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Development and Validation of an Animal Susceptibility Model

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Abstract. *An individual animal's stress level is the summation of stresses from three areas: the environment, animal, and management. A model was developed to predict the susceptibility of an individual animal to heat stress. The model utilizes a hierarchal knowledge-based fuzzy inference system with 11 animal characteristics (color, sex, species, temperament, hair thickness, previous exposure, age, condition score, previous cases of pneumonia, previous other health issues, and current health) to predict susceptibility to heat stress and certainty of the prediction. The model was validated using data collected on 192 cattle over a 3-year period. Sixty-four heifers of four different breeds (Angus, Charolais, and two cross-breeds Marc I and Marc III) were assigned to one of eight outdoor pens in each of three years (2004, 2005, and 2006). The correlation of susceptibility to growth rate, condition score change, respiration rate, and panting score provided the basis for validation. Respiration rate and panting score were significantly higher in the higher categories of susceptibility than the lower categories of susceptibility. Recommendations for further studies include validating the model using a more varied group of animals.*

Keywords. Heat stress, Modelling, Beef cattle, Susceptibility, Feedlot, Precision Animal Management.

Introduction

An individual animal's response to a particular heat event is dependent on a multitude of factors including genetic factors and previous environmental conditions. Hahn and Morrow-Tesch (1993) used the following figure (Figure 1) to describe the adaptability of an individual animal to different stresses (heat or environmental being only one). This figure also illustrates both the genetic and dynamic components of individual responses.

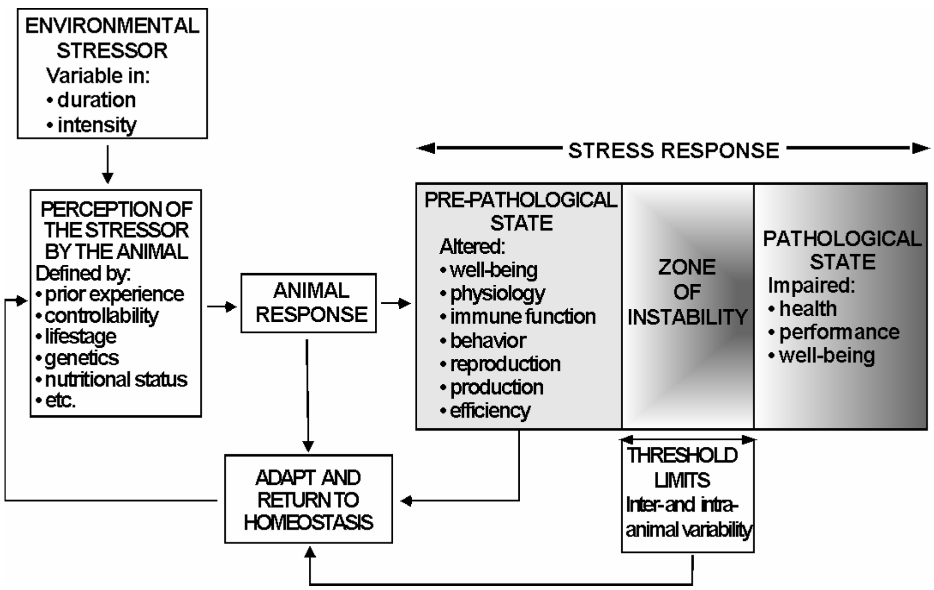

Figure 1. A model of the dynamic response of animals to environmental stressors from Moberg, 1985, adapted by Hahn and Morrow-Tesch (1993).

As methods of animal tracking and database management improve, these factors should become easier to document and transfer with the animal. If producers have easy access to these parameters, this information could help the producer manage animals, resulting in reduced stress and improved well-being and performance of the animal.

One of the most costly forms of stress a producer commonly encounters is heat stress in feedlot cattle. Heat stress in feedlot cattle is a common summertime occurrence in cattle producing areas of the United States and Australia. The overall impact of heat stress on feedlot cattle are quite varied, from little to no effect in a brief exposure, to causing reductions in feed intake, growth, and well-being of the cattle in a moderate event, and to death of susceptible animals during a extreme event (Hahn et al., 1999; Hahn and Mader, 1997). Several authors have noted different factors which can increase animal susceptibility to heat stress. Factors include species of cattle; *Bos taurus* cattle are more vulnerable to heat stress than either *Bos indicus* or crossbred cattle. Cattle with dark or black hides (Busby and Loy, 1996; Hungerford et al., 2000) rather than light-colored hides tend to be more impacted. Common perception is that a currently compromised immune system and/or prior case of pneumonia (Brown-Brandl et al., 2006) can cause an increased impact due to hot weather. Animals that are close to finished weight or have more fat cover (Brown-Brandl et al., 2006) were reported to be more susceptible to heat stress. The last factor that has been documented to increase an animal's susceptibility is excitable temperament (Brown-Brandl et al., 2006).

The level of heat stress that an animal experiences is related to three main factors: the weather conditions that exist (Hahn, 1999), susceptibility of the animal in question (Brown-Brandl et al., 2006), and management protocols used (for example sprinkling, shades, dietary management, waterer space available [cm/animal], surface conditions, and others). There are several manuscripts which document various types of environmental models (Brown-Brandl et al., 2005b; Eigenberg et al., 2005; Hahn et al., 1999; Mader et al., 2006; Thom, 1959). All of these models have one common objective – to quantify the environment that an animal experiences into a single "risk category" in an attempt to develop a simple but accurate summary of environmental impact. Each model summarizes the environment using some measure of temperature and humidity; more recently wind speed and solar radiation parameters have been added.

Several management options have been studied including shade (Blackshaw and Blackshaw, 1994; Brown-Brandl et al., 2005a; Eigenberg et al., 2005), sprinkling, ground cooling or combination of several strategies (Davis et al., 2003; Mitloehner et al., 2001). The results of these and other studies generally show some benefits to varying degrees due to the weather conditions during the study and the animals used for the study.

The vulnerability of animals is difficult to study due to the inherently interactive and compounding effects. Both Busby and Loy (1996) and Hungerford et al. (2000) have mentioned risk factors of vulnerable cattle during their post assessments of devastating heat waves, which resulted in significant losses of animals. Brown-Brandl et al. (2006) used evaluated risk factors of color, previous diagnosis of pneumonia, condition score or finish, and temperament. Katestone Environmental and MLA (Meat and Livestock Australia) have a website which offers a risk analysis program (Katestone Environmental, 2007). This program adjusts heat stress threshold values for various animal parameters including species, color, health status, days on feed, and several management options including shades, and water tank temperature.

To effectively manage animals using the fewest resources (precision animal management) requires some knowledge of the interactions between the environmental conditions, animal susceptibility, and management options. The interactions of these three components are unknown to date, and are very difficult to determine experimentally due to the complex nature of this subject. However, the complex nature of this subject makes this an excellent candidate for a knowledge-based model. The objective of this paper is to document the development and the validation of the knowledge-based fuzzy inference system model to predict animal susceptibility.

Materials and Methods

Model description

An animal susceptibility model was developed using a hierarchal knowledge-based fuzzy inference system using MatLab® version 7.0 with the Fuzzy Logic Toolbox application package. A schematic of the Animal Susceptibility Model is shown in Figure 2. Susceptibility is predicted using 11 individual animal parameters including: species (*Bos taurus, Bos indicus*, or crossbred), sex, color, temperament, previous exposure, hair thickness, age, condition score, current health, previous cases of pneumonia, and other previous health issues.

The Model was developed using eight separate fuzzy inference system sub-models. The major two sub-models are Inherent Animal Factors and Transient Animal Factors. The Inherent Animal Factors sub-model includes the animal factors inherent to animal susceptibility; factors which do not change over time. Components include temperament and genetics. The Genetics sub-model has three inputs: color, species, and sex. Transient Animal Factors sub-model includes those factors which do change over time and includes main components of Acclimation, Finish, and Health. The Acclimation sub-model has two inputs—hair thickness and previous exposure; the Finish sub-model also has two inputs—condition score and age. The

Health sub-model is broken into two sub-components: the Current Health Model, which is a direct input, and the Previous Health Model which has two inputs—number of pneumonia cases, and other health related issues.

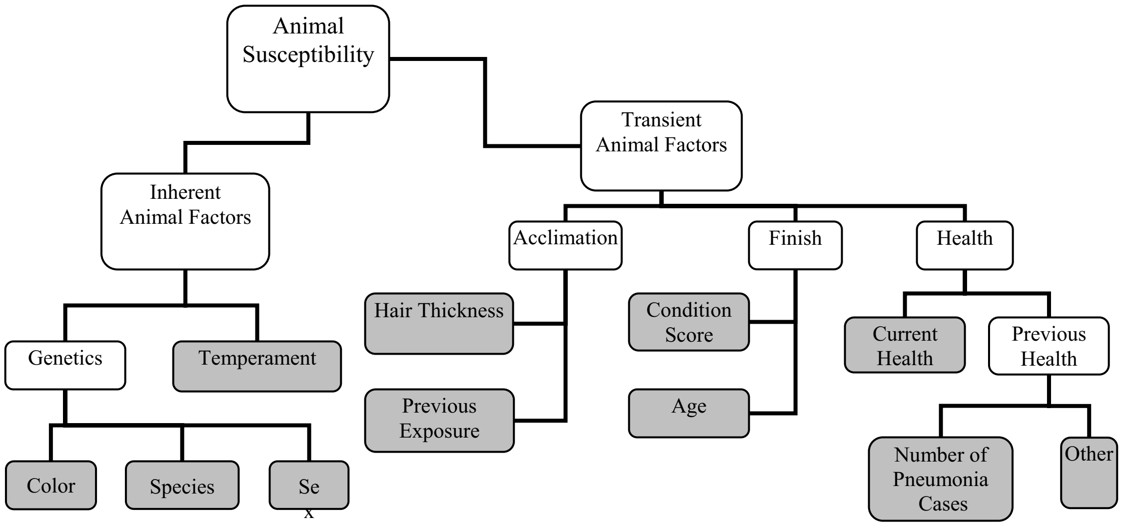

Figure 2. Schematic of Animal Susceptibility Model. Gray boxes indicate input boxes, while white boxes indicate knowledge-based fuzzy inference systems.

The Model was designed to give the user two outputs: *Animal Susceptibility* and the certainty of the susceptibility score or *Total Ambiguity*. Only the *Animal Susceptibility* output was validated during this study.

To illustrate the structure and function of the model, one sub-model was chosen, Health, to be discussed in detail. This sub-model was chosen because it contains both types of inputs: a user input and an input generated from the output of a previous sub-model. This sub-model uses 26 rules to generate the two outputs (fig. 3). The inputs to the health model include 1 user input, *Current Health*, and 2 inputs generated from the Previous Health sub-model, *Previous Healt*h and *Previous Health Ambiguity*. For the example shown in figure 3, *Current Health* was considered "Healthy" so a value of 0 was chosen. Previous health in this example was one case of pneumonia and one case of foot rot; so the inputs into the Previous Health model were 0.25 for *Number of Pneumonia Cases* and 0.25 for *Other Health Issues*. The outputs from the Previous Health model were 0.574 for *Previous Health* and 0.275 for *Previous Health Ambiguity.* These outputs then become inputs into the Health Model. So, the in the inputs to the Health Model were Current Health = 0, Previous Health = 0.574, Previous Health Ambiguity = 0.275. The resulting outputs were Health = 0.615 and Health Ambiguity = 0.222. These outputs are then used as inputs to the next model up the hierarch, Transient Animal Factors.

For more details on the Model development and the modeling techniques used see Brown-Brandl et al. (2006a, 2006b).

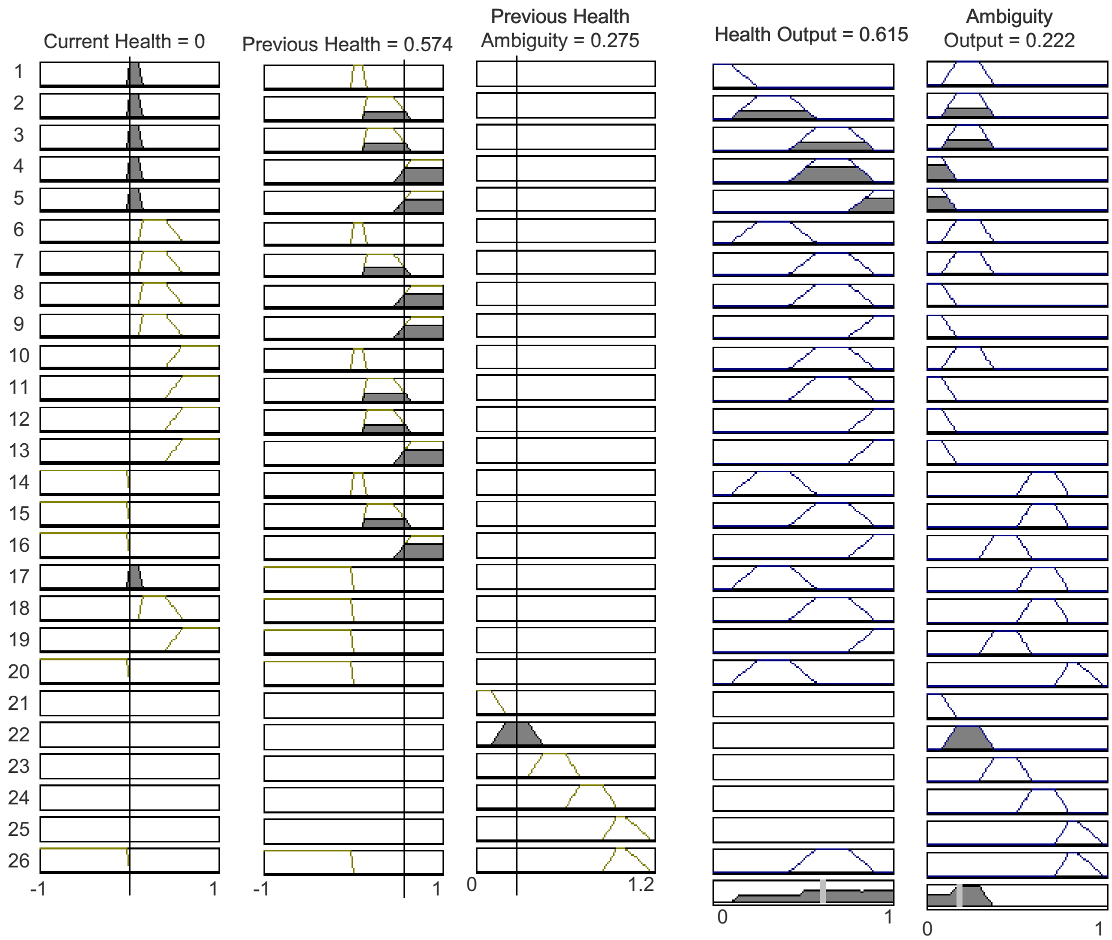

Figure 3. An example of the interactive interface generated by Matlab (Mathworks, Inc., 2000) describing the fuzzy inference system of health sub-model which is one part of the entire animal susceptibility hierarchal model. In this example, the inputs as illustrated above were the user input of *current health* and inputs generated from the previous health sub-model outputs of *previous health* and *previous health ambiguity.* In this example, the user inputs of *current health* of 0 (which represents no current health issue or a healthy animal), and an input from the previous health model of 0.574 for *previous health* and 0.275 for *previous health ambiguity*. The resulting outputs from each of the 26 rules are illustrated by the position of the vertical bar in the columns labeled Health and Health Ambiguity. The last graph in this each of these two columns show the relative contributions of the 26 rules to the final output.

Data Inputs

The user inputs data into the model by one of two possible means, either a user interface using slider bars to depict approximate values, or a data file which can be read into the model for ease of entering multiple animals. All the inputs are real numbers ranging in values from 0 to 1. If an individual parameter is unknown, then a value of -1 is entered. Table 1 shows the normalization of the input data to a 0 to 1 scale.

Table 1. The modification of inputs of individual animal parameters for use in the Animal Susceptibility Model. Input parameters need to be between zero and one if known, and a negative one if the parameter is unknown.

Input Variable	Original Values	Modification
Species	*Bos indicus*, *Bos taurus*, Crossbred	*Bos indicus* = 0 *Bos taurus* = 1 Crossbred between 0 and 1 depending on % *Bos taurus*
Sex	Male or Female	Discrete inputs only Male = 0 Female = 1
Color	Black, Red, Tan, White	0 to 1 assigned based on pictures taken of individual animals at the time of initial processing: Black = 1; White = 0; Red = 0.4 - 0.9; Tan or Cream = 0. 1- 0.5
Temperament	1 to 5 assigned according to the Limousine Breed Association temperament scoring	Temperament score divided by 5
Hair thickness	Ranging from Very Short and Thin to Thick and Wooly	0 to 1 assigned based on pictures: 1 is equal to a wooly animal (thick winter coat). 0 is equal to a thin short hair of a *Bos indicus*.
Previous exposure	Date placed in the pens. Should be adjusted to individual groups of animals – those raised in Kentucky will be exposed to more hot weather in April than those raised in North Dakota.	For Clay Center it was assumed that by July 15 animals should be well acclimated to heat (value of 0).
Condition score	Varied. Either 1 to 5, 1 to 9, or 1 to 27	Condition score divided by max score (for our data the maximum value was 27)
Age	Age in months	Divide age in months by 21
Current health	General look of the animal	0 to 1
Previous pneumonia	Taken from health records	Times treated divided by 4 (Max value for input = 1)
Previous other health issues	Taken from health records – all treatments (except pneumonia) are treated equal. Typical entries included dehorning and foot rot.	Times treated divided by 4 (Max value for input = 1)

Model Validation

The Model was validated using data collected on three groups of outdoor penned feedlot heifers. Feedlot heifers (192 total) of four genotypes (Angus, Charolais, and two different crossbreds MARC I [¼ Charolais, ¼ Braunvieh, ¼ Limousin, ⅛ Angus, ⅛ Hereford] and MARC III [¼ Pinzgauer, ¼ Red Poll, ¼ Hereford, and ¼ Angus]) were used in three consecutive years

(64 heifers in 2004, 2005, and 2006). Cattle were randomly selected and placed in one of eight outdoor pens on the basis of weight, and previous cases of pneumonia; each pen will had a total of eight heifers, two of each breed. These heifers were hormone treated and fed standard feedlot diets, twice daily. Heifers were weighed, condition scored, and temperament scored every 28 days. Condition scores were assigned using an expanded 27-point scale due to the relative similarity of the animals in the study. Temperament scores were assigned to animals based on their behavior in the scale. Animals were assigned a 1 to 5 value based on the Limousin Breed Association's method (British Limousin Cattle Society, 2007).

The heifers were evaluated for heat tolerance by measurements of respiration rate and panting score (Mader and Davis, 2002). Five days a week throughout June and July respiration rate and panting scores were taken at 0800 and 1500 h on a total of 16 pre-selected animals. Two observers recorded respiration rates by using a stopwatch to time 10 flank movements, and assigned panting scores based on visual observation of the animal behavior (Table 2).

Table 2. Description of panting scores.

Score	Description[1]
0	Normal respiration, ~60 or less bpm[2]
1	Slightly elevated respiration, 60 – 90 bpm
2	Moderate panting and/or the presence of drool or small amount of saliva, 90 – 120 bpm
3	Heavy open-mouthed panting; saliva usually present, 120 – 150 bpm
4	Severe open-mouthed panting, accompanied by protruding tongue and excessive salivation

[1] Panting scores were assigned based on visual observation of behavior, not on the estimated respiration rates
[2] bpm = breaths per minute

The temperature, humidity, wind speed, and solar radiation were collected before and after the daily stress measurements using a weather station placed in the vicinity of the animals being observed. The Temperature Humidity Index (THI; Thom, 1959) was calculated using the average of the two readings taken at each measurement period using the following equation:

$$THI = 0.8 \times T_{db} + \frac{RH}{100} \times (T_{db} - 14.4) + 46.4 \quad (1)$$

Where: THI is Temperature Humidity Index, T_{db} is dry bulb temperature in °C, and RH is relative humidity in percent.

The data collected on the initial day of processing (health history, age, condition score, and temperament score) were used as inputs to the model. A digital picture of each individual animal was taken during the initial processing and used to assess color and hair thickness.

Statistics

The Model was used to assess the susceptibility of each of the 192 heifers individually. Animal susceptibility (the output of the model) was statistically compared to individual stress measurements of respiration rate and panting score, and production traits of weight gain and change in condition score.

The model accuracy was determined using a regression analysis (SAS, 2000) of the raw susceptibility output of 0 to 1, and respiration rate and panting scores from the afternoon reading throughout the three summers. The Model equation used is shown in equation 2.

$$y = a \cdot x + b \cdot x + c \tag{2}$$

Where: a is the regression coefficient for the effect of THI and b is the regression coefficient for the effect of animal susceptibility as predict by the model and c in the intercept term.

The Model output was then categorized into a risk category as described in Table 3. The risk category represented a fuzzy description of the animal risk. The THI was classified into four categories to be used in the following analysis. The THI categories were originally described by the LCI in 1970 and are as follows: Normal (THI < 74), Alert (74 ≤ THI < 79), Danger (79 ≤ THI < 84), Emergency (THI ≥ 84) (LCI, 1970).

The General Linear Model (GLM) (SAS, 2000) procedure was used to analyze each year's production data (weight gain and condition score). Production data was tested for effects of susceptibility category using the following model.

$$y_{ij} = \mu + \alpha_i + \varepsilon_{ij} \tag{3}$$

Where: μ is the overall mean, α_i is the effect of the i^{th} susceptibility category and the error term of ε_{ij}. Each year's data were analyzed separately and no comparisons were made between years.

An analysis was preformed using general linear model procedure to analyze the effects of susceptibility category, THI category, and the interaction of susceptibility and THI on daily afternoon respiration rates and panting score. The following model was used to complete these analyses.

$$y_{ij} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + \varepsilon_{ij} \tag{4}$$

Where: μ is the overall mean, α_i is the effect of the i^{th} susceptibility category, β_j is the effect of the j^{th} THI category, $\alpha\beta_{ij}$ is the interaction term of i^{th} susceptibility category in the j^{th} THI category, and the error term of ε_{ij}. Each year's data were analyzed separately and no comparisons were made between years.

Table 3. Description and numerical definitions of risk categories as assessed by the Animal Susceptibility Model.

Numerical Category	Description of category	Output numerical range
1	Low Risk	0 – 0.174
2	Slight Risk	0.175 – 0.374
3	Moderate-low Risk	0.375 – 0.574
4	Moderate Risk	0.575 – 0.724
5	Moderate-high Risk	0.725 – 0.824
6	High Risk	0.825 – 0.924
7	Ultra-High Risk	0.925 – 1.0

Results

When the Animal Susceptibility Model was used to assess the 192 heifers (Table 1) used in the validation, no heifers were rated in category 1 (Low Risk), seven were rated in category 2 (Slight Risk), 72 in category 3 (Moderate-low Risk), 104 in category 4 (Moderate Risk), seven in category 5 (Moderate-high Risk), four in category 6 (High Risk), and no animals were rated in category 7, the highest category (Ultrahigh Risk); see Table 4. This distribution seems reasonable, while the model incorporates *Bos taurus* cattle, there were no *Bos indicus* or crossbred cattle in the validation studies. *Bos indicus* cattle would be on the lower end of susceptibility. No cattle were rated in category 7, the highest susceptibility (Ultra-high risk)—this is also reasonable; very few cattle in the feedlot should be rated in this category.

Table 4. Number of heifers in each susceptibility category used in the validation study as assessed by the Susceptibility Model.

	Year			
Model Categories	2004	2005	2006	Total
1. Low Risk	0	0	0	0
2. Slight Risk	3	0	4	7
3. Moderate-low Risk	30	16	26	72
4. Moderate Risk	24	45	33	102
5. Moderate-high Risk	4	2	1	7
6. High Risk	3	1	0	4
7. Ultra-High Risk	0	0	0	0
Total	64	64	64	192

The regression analysis resulted in the following two equations:

$$RR = -196 + 26.4 \times S + 3.54 \times THI \ldots R^2 = 0.48 \quad (5)$$

$$PS = -3.32 + 0.38 \times S + 0.05 \times THI \ldots R^2 = 0.18 \quad (6)$$

Where:
RR = Respiration rate (breaths/min)
PS = Panting score
S =Raw susceptibility score (0 – 1)
THI = Temperature Humidity Index

The susceptibility accounted for about 2% of variation in the stress prediction (2.21% for panting score and 1.84% for respiration rate), while THI accounted for the remaining approximately 98% of the variation. While susceptibility did not account for much of the variation, results indicate that susceptibility increased respiration rate approximately 25 breaths/min and almost half a step in panting score (0.38). Eigenberg et al. (2005) reported thresholds for estimating stress by using respiration rate; the categories they reported are Normal (less than 90 breaths/min), Alert (between 90 and 110 breaths/min), Danger (between 110 and 130 breaths/min), and Emergency (over 130 breathes/min). When using our data and Eigenberg et al. (2005) categories, the importance of risk assessment in individual animals can be illustrated; during a mild stress, a producer could expect to see animals under no stress (<60 breaths/min for a category 2 or 3 animal), and under extreme stress (>140 breaths/min for a category 5 or 6 animal).

The GLM procedure found that performance characteristics (Tables 5 and 6) were not significantly affected by model category (gain, P=0.32; condition score change, P=0.38). Although not significant, gain at the lowest category was higher than gain at the highest category across all years (Cat 2 – 3.28 vs. Cat 6 -- 2.54 for 2004; Cat 3 – 3.47 vs. Cat 5 – 3.39 for 2005; Cat 2 – 2.95 vs. Cat 6 – 2.62). There were very few animals in the lowest and highest categories, therefore, the standard error is high in those categories compared to the middle categories.

Table 5. Effects of susceptibility on weight gain over the experimental period.

	Year		
Model Categories	2004	2005	2006
2. Slight Risk	3.28 ± 0.64	--	2.95 ± 0.43
3. Moderate-low Risk	2.62 ± 0.11	3.47 ± 0.17	2.79 ± 0.91
4. Moderate Risk	2.96 ± 0.14	3.20 ± 0.09	2.95 ± 0.07
5. Moderate-high Risk	2.82 ± 0.32	3.39 ± 0.43	2.62 ± 0.21
6. High Risk	2.54 ± 0.37		

The change in condition also numerically decreased between the highest and lowest categories in all years (Cat 2 – 0.073 vs. Cat 6 – 0.61 for 2004; Cat 3 – 0.048 vs. Cat 5 – 0.44 for 2005; Cat 2 – 0.089 vs. Cat 5 – 0.071 for 2006). Although the production traits did not prove to be significant, the trend was in the correct direction in that animals with a higher susceptibility for heat stress have a more difficult time maintaining high levels of gain and continuing to fatten under summertime conditions.

Table 6. Effects of susceptibility on condition score change over the experimental period.

	Year		
Model Categories	2004	2005	2006
2. Slight Risk	0.073 ± 0.021		0.089 ± 0.017
3. Moderate-low Risk	0.062 ± 0.004	0.048 ± 0.006	0.066 ± 0.004
4. Moderate Risk	0.073 ± 0.004	0.046 ± 0.003	0.063 ± 0.003
5. Moderate-high Risk	0.059 ± 0.011	0.044 ± 0.015	0.071 ± 0.009
6. High Risk	0.061 ± 0.012		

When the GLM procedure was run on the data, one day in 2006 had to be eliminated from the dataset. Only one day ended in the Emergency category during our readings; because there was only one Emergency day there was no statistical comparisons that could accurately be made. The analysis for respiration rate showed significant effects of model category and THI category for all years (P<0.001); the interaction of model category and THI category was not significant in any years (P>0.4). The analysis for panting score showed significant effects of model category, THI category in all years, and a significant interaction term only in 2004.

Upon a closer evaluation of the data, some interesting effects start to emerge. While comparing the respiration rates for animals, the highest and lowest model categories do not always show a significant effect, probably due to relatively small numbers of animals in category 2 (three in 2004; four in 2005). When using category 3 in the same comparison (2004, 2006 – model categories 3 vs. 6; 2005 – model categories 3 vs. 5), the animals ranked in the higher categories had a significantly higher respiration rate (Table7).

A similar trend can be reported for panting score (Table 8), with one exception. In 2006, while panting scores are numerically higher for animals in category 6 than the responses recorded for category 3, the differences are not significant.

Table 7. Effects of susceptibility on respiration rate over the experimental period.

	Year		
Model Categories	2004[1]	2005	2006
2. Slight Risk	111.1 ± 11.9^{ab}		88.1 ± 5.8^{ab}
3. Moderate-low Risk	107.1 ± 1.8^{ac}	105.4 ± 2.0^{a}	91.6 ± 1.1^{a}
4. Moderate Risk	120.0 ± 2.2^{b}	114.6 ± 1.0^{b}	98.1 ± 0.85^{bc}
5. Moderate-high Risk	109.2 ± 5.3^{bc}	116.5 ± 5.1^{b}	101.4 ± 2.9^{c}
6. High Risk	123.0 ± 6.0^{b}		

[1.] Rows with differing superscripts in the same columns are significantly different (P<0.05).

Table 8. Effects of susceptibility on panting score over the experimental period.

	Year		
Model Categories	2004	2005	2006
2. Slight Risk	1.05 ± 0.19^{ac}		0.58 ± 0.20^{ab}
3. Moderate-low Risk	0.48 ± 0.03^{b}	0.47 ± 0.06^{a}	0.53 ± 0.04^{a}
4. Moderate Risk	0.72 ± 0.04^{a}	0.77 ± 0.03^{b}	0.70 ± 0.03^{b}
5. Moderate-high Risk	0.50 ± 0.08^{b}	0.87 ± 0.15^{b}	0.65 ± 0.10^{ab}
6. High Risk	0.94 ± 0.10^{c}		

[1.] Rows with differing superscripts in the same columns are significantly different (P<0.05).

Discussion

The potential benefits of a susceptibility model in animal production would be to employ methods of precision animal management. Precision animal management could be defined as the individualized care of animals to maximize the animal's production and well-being. To practically employ such strategies in a large feedlot setting, animals must be separated into pen sized groups of animals needing similar care. Animals should be grouped by growth potential and other production considerations for dietary and management needs. The Animal Susceptibility Model would be used to sort off the highly susceptible animals first, then the remaining animals could be sorted by growth potential or other production considerations the operator would like to carefully monitor. The benefits of identifying highly susceptible animals would be to provide specialized care for these animals under extreme summertime conditions.

Specialized care (shade, sprinkle cooling, dietary management, etc.) for these animals would lower potential losses due to heat waves, while minimizing the cost of such care.

The validation of this Animal Susceptibility Model is very difficult, because there is no measurement to be taken on the animal that directly compares to the model output of susceptibility. While the susceptibility output of this Model was compared to the production and stress parameters measured, those traits are not only affected by susceptibility but also by the weather conditions and management. While the management of the animal remained as consistent as possible, weather varied significantly from year to year. The effects of animal susceptibility are more observable during extreme weather, therefore, during a mild year, animals will respond differently from an extreme summer.

Conclusion

An Animal Susceptibility Model was developed using a knowledge-based hierarchal fuzzy inference system. The Model was designed to predict the susceptibility of an individual animal to heat stress and the degree of certainty in the prediction made. To accomplish this, the Model uses 11 input parameters (temperament, hair coat color, species [*Bos taurus or Bos indicus*], sex, hair thickness, previous exposure to hot temperatures, condition score, age, previous cases of pneumonia, other previous health issues, and current health state). The output of Animal Susceptibility Model is created by the combination of eight smaller models that use either original input data, output data from a lower level model, or a combination of both to make knowledge-based decisions. The degree of certainty of the Animal Susceptibility Model prediction is based on the knowledge of the combination of inputs, the certainty that the data is correct (in the case of health data), and the quantity of the input data.

The validation of the Model showed that animal categorized in the higher susceptibility categories had numerically lower gains and condition score changes than the animals in the lower susceptibility categories. It was also shown that stress (respiration rate and panting score) was significantly impacted by both THI category and Susceptibility category, where animals in the Lower Susceptibility category had lower stress than those in the Higher Susceptibility category.

While results of the Model validation are not ideal, they may be realistic. As animals and weather condition vary, the absolute stress measurement on any animal and any given day can vary immensely, therefore a small number of observations in a given susceptibility and THI category do not necessarily reflect the same picture as a large number of measurements on many animals. Also, remembering the long-term goal of this project is to identify only the highly susceptible animals, small differences in the lower categories, while nice for validation purposes, have little practical application.

The animals tested in these validation studies were similar in most parameters -- all were *Bos taurus* heifers with a similar age and similar preconditioning. Other parameters should be tested in future validation tests, such as B*os indicus* and *Bos taurus x Bos indicus*. For future studies a more varied set of animals should be used, which should result in a wider range of responses thus making validation more definitive.

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