A real time heat strain risk classifier using non-invasive measures of heart rate and skin temperature

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Abstract

For the military and civilian first responders heat injury is a very real concern. Several real-time physiological monitoring systems exist that can utilize heat strain indexes [e.g. physiological strain index (PSI)] and provide alerts to medical personnel. However, these systems depend on core temperature measurement using ingested pill thermometers which can suffer inaccuracies from ingested water. In order to find a better solution and to overcome this problem we suggest the use of a layered heat strain management system which identifies individuals “at risk” from heat injury using non-invasive measures. The intent is to identify individuals that need closer monitoring or heat injury mitigation strategies. This paper proposes a logistic regression classification model built from a data set containing 81 bouts of exercise from 49 subjects with and without personal protective equipment. Labels of “at risk” and “not at risk” were determined a priori based upon a PSI threshold of 7.5. The model has a classification error rate of 10% with only one false negative. An earlier classification model and a least squares regression model had classification errors of 21% and 14%, respectively. In addition classifying “at risk” subjects the model provides a decision boundary that can be set based upon mission needs and risk. We conclude that the logistic regression model would provide a valuable tool in a layered heat strain management system.

Introduction

The ability to prevent or reduce the incidence of heat injury using cost effective physiological monitoring technologies would enhance occupational safety measures for workers engaged in physically demanding tasks in high heat strain environments. Heat injury is a concern to both military and first responders. In 2005, the US Army reported over 1100 cases of heat injury, with 204 cases of heat stroke (US Army 2006). Heat strain has also been suggested as a possible contributing factor in the sudden cardiac death of firefighters - the leading cause of US firefighter deaths (Fahy and LeBlanc 2006) - where the cardiovascular system is stressed from the competing needs of thermo-regulation and metabolic requirements (Smith et al., 2001). Additionally the effect of heat strain on workers encapsulated in personal protective equipment (PPE) has long been viewed as a problem (Muza et al 2001; Givoni and Goldman 1972). Finding the appropriate physiological indicators that identify impending heat strain and which are also simple to measure is key to producing a practical heat injury prevention tool.

Various techniques have been proposed to monitor and assess heat strain. The National Institute for Occupational Safety and Health (NIOSH) suggest the monitoring of core body temperature, skin temperature, sweat, and heart rate may be appropriate to indicate heat strain (NIOSH 1986). Moran et al (1998) developed a comprehensive heat strain indicator that combines two of these parameters – heart rate and core body temperature – into a single measurement that they termed the physiological strain index (PSI). The PSI has demonstrated efficacy in identifying individuals with heat strain in both hot-dry and hot-wet environments with or without PPE (Moran 2000). Recent technological advances have also provided the possibility of real time monitoring of PSI for both warfighters and first responders [e.g., U. S. Army Warfighter Physiological Status Monitoring (WPSM) system, (Buller et al 2007)]. These physiological monitoring systems could be used to reduce the incidence of heat injury by setting mission specific PSI thresholds. When a threshold is obtained heat strain mitigation strategies can be adopted. However, the use of PSI in this way is dependent on obtaining reliable core body temperatures.

While ingestible core temperature thermometer pills (e.g., Mini Mitter Inc. Bend, OR; O'Brien et al 1998) have been used successfully to measure core temperature in ambulatory settings (Hoyt et al 2001) they have a downside for use in a heat injury prevention system. After a core temperature pill is ingested measurements suffer from inaccuracies from ingested fluids until the pill transits the upper portion of the gastro-intestinal tract (Wilkinson et al 2008). If a pill has been in the body for less than 8 hours impending heat casualties can be missed as the true core temperature may be masked by recent cold drinks. However, by simplifying the problem from continuously measuring PSI to determining "at risk" individuals, it may be possible to remove the need for continuous core temperature monitoring and use measurements not influenced by drinking behavior.

The WPSM system proposes a layered architecture (Buller et al 2005; Tatbul et al 2004) where multiple algorithms of differing complexity are used to assess heat strain based upon risk level. In this architecture, a PSI measurement may only be needed when closer monitoring is called for as a worker enters an "at risk" status. The criteria to enter an "at risk" status could be influenced by mission characteristics, environmental conditions, clothing requirements, or previous heat injury. The key to the success of this type of layered system is to have a reliable method to determine whether an individual is "at risk" or "not at risk". In 2005, Yokota et al constructed such an algorithm to serve this purpose for the WPSM system. The algorithm was based upon determining heat strain risk from heart rate, skin temperature, and body mass index where risk was determined from core temperature ("at risk" ≥ 38.5 ºC and "not at risk" <38.5 ºC). While the algorithm classification error rate was high, ~ 21%, the work, as a pilot study, showed that the relationship of skin temperature and heart rate to heat strain showed promise.

The purpose of this study was to construct a new model for use in a layered heat strain management system which will identify individual's who are "at risk" from heat strain. The model will be derived directly from heart rate, skin temperature, and PSI data using statistical classification techniques. The intent is to provide a model that produces the lowest number of classification errors, while allowing classification thresholds to be adjusted based upon mission needs and risk.

Methods

Two different data sets of approximately equal size containing examples of exercising individuals with and without PPE were assembled. Both data sets contained the same variables of heart rate, core body temperature, and chest skin temperature taken at the end point in a bout of exercise. One data set was used to develop the initial model while the second data set was used for validation.

Subjects and data sets

Group 1 Training Data: comprised of 40 distinct bouts of exercise assembled from eight different male subjects (Age = 23 ± 6 yr, body mass index = 24.5 ± 4.1), who participated in a series of trials involving two bouts of exercise without PPE and three bouts of exercise with PPE (Latzka et al 1997; Latzka et al 1998). Exercise sessions without PPE were conducted on a treadmill individually set for each subject to work at ~45% of VO_{2max} (1.56 – 1.65 m/s @ 4-9% grade). Exercise sessions with PPE were conducted on a treadmill individually set for each subject to work at ~55% of VO_{2max} . For all sessions environmental conditions were set at ambient temperature = 34.9 ± 0.1 ºC, dew point = 25.9 ± 0.6 ºC. All subjects were acclimatized to exercising in these temperatures.

Group 2 Validation Data: comprised of thirty four male and seven female subjects assembled from four different studies (Age = 22 ± 3 yr, body mass index = 24.2 ± 3.2). Table 1 presents the exercise regime, environmental conditions and clothing for each of the referenced studies.

Table 1. Validation data drawn from four different studies, showing environmental conditions; walking speed and grade; and clothing. PPE = personal protective equipment, and PT = shorts and T-shirt.

Reference	N	Environment	Walking Exercise	Clothing	Duration
Levine et al 2003	5	38ºC, 30%RH	0.89 $m \cdot s^{-1}$, 0% grade	PPE	240 min
Cheuvront et al 2003	5	30ºC, 30%RH	1.46 $m \cdot s^{-1}$, 2% grade	PPE	80 min
Stephenson et al 1999	7	30ºC, 38%RH	1.34 $m \cdot s^{-1}$, 2% grade	PPE	45–90 min
Moran et al 2004	24	40ºC, 40%RH	1.39 $m \cdot s^{-1}$, 2% grade	PT	120 min

Measures

Physiological Strain Index (PSI): A PSI (Moran et al 1998) threshold was used to classify both the training and validation data a priori into "at risk" and "not at risk" heat strain groups. The PSI categorizes physiological strain in a scale from 0 – 10, and was calculated for all subjects using core body temperature (T_{core}) and heart rate (HR) with the following formula:

$$PSI = 5(T_{core(t)} - T_{core(0)}) \bullet (39.5 - T_{core(0)})^{-1} + 5(HR_{(t)} - HR_{(0)}) \bullet (180 - HR_{(0)})^{-1} \qquad (1)$$

As initial resting values of $T_{core(0)}$ and $HR_{(0)}$ were not available for most subjects these values were set to $T_{core(0)}$ = 37.12 ºC and $HR_{(0)}$ = 71 beats/min - the mean resting values for 100 subjects presented in Moran et al (1998).

With a desire to make the model conservative we chose a PSI threshold value of 7.5 with the following rationale: (1) Our human use review guidelines set core temperature and heart rate thresholds that are exceeded at a PSI value of 8, and (2) Moran labels a PSI of 7 to be "High" strain. Thus, to identify the transition from "High" physiological strain, to a physiological strain that exceeds our human use review safety limits we chose a threshold value of PSI = 7.5. Classification labels were assigned based upon PSI ≥ 7.5 = "at risk" and PSI < 7.5 = "not at risk".

Skin Temperature: While data were available for several skin temperature locations chest skin temperature was chosen for two main reasons. First, most ambulatory monitoring devices that measure heart rate also provide a measure of chest skin temperature (e.g., Equivital System Hidalgo Ltd, Cambridge UK; VivoResponder, VivoMetrics Inc. Ventura CA.); and second, in an earlier unpublished mutual information analysis of the Group 2 data, chest skin temperature explained more of the variance in core body temperature than thigh skin temperature or mean weighted skin temperature.

Modeling approach

The goal of this analysis was to develop a classification model that provides a physiological reasonable decision boundary for identifying individuals "at risk" and "not at risk" of heat strain. An idealized boundary would have three properties and appear similar in shape to Yokota et al's "Red Zone" threshold, taking the form of an inverted "S" (see figure 1). From figure 1 the three properties would be: (1) the top right quadrant of figure would represent the "at risk" class, where subjects have both high heart rate and high skin temperature; (2) subjects with high heart rates from exercise and lower skin temperatures would be classified as "not at risk"; and (3) Subjects just having high skin temperatures regardless of heart rate would be classified as "at risk". The assumption here is that in general, high skin temperatures are likely to indicate high heat strain. When this is not the case context can be used to ignore the "at risk" classification.

Logistic regression is used to derive our decision boundary directly from the data. Logistic regression has an advantage that the derived decision boundary is probabilistic in nature, allowing the classifications to be modified based upon the level of risk or certainty. To ensure that the logistic regression approach does not over fit the data we initially generated a model from Group 1, and then applied this model to Group 2. Finally a logistic regression model is generated from the combined data set of Groups 1 and 2. The classification performance of our final model is compared to a multivariate least squares linear regression model also generated from the combined Group 1 & 2 data, also estimating PSI from chest skin temperature and heart rate. Additionally subjects were also classified as "at risk" or "not at risk" using Yokota et al's (2005) "Red Zone" threshold algorithm.

In logistic regression the optimal decision boundary is given where the log-odds ratio equates to 0. This is shown in equation (2) where y=1 is the "at risk" class and y=0 is the "not at risk" class. Here, given **x** (in our case a vector of the input data) the probability (p) that the classification is "at risk" (y=1) is equal to the probability that the classification is "not at risk" (y=0):

$$\log \frac{p(y=1 \mid \mathbf{x})}{p(y=0 \mid \mathbf{x})} = 0 \tag{2}$$

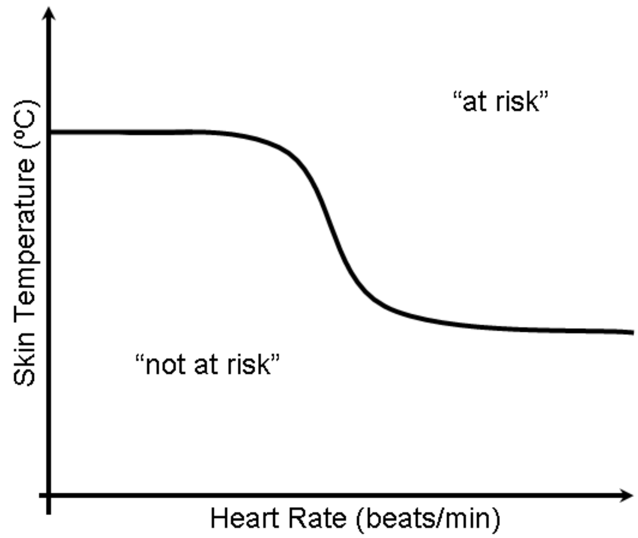

Figure 1. Idealized form of the heat strain "at risk" / "not at risk" decision boundary.

The decision boundary is modeled directly by the dot product of a vector of weighting coefficients (**w**) and a vector of input variables (**x**) given by the following linear algebra expression:

$$\log \frac{p(y=1|\mathbf{x})}{p(y=0|\mathbf{x})} = \mathbf{w}^{\mathrm{T}}\mathbf{x} \tag{3}$$

The probability that a data point **x** is in class "at risk" (y=1) is given by the following logistic model:

$$p(y=1|\mathbf{x}) = \frac{1}{1+\exp(-\mathbf{w}^{\mathrm{T}}\mathbf{x})} \tag{4}$$

Given a set of training data the weighting coefficients for the decision boundary are learned by finding the maximum likelihood (ML) solution for the logistic model shown in equation (4). The mathematics of finding the ML solution are beyond the scope of this paper, however, Bishop (2006) provides more detail of this topic.

Specifically in our model the "at risk" group (PSI ≥ 7.5) is defined as the class $y = 1$, and the "not at risk" group (PSI < 7.5) is defined as the class y = 0. Our model contains two input variables; heart rate and chest skin temperature which form the vector: **x = [$\mathbf{x_1}$, $\mathbf{x_2}$]**, where **$\mathbf{x_1}$ = heart rate (beats/min)**, and **$\mathbf{x_2}$ = chest skin temperature (ºC)**. To achieve our idealized decision boundary we map our input data into a cubic polynomial. Thus, our input data vector **x** takes the form:

$$\mathbf{x} = [\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_1^2, \mathrm{x}_2^2, \mathrm{x}_1^3, \mathrm{x}_2^3, \mathrm{x}_1\mathrm{x}_2, \mathrm{x}_1^2\mathrm{x}_2, \mathrm{x}_1\mathrm{x}_2^2] \tag{5}$$

When a data point is evaluated, the model equation (4) returns the probability that the data point **x** is in the "at risk" category. Since a probability is returned, the threshold to classify a point as “at risk” or “not at risk” can be set based upon the desired risk level. An example of this calculation is given in the addendum.

Results

Group 1: training data

A logistic regression model was developed on the group 1 training data and the decision boundary was set at a probability of 50%. Figure 2 depicts the training data by class (“at risk” or “not at risk”), the logistic regression decision boundary, and the classification errors. There was only one false positive classification error.

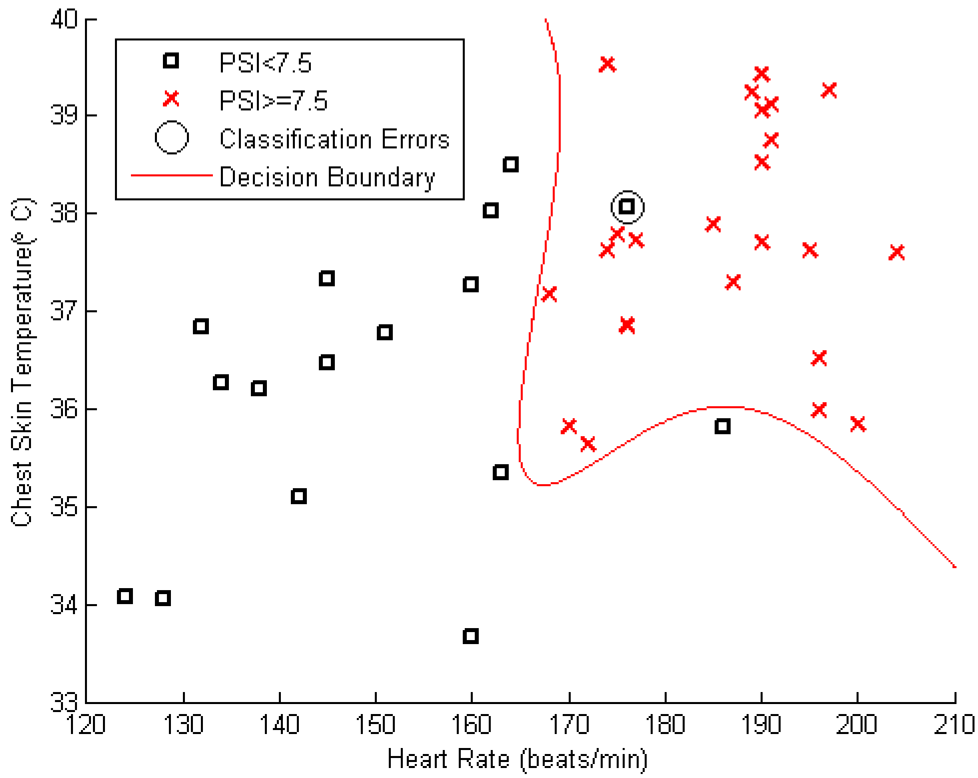

Figure 2. Training data by class (“at risk” or “not at risk”), logistic regression decision boundary and classification errors.

Group 2: validation data

Next we applied the logistic model generated from Group 1 to Group 2. Figure 3 shows the Group 2 data by class (“at risk” or “not at risk”), the classification errors with the logistic regression decision boundary set at 2%, and the decision boundaries for 50, 40, 30, 20, and 5%. Table 2 shows the number of false negatives and false positives for a number of decision boundaries. This table shows the classification results as the decision boundary is moved from 50% (where a point is classified “at risk” if it has ≥ 50% probability of being in the at risk class) to a conservative 2% decision boundary (where a point is classified “at risk” if it has ≥ 2% probability of being in the “at risk” class).

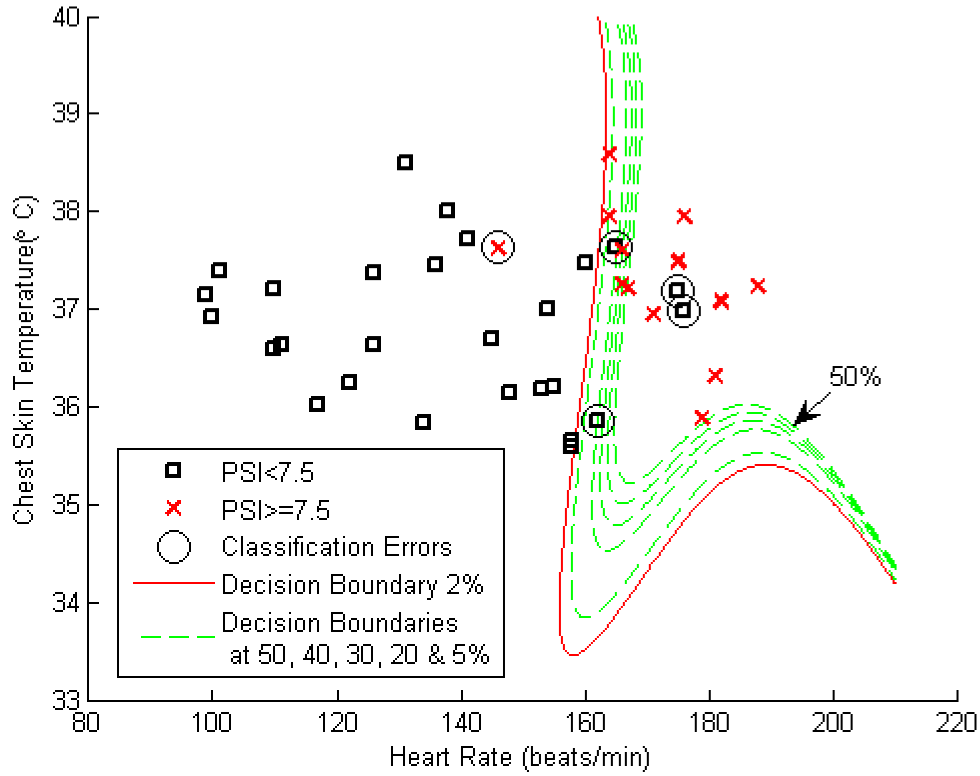

Figure 3. Group 2 data by class ("at risk" or "not at risk"), with the classification errors with the logistic regression decision boundary learned from Group 1 set at 2%, and additional decision boundaries at: 50, 40, 30, 20, and 5%.

Table 2. The number of false negative or false positives in the Group 2 validation data using the logistic regression model generated from the Group 1 with the decision boundary set at 50, 40, 30, 20, 5, and 2%.

	Decision Boundary					
	50%	40%	30%	20%	5%	2%
At Risk (N=14)	5 (35.7%)	5 (35.7%)	4 (28.6%)	3 (21.4%)	2 (14.2%)	1 (7.1%)
Not At Risk (N=27)	2 (7.4%)	2 (7.4%)	2 (7.4%)	2 (7.4%)	4 (18.8%)	4 (18.8%)
Total Errors	7 (17.1%)	7 (17.1%)	6 (14.6%)	5 (12.2%)	6 (14.6%)	5 (12.2%)

The model generated from the Group 1 data had the least number of misclassifications at both the 20% and 2% decision boundary with 5 classification errors. However, as a heat risk indicator the model performed best at the conservative 2% decision boundary with only 1 false negative error compared to 3 with the 20% boundary.

Combined model

A new logistic regression model was developed on the combined data of Groups 1 and 2. Figure 4 shows the combined data set by class, the classification errors with the decision boundary set at 40%, and the decision boundaries at 50, 30, 20, and 10%. Table 4 presents the confusion matrix generated using decision boundaries of 50% and 40% on the combined data set and the classification results of the multivariate linear least-squares regression model, and the classification results using the "Red Zone" threshold model.

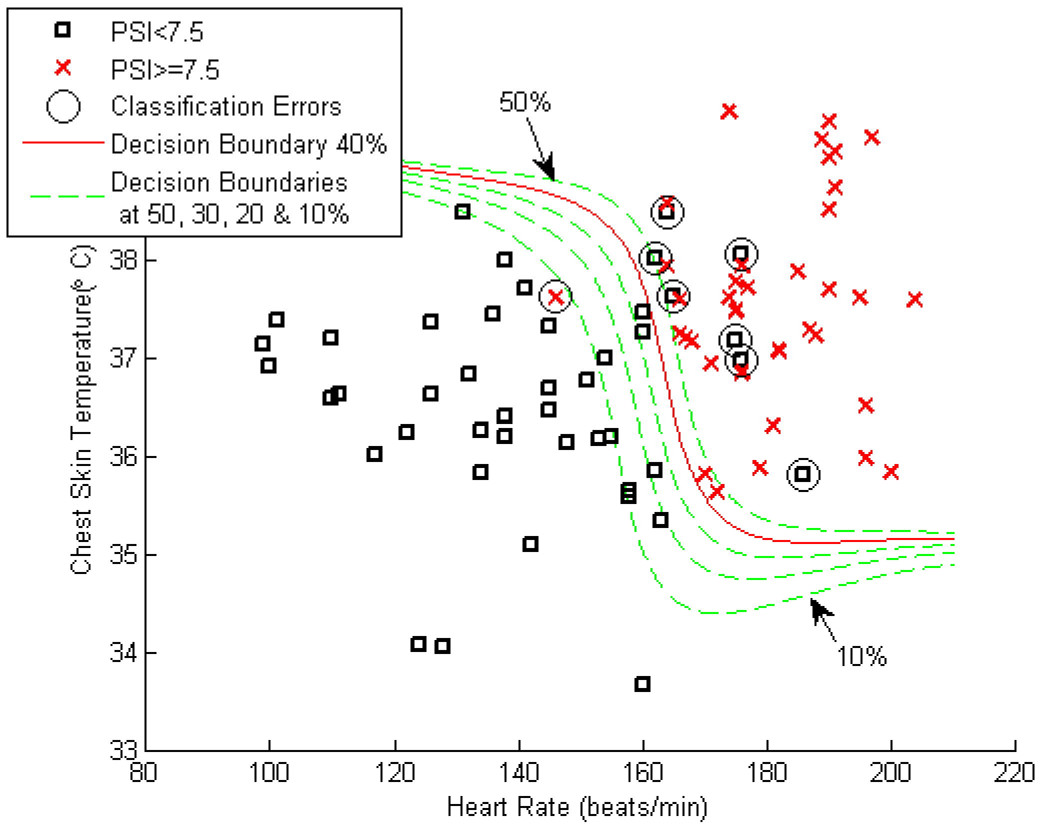

Figure 4. Data pooled from Group 1 and Group 2 by class ("at risk" or "not at risk"), with classification errors for the logistic regression decision boundary learned from the combined data set at 40%. Additional decision boundary contours are shown at: 50, 30, 20 and 10%.

Table 4. Confusion matrix for classifications based upon the logistic regression model derived from the pooled data of Groups 1 and 2, the linear regression model, and the "Red Zone" model.

	Decision Boundary = 50%		Decision Boundary = 40%		Linear Regression Model		"Red Zone" Model	
Actual Class	classified "at risk"	classified "not at risk"	classified "at risk"	classified "not at risk"	classified "at risk"	classified "not at risk"	classified "at risk"	classified "not at risk"
"at risk" (N=37)	34 (91.9%)	3 (8.1%)	36 (97.3%)	1 (2.7%)	30 (81.1%)	7 (18.9%)	35 (94.6%)	2 (5.4%)
"not at risk" (N=44)	7 (15.9%)	37 (84.1%)	7 (15.9%)	37 (84.1%)	4 (9.1%)	40 (90.9%)	15 (34.1%)	29 (65.9%)

Discussion

The purpose of this investigation was to generate a model that could distinguish between subjects "at risk" of thermal injury and subjects "not at risk" of thermal injury using non-invasive and readily available measures of heart rate and chest skin temperature. The logistic regression model generated from group 1 provided a model that correctly distinguished all "at risk" subjects while mislabeling one "not at risk" individual as "at risk". The decision boundary, while not perfect, did meet two of the three idealized criteria: (1) subjects with high heart rates and high chest skin temperature are classified "at risk"; and (2) subjects with only high heart rates are classified as "not at risk".

Initially when this model is applied to the Group 2 data using a 50% classification threshold, performance seems poor with an overall misclassification rate of 17.1% comprising of 5 false negative errors and 2 false positive errors. However, when the classification threshold is adjusted to be more conservative at 2%, the performance improves in two ways. Compared to the 50% classification boundary the total number of errors decreases to 12.2%; and the number of false negative classification errors decreases to 1. As would be expected, when the threshold is reduced the number of false negatives decreases while the number of false positives increases. However, for our intended use we would prefer to bias the model to correctly identify the "at risk" people while tolerating a few extra false positives. Thus, to ensure that we identify all the "at risk" subjects it is not unreasonable to set a more conservative or lower classification threshold value.

While the model generated from Group 1 performs increasingly well as the classification threshold value is reduced, the decision boundary increasingly suffers deformation from our idealized pattern (see figures 1 and 3). Applying this model to new data would not be wise as subjects with heart rates between 155 - 165 beats/min with relatively moderate chest skin temperatures (33 - 35 ºC) would generate artificial false positives. Additionally, the model would also incorrectly classify workers with very high skin temperatures (> 38.0 ºC) and heart rates < 165 BPM as "not at risk". In order to improve the model and generate a decision boundary more like our idealized pattern we pooled our data from both groups and trained a new logistic regression model.

The new suggested model performs similarly against the whole data set as compared to the best performance of the original model trained on the Group 1 data (9.9% compared to 7.4%). However, we suggest that the new model has the advantage of a decision boundary that closely resembles our idealized pattern (see figure 1), allowing it to be applied more generally. In addition, the new model performs best when the classification threshold is set to 40% rather than the 2% needed by the original model.

Compared to the baseline models the combined data logistic regression model performs better than both. The least squares regression has a total of 11 (13.6%) classification errors including 4 false negatives, and the "Red Zone" model has a total of 17 errors (21.0%) compared to the logistic regression model's 8 errors (9.9%). Additionally the logistic regression model identifies almost all of the "at risk" population with only 1 false negative classification and provides a classification boundary that can be adjusted based upon the level of risk or confidence. This ability is not available with either the least-squares regression or the "Red Zone" techniques. Importantly, the logistic regression model also meets all three of our idealized decision boundary properties.

Limitations

While we understand that the suggested model is more generalizable it was generated using the combined data set and thus has had no independent validation. The model was also generated from a fit young population, and it is likely that the decision boundary may differ with an older subject pool with lower maximal heart rates. Additionally, the model does not explicitly include individual differences, but the differential response of heart rate may provide some insight into how larger, less fit subjects may respond to work loads in the heat (Gisolfi and Robinson 1969). Since the model can provide false negative errors it should not replace any existing heat injury prevention measures but be used as an additional tool.

Conclusion

The data suggest that the logistic regression model generated from the combined data is effective at identifying subjects with a PSI ≥ 7.5 with minimal false negative errors, and presents a decision boundary that could be used to assess risk of heat injury. As this model uses two easy-to measure parameters it could be simply implemented as an additional tool to ensure the health and welfare of workers exposed to thermally stressful environments. Heat strain warnings could be used by medical personnel to monitor "at risk" individuals or allow team members to be managed or rotated based upon heat strain risk. This new model allows medical and command personnel to change the classification threshold to be more conservative or liberal depending upon mission demands. The model has the advantage of using PSI as a basis for determining heat strain making it applicable in encapsulated and un-encapsulated situations. In addition it also has the advantage of using two parameters that are easily measured with today's ambulatory physiological monitoring technologies. Thus, we conclude that the model has the potential to be used as a real time non-invasive indicator of heat stress for first responders or military personnel in a comprehensive heat casualty prevention system.

Disclaimer

The opinions or assertions contained herein are the private views of the authors and are not to be construed as official or as reflecting the views of the Army or the Department of Defense. The investigators have adhered to the policies for protection of human subjects as prescribed in Army Regulation 70-25, and the research was conducted in adherence with the provisions of 32 CFR Part 219. Citations of commercial organizations and trade names in this report do not constitute an official Department of the Army endorsement or approval of the products or services of these organizations.

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Addendum: Logistic Regression Model Example

Equation 6, given below, is used to calculate the probability that an individual is in the “at risk” group versus the “not at risk” group.

$$p(y=1\,|\,\mathbf{x}) = \frac{1}{1+\exp(-\mathbf{w}^{\mathrm{T}}\mathbf{x})} \qquad (6)$$

Where y = 1 is class “at risk”.

The logistic regression model is captured in the weighting coefficients (**w**) shown in table 5.

Table 5. Model weighting coefficients, and mapped input data

Model Coefficients **w**	**Input Parameters Mapped Into A Polynomial** **X**	**Example Input Parameters** **x**
-0.0296505547	1	1
-1.4168313955	x_1 (Heart Rate)	176
-0.4039704255	x_2 (Skin Temp.)	37.94
-0.0746402042	x_1^2	30976
-1.6203228042	x_2^2	1439.4436
0.0000356471	x_1^3	5451776
0.0400047846	x_2^3	54612.4902
0.7706539390	x_1x_2	6677.44
0.0015188307	$x_1^2x_2$	1175229.44
-0.0173642989	$x_1x_2^2$	253342.0736

$\mathbf{w}^{\mathrm{T}}\mathbf{x}$ = (-0. 0296505547* 1) + (-1. 4168313955* 176) + (-0. 4039704255* 37.94) +
(-0. 0746402042* 30976) + (-1. 6203228042* 1439.4436) + (0. 0000356471* 5451776) +
(0. 0400047846* 54612.4902) + (0. 7706539390* 6677.44) +
(0. 0015188307* 1175229.44) + (-0. 0173642989* 253342.0736)

$\mathbf{w}^{\mathrm{T}}\mathbf{x}$ = 1.8276

Substituting in equation 69:

$$p(y=1\,|\,\mathbf{x}) = \frac{1}{1+\exp(-1.8276)}$$

$$p(y=1\,|\,\mathbf{x}) = 0.8615$$