sensor-based behaviour (Becker et al. 2021; Brito et al. 2025; Ferreira et al. 2025; Gorczyca and Gebremedhin 2020; Hasan et al. 2025; Lee et al. 2024a; Lemal et al. 2026; Marett et al. 2026; Pacheco et al. 2020; Pacheco et al. 2022; Rodrigues et al. 2023; Singaravadivelan et al. 2025; Shu et al. 2023; Woodward et al. 2024; Woodward et al. 2025; Yan et al. 2024; Zhou et al. 2022). These developments have sharpened the biological interpretation of heat stress and have expanded the analytical toolkit available for animal monitoring. They also show that dairy heat stress is organized by nonlinear interactions among the environment, the animal, and management. That shift has raised expectations for what a convincing heat-stress study should contribute.

The analytical frontier and the operational frontier address different needs. Advanced sensing, imaging, and physiology-based prediction deepen biological resolution, but routine barn control still depends on signals that can be measured continuously, maintained reliably, and interpreted quickly under commercial conditions (Bruto et al. 2025; Cockburn 2020; Ferreira et al. 2025; Fournel et al. 2017; Singaravadivelan et al. 2025). Farms that can sustain dense sensor networks, thermal cameras, or animal-mounted devices represent one end of the adoption spectrum. A far larger set of barns must act on a smaller environmental core. For those systems, the central question is how much of the conventional decision structure survives when the predictor space is reduced to the variables that barns monitor most consistently.

That question is sharper than it appears. Dry-bulb temperature and relative humidity sit near the center of practical barn monitoring, but the conventional indices differ in the broader environmental information they encode. THI is explicitly grounded in temperature and humidity, BGHI introduces black-globe temperature as a proxy for combined radiant and convective conditions, and enthalpy-based formulations summarize a wider psychrometric state (Berman et al. 2016; Castro Júnior and Silva 2021; Furlan and Folegatti 2002; Thom 1959; Yan et al. 2022). A reduced-input model is therefore informative

only if it recovers the class structure of these systems with sufficient fidelity to preserve management meaning. Otherwise, simplification merely obscures thermal risk.

The environment also plays a significant role. A commercial compost barn produces repeated exposure to the same building geometry, the same ventilation architecture, and the same management routine across many diurnal cycles. That consistency is an advantage when the aim is to identify whether class structure itself is recoverable, because it allows the analysis to focus on the environmental organization of the signal before it is diluted by between-farm heterogeneity. Within that setting, a dense time series captures the transitions that matter most for environmental alerts, including the rise from dawn to morning load, afternoon accumulation, and evening relaxation. A reduced-input framework that succeeds under these conditions offers a practical basis for broader validation across barns, climates, and management systems.

Machine learning offers a direct way to test this hypothesis because it can be framed as a supervised classification problem. The target is the conventional environmental class, and the predictor space can be intentionally restricted to determine how much class information remains. This design places the methodological burden exactly where the operational question lies, that is, on recoverability of class boundaries under limited inputs. Decision trees are useful in this setting because they expose threshold structure in an interpretable way, whereas artificial neural networks can represent smoother nonlinear boundaries in the same environmental space (Becker et al. 2021; Cheng and Lin 2024; Demilie 2024; García Leiva et al. 2019; Mahesh 2019; Zafra et al. 2024). Comparing these model families therefore reveals both how much information is preserved and what kind of classifier extracts it most effectively.

Here, we used 6,624 environmental observations collected every 10 minutes over 46 days in a commercial tropical compost barn in Sergipe, Brazil, to test whether conventional dairy-cow heat-stress classes can be recovered from dry-bulb temperature and relative humidity alone. We calculated THI, BGHI, and CEI from the monitored barn climate, assigned each record to suitable, alert, danger, or emergency classes, and trained decision tree and artificial neural network classifiers under full-input and reduced-input scenarios. This design was chosen to evaluate the practical recoverability of established class systems in a working barn and to identify the compact environmental core that can sustain continuous screening under commercial dairy conditions.

This question links statistical parsimony to farm action. A compact signal is only useful when it preserves the ordering and separation of the risk classes that guide intervention. The study therefore treats class recoverability as both a data-science problem and a management problem. In that sense, microclimate classification becomes the bridge between continuous sensing and daily herd management.

Materials and Methods

The study followed an eleven-step analytical workflow, from environmental monitoring and index calculation through machine-learning model training and performance assessment, as illustrated in

Study site, barn, and herd

The study was conducted in a commercial compost-barn dairy in Nossa Senhora da Glória, Sergipe, Brazil (10°13'22.2" S, 37°24'33.1" W; 279 m altitude). The region has an Aw climate under the Köppen classification, with a dry season from September to March and a rainy season from April to August. Average maximum temperature reaches about 34°C during the dry season and about 28°C during the rainy season, while minimum temperatures are about 22°C and 18°C, respectively (Alvares et al. 2013). This climatic context was appropriate for evaluating a barn-level environmental classifier because it combines marked thermal load with regular diurnal variation in humidity and temperature. The barn was oriented northwest to southeast and measured 22 × 60 m, with 3.75 m eave height and 7.0 m ridge height. The compost-bedded area measured 14 × 60 m, providing 840 m² of bedding area and about 10 m² per cow for a nominal capacity of 84 animals. The feeding alley measured 4 × 60 m and included a 0.70 × 60 m feed bunk. Five water troughs of approximately 400 L each were distributed along the feeding area. This configuration defined the environmental volume from which the monitoring data were drawn and therefore the microclimate represented by the classification task. Mechanical ventilation was supplied by two rows of fans totaling 10 units, each with three blades and a 1 hp motor. The system delivered air movement up to 10 m at approximately 8 m s⁻¹ and operated on an automatic schedule that cycled across the day and night. The herd comprised 137 transition cows ranging from Gir-Holstein to Holstein, with approximately 80% of the herd identified as Holstein and animals reported as descendants of 31/32 Holstein stock. Mean milk yield was about 25 kg cow⁻¹ d⁻¹.

Environmental monitoring design

Environmental data were collected over 46 consecutive days, from 22 February to 8 April 2021. Measurements were recorded every 10 min across the full 24-hour day, yielding 144 observations per day and 6,624 observations overall. Monitoring focused on the internal barn environment. Relative humidity was measured with an HTU21d sensor with an operating range of 0 to 100% RH and manufacturer-reported accuracy of ± 1%. Temperature was measured with a DS18B20 sensor with an operating range of - 55 to 125°C and accuracy of ± 0.5°C. A temperature sensor enclosed in a black globe made from thermoplastic polylactic-acid polymer provided black-globe temperature. All sensors were installed 1.5 m above the floor.

Measured and derived environmental variables

The directly monitored variables were dry-bulb temperature (DBT), relative humidity (RH), and black-globe temperature (BGT). From these data, additional psychrometric variables were calculated, namely wet-bulb temperature (WBT), dew-point temperature (DPT), vapor saturation pressure (es), actual vapor pressure (ea), absolute humidity (UA), and saturation humidity (US). Three conventional environmental

indices were calculated: the temperature-humidity index (THI), the black globe humidity index (BGHI), and the comfort enthalpy index (CEI). THI emphasizes the joint contribution of dry-bulb and wet-bulb temperature. BGHI incorporates black-globe and dew-point temperature. CEI represents the air state through an enthalpy formulation that combines temperature and humidity terms (Berman et al. 2016; Castro Júnior and Silva 2021; Furlan and Folegatti 2002; Thom 1959; Yan et al. 2022).

Heat-risk class construction

Each observation was assigned to one of four thermal classes — suitable, alert, danger, or emergency — for each index. The THI thresholds followed the ranges $THI \leq 72$, $72 \leq THI < 79$, $79 \leq THI < 89$, and $89 \leq THI < 98$. The BGHI thresholds followed $BGHI < 74$, $74 \leq BGHI \leq 78$, $78 < BGHI \leq 84$, and $BGHI > 84$. The CEI thresholds followed $56.1 < CEI < 64.6$, $64.7 < CEI < 70.5$, $70.6 < CEI < 77.5$, and $77.6 < CEI < 93.1$ (Table 1).

Table 1
Thermal comfort classes according to the values of the comfort indices THI (Temperature and Humidity Index), BGHI (Black Globe Humidity Index), and CEI (Comfort Enthalpy Index).

Index	Reference	Comfort classes	Index range
THI	(Oliveira Júnior et al., 2019) (Berman et al., 2016)	Suitable	$THI \leq 72$
		Alert	$72 \leq THI < 79$
		Danger	$79 \leq THI < 89$
		Emergency	$89 \leq THI < 98$
BGHI	(Pacheco et al., 2020)	Suitable	$BGHI < 74$
		Alert	$74 \leq BGHI \leq 78$
		Danger	$78 < BGHI \leq 84$
		Emergency	$BGHI > 84$
CEI	(Harada et al., 2023)	Suitable	$56.1 < CEI < 64.6$
		Alert	$64.7 < CEI < 70.5$
		Danger	$70.6 < CEI < 77.5$
		Emergency	$77.6 < CEI < 93.1$

Descriptive analysis of barn climate

Before model development, the environmental and index series were summarized descriptively across four periods of the day: dawn (00:00 to 05:59), morning (06:00 to 11:59), afternoon (12:00 to 17:59), and

evening (18:00 to 23:59). Mean, minimum, and maximum values were examined for DBT, BGT, DPT, RH, es, ea, UA, US, THI, BGHI, and CEI.

Feature-space restriction and exploratory analysis

All available environmental variables were initially considered as candidate predictors: DBT, WBT, BGT, DPT, RH, es, ea, UA, and US. Data were standardized by standard deviation before exploratory analysis. Spearman correlation analysis was used to examine relationships among the environmental variables and the three target index systems. The reduced-input framework centered on DBT and RH for both conceptual and operational reasons (Janni 2019; Yan et al. 2021). Pairwise visualization of DBT and RH against the class labels was also used to examine whether the classes occupied structured regions in two-dimensional environmental space.

Machine-learning framework

The classification task was carried out separately for each index, yielding three supervised problems. For each problem, two algorithms were trained: a decision tree (DT) and an artificial neural network (ANN). The DT provided an interpretable baseline based on recursive threshold splits (Cheng and Lin 2024; García Leiva et al. 2019). The ANN was implemented as a multilayer perceptron designed to capture nonlinear relationships among the environmental predictors and the heat-risk classes (Becker et al. 2021; Demilie 2024; Zafra et al. 2024). Two predictor scenarios were evaluated for each index and model family: a full-input scenario including DBT, WBT, BGT, DPT, RH, es, ea, UA, and US; and a reduced-input scenario including only DBT and RH.

Training, testing, and hyperparameter selection

The supervised dataset was randomly divided into training (70%) and testing (30%) subsets. Hyperparameter optimization was performed with GridSearchCV using five-fold cross-validation on the training subset (Gill and Gupta 2023; Mishra et al. 2024). For the decision tree, candidate depths were 3, 5, 10, and 15, with split criteria including Gini and entropy. The selected decision-tree configuration was maximum depth 3 with the Gini criterion. For the ANN, hidden-layer configurations included (5, 5), (5, 10), (5, 15), and (5, 20); activation functions included identity, logistic, tanh, and relu; solvers included lbfgs, sgd, and adam. The selected ANN configuration used hidden layers (5, 5), relu activation, the lbfgs solver, adaptive learning rate, and 1000 maximum iterations.

Performance metrics and confusion matrices

Model performance was evaluated with accuracy, the Matthews correlation coefficient (MCC), and the F1 score (Chicco and Jurman 2020; Delgado and Núñez-González 2019; Seliya et al. 2009). Confusion

matrices were generated for the best-performing models to examine the pattern of errors across the four ordered classes. Class-specific precision was also reported.

Software and reproducibility

All modeling procedures were implemented in Python 3.9.13 with scikit-learn version 1.1 (Pedregosa et al. 2011). The same software environment was used for parameter search, model training, metric calculation, and confusion-matrix generation.

Results

The barn was dominated by actionable heat-risk states

The 6,624 observations captured a pronounced diurnal thermal cycle within the compost barn. Dry-bulb temperature (DBT), black-globe temperature (BGT), vapor saturation pressure (es), and saturation humidity (US) all rose from dawn toward afternoon, while dew-point temperature (DPT), relative humidity (RH), actual vapor pressure (ea), and absolute humidity (UA) followed the opposing trend (Fig. 2). Afternoon conditions consistently formed the warmest and driest period of the day, evening conditions relaxed only partially, and dawn provided the only sustained interval of lower environmental load.

The index distributions followed the same daily structure (Fig. 3). Mean THI and BGHI were 76.6 and 77.2, respectively, placing the average barn condition within the alert range for both indices. Mean CEI was 70.6, placing the average air state within the danger range.

Class frequencies show that only 1,000 THI observations (15.1%) fell in the suitable class, whereas 2,763 (41.7%) fell in alert and 2,477 (37.4%) fell in danger. The emergency THI class accounted for 384 observations (5.8%). BGHI was distributed more evenly: 1,961 observations (29.6%) classified as suitable, 2,074 (31.3%) as alert, and 2,105 (31.8%) as danger; emergency accounted for 484 observations (7.3%). CEI was the most severe index in distributional terms: only 267 observations (4.0%) were suitable, 3,040 (45.9%) were alert, 1,660 (25.1%) were danger, and 1,657 (25.0%) were emergency (Table 2).

Table 2
Number of classified classes according to the indexes: THI (Temperature and Humidity Index), BGHI (Black Globe Humidity Index), and CEI (Comfort Enthalpy Index).

Comfort class	THI	BGHI	CEI
Suitable	1000	1961	267
Alert	2763	2074	3040
Danger	2477	2105	1660
Emergency	384	484	1657

Conventional heat-risk classes were organized along a shared DBT–RH gradient

When the three class systems were projected onto dry-bulb temperature and relative humidity, each formed an ordered structure along a common negative temperature-humidity gradient (Fig. 4). Suitable observations occupied the coolest end of the plane. Alert and danger formed intermediate bands. Emergency concentrated at the warm end of the gradient. THI and BGHI partitioned that space relatively tightly, while CEI occupied a wider region of the plane, especially toward the higher-temperature end, where alert, danger, and emergency extended across a broader RH range.

Reduced-input classification preserved most of the conventional class structure

For the decision tree, performance declined after the input space was restricted to DBT and RH (Table 3). THI accuracy fell from 0.89 under full inputs to 0.87 under reduced inputs. BGHI showed the largest decision-tree penalty, with accuracy declining from 0.93 to 0.86, MCC from 0.90 to 0.82, and F1 from 0.93 to 0.86. CEI declined from 0.77 to 0.75 in accuracy, with MCC rising slightly from 0.65 to 0.69.

Table 3
Decision Tree performance using all variables and dry bulb temperature (DBT) and water vapor pressure (ea). THI (Temperature and Humidity Index), BGHI (Black Globe Humidity Index), and CEI (Comfort Enthalpy Index).

TCI	Accuracy		MCC		F1-score	
	All variables	DBT and RH	All variables	DBT and RH	All variables	DBT and RH
THI	0.89	0.87	0.83	0.84	0.89	0.87
BGHI	0.93	0.86	0.90	0.82	0.93	0.86
CEI	0.77	0.75	0.65	0.69	0.74	0.74

The artificial neural network behaved differently. Under the full-input scenario, ANN accuracies reached 0.98 for THI, 0.99 for BGHI, and 0.95 for CEI. Under the reduced-input DBT + RH scenario, accuracies remained at 0.97 for THI, 0.92 for BGHI, and 0.94 for CEI. MCC values were 0.95, 0.89, and 0.94, respectively, and F1 values were 0.98, 0.93, and 0.94. Expressed relative to the full-input benchmark, the reduced-input ANN retained approximately 99% of full-input accuracy for THI, 93% for BGHI, and 99% for CEI (Table 4).

Table 4

Neural Networks performance using all variables and dry bulb temperature (DBT) and water vapor pressure (ea). THI (Temperature and Humidity Index), BGHI (Black Globe Humidity Index), and CEI (Comfort Enthalpy Index).

TCI	Accuracy		MCC		F1-score	
	All variables	DBT and RH	All variables	DBT and RH	All variables	DBT and RH
THI	0.98	0.97	0.98	0.95	0.98	0.98
BGHI	0.99	0.92	0.99	0.89	0.93	0.93
CEI	0.95	0.94	0.92	0.94	0.95	0.94

Reduced-input errors remained adjacent to class boundaries

For THI under full inputs, ANN precision reached 93.5% for suitable, 99.6% for alert, 99.4% for danger, and 98.3% for emergency. Under DBT + RH, these values remained at 95.0%, 98.0%, 98.0%, and 96.0%, respectively. BGHI showed the clearest upper-boundary penalty under reduced inputs: precision became 96.0% for suitable, 92.0% for alert, 93.0% for danger, and 78.0% for emergency (Fig. 5).

All 27 misclassified BGHI emergency observations shifted only one class lower, into danger. CEI showed a similarly ordered error structure: precision remained at 100% for suitable, 99.0% for alert, 86.0% for danger, and 90.0% for emergency under DBT + RH inputs (Table 5).

Table 5

Precision (%) of the Artificial Neural Networks (ANN) model using all variables and dry bulb temperature (DBT) and water vapor pressure (ea). THI (Temperature and Humidity Index), BGHI (Black Globe Humidity Index), and CEI (Comfort Enthalpy Index).

Class	THI		BGHI		CEI	
	All variables	DBT and RH	All variables	DBT and RH	All variables	DBT and RH
Suitable	93.5	95.0	99.5	96.0	98.8	100
Alert	99.6	98.0	99.7	92.0	100	99.0
Danger	99.4	98.0	99.7	93.0	89.7	86.0
Emergency	98.3	96.0	100	78.0	90.0	90.0

Discussion

By combining conventional index-derived class labels with paired full-input and reduced-input machine-learning models, this study shows that the operational structure of three widely used environmental heat-stress systems for dairy cows is largely preserved in a two-variable barn microclimate. The main finding is that dry-bulb temperature and relative humidity carried enough information to recover most of the class organization of THI, BGHI, and CEI in a commercial tropical compost barn, and artificial neural networks extracted that structure with consistently high fidelity. The study therefore contributes a data-driven, reduced-input environmental screening framework for dairy heat-risk management.

That contribution helps address a persistent operational bottleneck in precision livestock farming. Much of the recent heat-stress literature has moved toward richer animal-centered or sensor-dense prediction (Becker et al. 2021; Brito et al. 2025; Ferreira et al. 2025; Hasan et al. 2025; Lemal et al. 2026; Marett et al. 2026; Pacheco et al. 2020; Pacheco et al. 2022; Rodrigues et al. 2023; Singaravadivelan et al. 2025; Shu et al. 2023; Woodward et al. 2024; Woodward et al. 2025; Yan et al. 2024; Zhou et al. 2022). Those approaches strengthen biological resolution and will remain central to advanced welfare monitoring. At the same time, barn management still depends on a smaller environmental core that can operate continuously with modest instrumentation (Bruto et al. 2025; Cockburn 2020; Fournel et al. 2017; Lovarelli et al. 2020; Singaravadivelan et al. 2025). The present study aligns directly with that requirement.

The contrast between ANN and DT clarifies how the class information is organized. Decision trees recovered much of the class structure, but their performance declined more visibly once the input space was restricted, especially for BGHI. Artificial neural networks retained far more of the full-input benchmark. This asymmetry is consistent with the environmental geometry of the problem: a nonlinear model can learn smooth transitions across gradients more efficiently than a tree that partitions the space through successive hard thresholds (Cheng and Lin 2024; Demilie 2024; García Leiva et al. 2019; Mahesh 2019; Yeom et al. 2018; Zafra et al. 2024).

The error structure strengthens this interpretation. Reduced-input ANN misclassifications remained concentrated at adjacent class boundaries. THI primarily exchanged neighboring states. BGHI emergency records shifted one level lower into danger when classification error occurred. CEI residual error was concentrated within the danger-emergency boundary. This is the error pattern expected from a model that captures the broad environmental ordering correctly and loses precision mainly where the conventional thresholds crowd most tightly. From a management perspective, that is a favorable structure because it preserves the ranking of thermal risk while concentrating uncertainty near transition zones where operational assessment is most active.

CEI deserves separate attention because it posed the most complex classification landscape. Its class distribution placed three-quarters of the records in alert, danger, and emergency, and its DBT-RH geometry spread the warm-end classes across a broader range than THI or BGHI. Even so, the reduced-input ANN preserved 0.94 accuracy and 0.94 MCC, with greater precision for both the suitable and alert

classes. These results support the value of enthalpy-based classification in environmental screening (Castro Júnior and Silva 2021; Harada et al. 2023) and also show that its class system places greater demands on the classifier when the predictor space is collapsed.

The study setting also contributes to the strength of the result. A commercial compost barn provides repeated exposure to one coherent housing geometry, one ventilation schedule, and one management routine across many diurnal cycles. That structure makes it possible to test reduced-input recoverability under conditions that are both operationally real and analytically stable. The practical implication includes a reduced-input classifier based on DBT and RH that can serve as an analytical layer in a heat-risk monitoring architecture, providing continuous classification of conventional environmental states and triggering timely action in ventilation, cooling, inspection, or escalation to richer measurements.

The next stage follows from the study's strengths and limitations. The same reduced-input logic should be evaluated under temporally blocked validation, across additional barns, and alongside animal-based outcomes such as respiration rate, body temperature, and milk response (Cuellar et al. 2023; Dalcin et al. 2016; Janni 2019; Lee et al. 2024b; Woodward et al. 2025; Wang et al. 2024; Yan et al. 2021; Yan et al. 2024). That progression will show how a compact environmental classifier integrates with broader precision-livestock frameworks rather than competing with them.

Conclusions

This study shows that dry-bulb temperature and relative humidity allow recovery of the operational class structure of THI, BGHI, and CEI in a tropical compost-barn dairy. Across 6,624 observations collected every 10 min over 46 d, the barn environment generated repeated transitions among suitable, alert, danger, and emergency states, and those transitions were strongly organized within a shared DBT–RH space. Artificial neural networks recovered that structure with high fidelity under reduced inputs, achieving accuracies of 0.97 for THI, 0.92 for BGHI, and 0.94 for CEI. Decision trees also recovered substantial structure, but the neural network preserved the environmental gradients more effectively. By showing that two routinely monitored variables can sustain classification of three conventional environmental index systems, the study provides a methodological framework that could support real-time monitoring and rapid management response in commercial dairy housing. The same framework should be extended across barns, climates, and management conditions and linked to physiological and production responses.

Declarations

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose

Author Contributions

J. N. Silva: Data curation, Formal analysis, Writing – original draft. M. D. Meneses: Conceptualization, Methodology, Writing – review & editing. B. R. A. Moreira: Writing – review & editing . P. A. C. B. do Vale: Resources, Writing – review. G. S. Rolim: Methodology, Writing – review. W. G. do Vale: Resources, Supervision, Writing – review.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

Ethics Approval

This study involved non-invasive environmental monitoring only. No experimental procedures were performed on animals, and therefore formal ethics committee approval was not required under the applicable national guidelines

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Figures

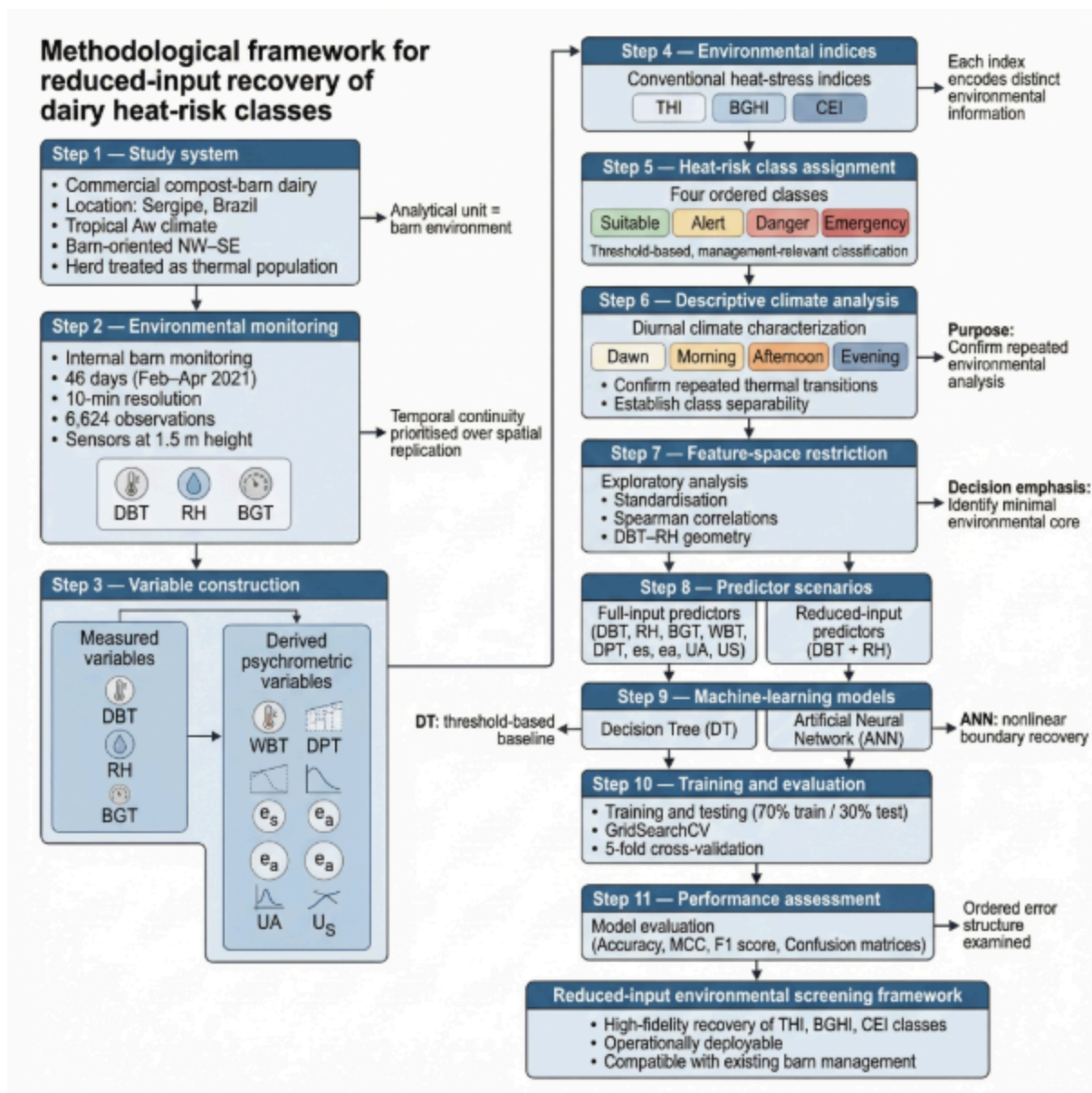


Figure 1

Methodological framework for reduced-input recovery of dairy heat-risk classes. The workflow spans eleven steps from study system characterization and environmental monitoring (Steps 1–3) through index calculation and class assignment (Steps 4–5), descriptive and exploratory analysis (Steps 6–7), predictor scenario definition (Steps 8), model training and evaluation (Steps 9–11), to the resulting reduced-input environmental screening framework

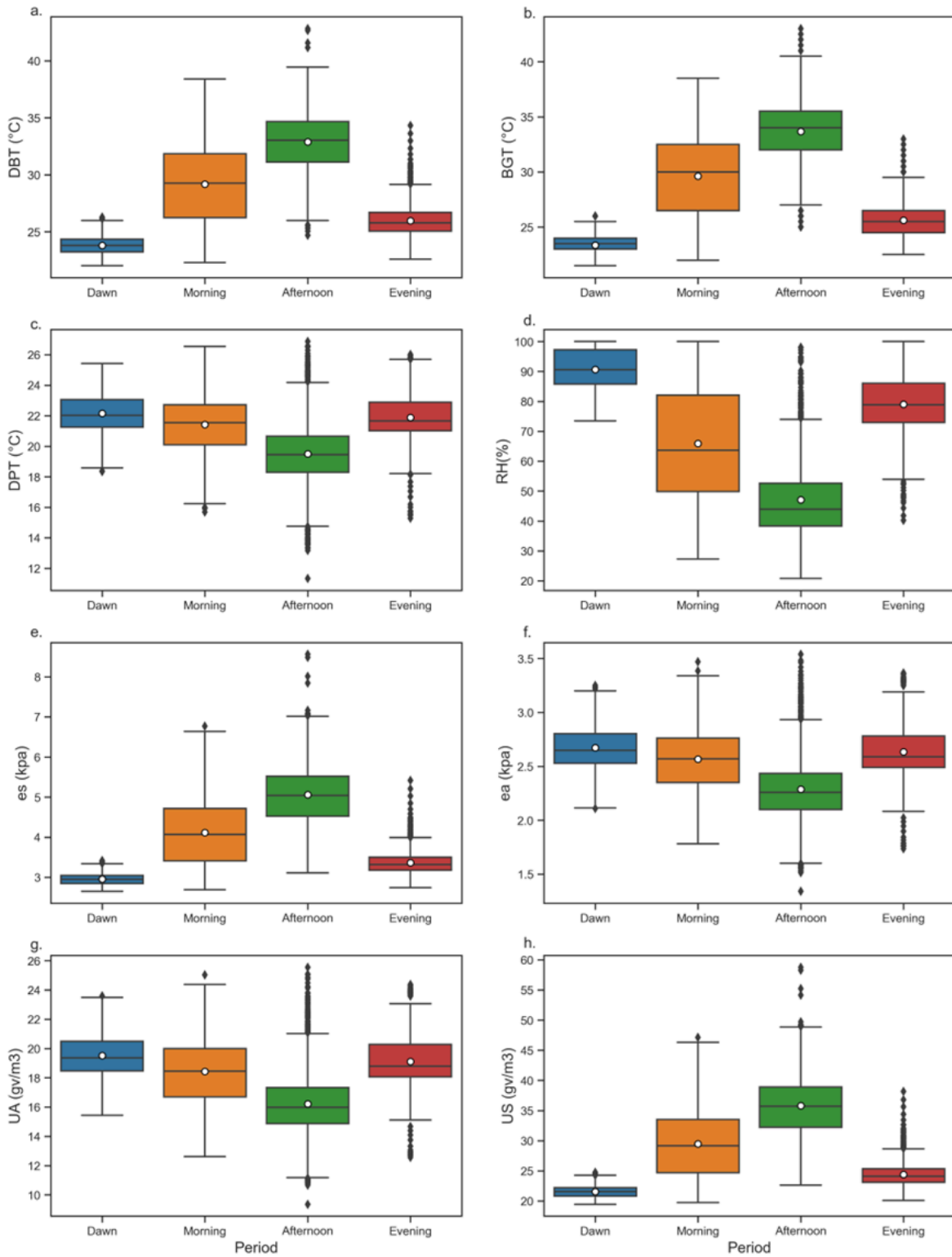


Figure 2

Boxplot of the distribution of the: a. Dry bulb temperature (DBT); b. Black Globe temperature (BGT), c. Dew point temperature (DPT), d. Relative humidity (RH), e. es, f. ea, g. UA, and h. US, during the four periods of the days. The boxes represent the interquartile range from the first quartile to the third quartile, the horizontal line inside the box represents the median value of the data, the whisker represent the minimum and maximum values, and the white point the mean.

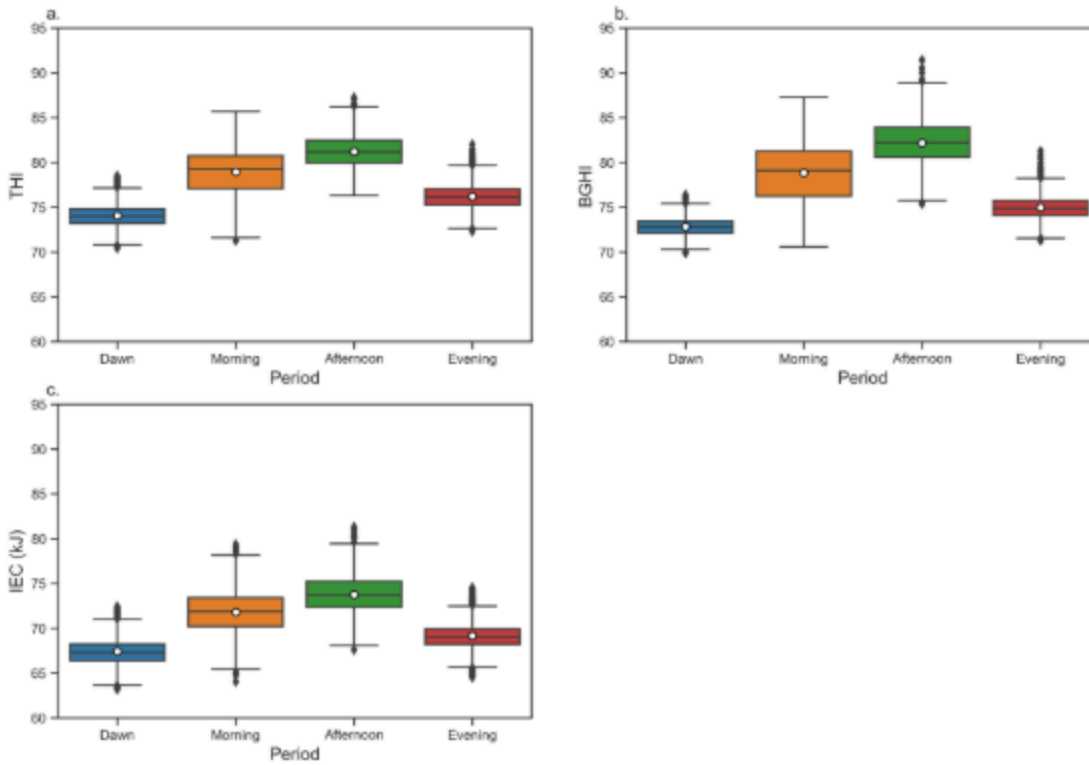


Figure 3

Boxplot of the distribution of the thermal comfort indices, THI (Temperature and Humidity Index), BGHI (Black Globe Humidity Index), and CEI (Comfort Enthalpy Index), during the four periods of the days. The boxes represent the interquartile range from the first quartile to the third quartile, the horizontal line inside the box represents the median value of the data, the whisker represent the minimum and maximum values, and the white point the mean.

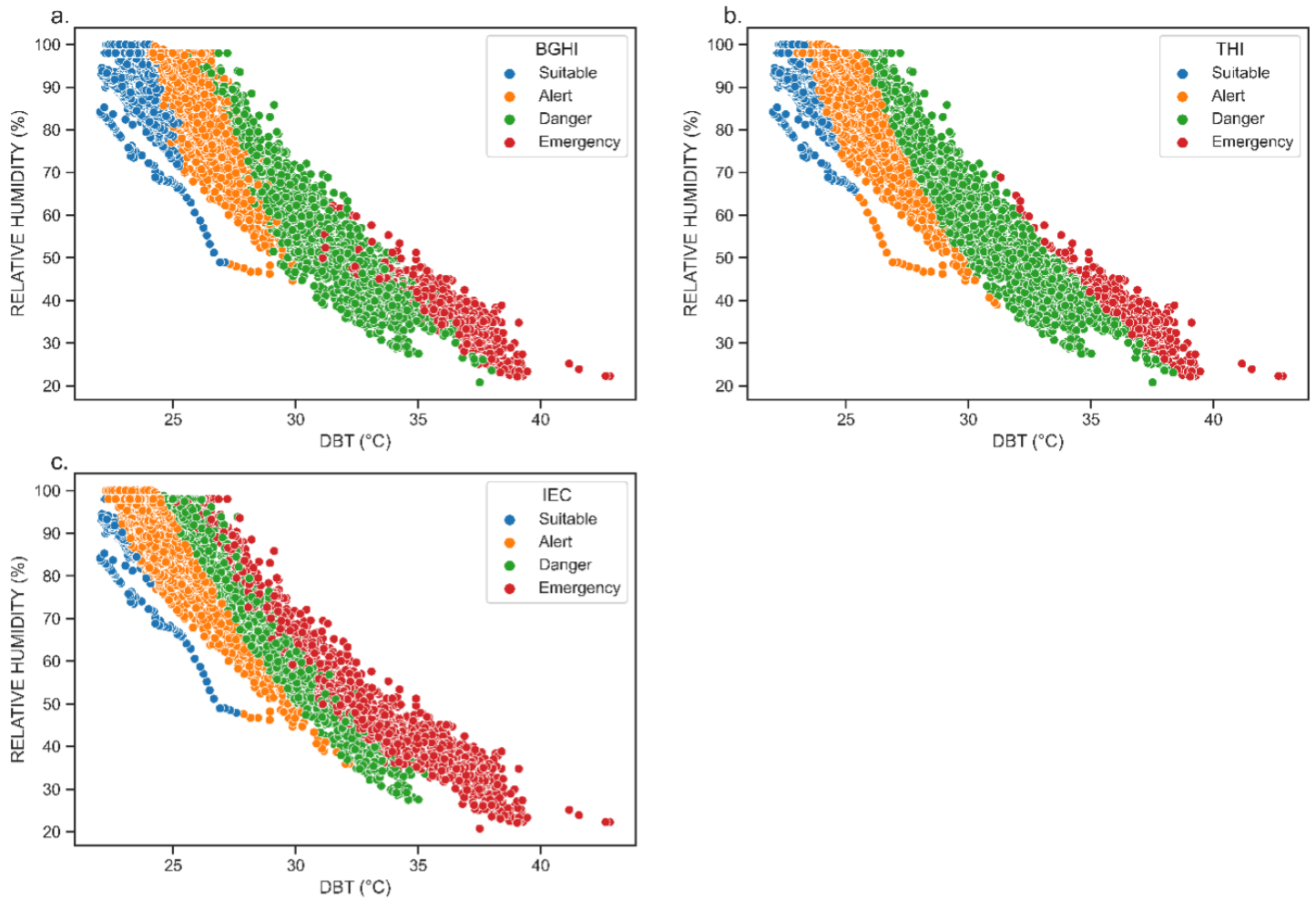


Figure 4

Pairplot of the selected variables dry bulb temperature (DBT) and relative humidity according the indexes: a. BGHI (Black Globe Humidity Index), b. THI (Temperature and Humidity Index), and c. CEI (Comfort Enthalpy Index).

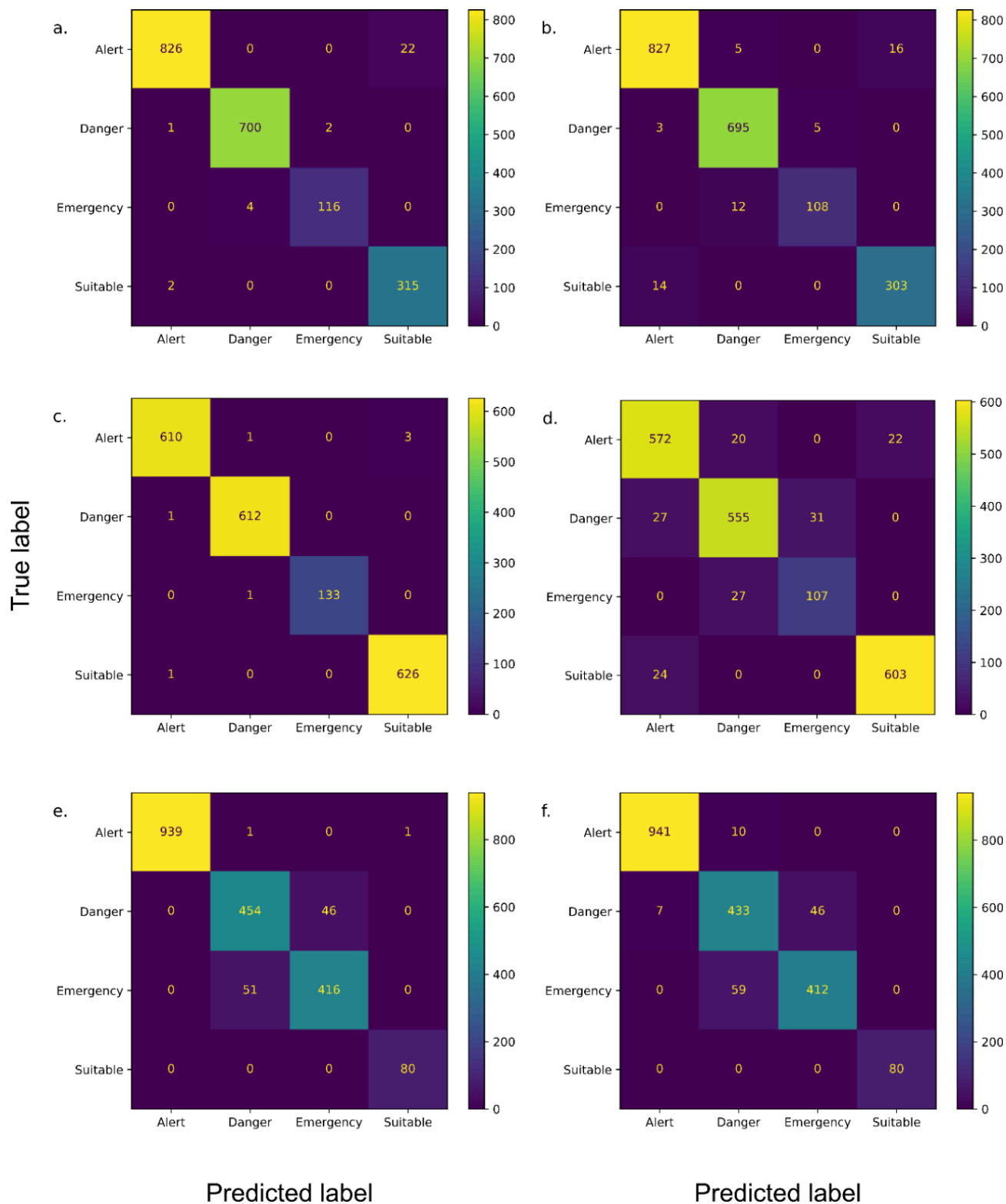


Figure 5

Confusion matrix of the testing samples for: a. THI with all variables as features, b. THI with DBT and RH as features, c. BGHI with all variables as features, d. BGHI with DBT and RH as features, e. CEI with all variables as features and, f. CEI with DBT and RH as features.

Supplementary Files

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