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HEAT STRAIN DECISION AID (HSDA) ACCEPTABLY PREDICTS CORE BODY TEMPERATURE DURING SELF-PACED LOAD CARRIAGE WITHIN MULTIPLE ENVIRONMENTAL CONDITIONS

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ABSTRACT

The accuracy of the Heat Strain Decision Aid (HSDA) was assessed for predicting core body temperature (Tc) associated with US Army Ranger Training Brigade (RTB) self-paced road marches during Spring, Summer, and Winter classes. Physiological data was collected from 65 Ranger students (Spring: n = 15, Summer: n = 20, Winter: n = 30) along with an assessment of clothing and equipment worn, and continuous measurements were taken of the environment. This observed data was used as inputs into HSDA and comparisons were made between observations and predictions. Five statistical assessments methods were used to assess the validity of HSDA to predict Tc; Bias, mean absolute error (MAE), root mean square deviation (RMSD), limits of agreement (LoA) and a non-parametric comparison similar to a Bland-Altman analysis. Calculated Bias, MAE, and RMSD between predicted and actual Tc showed a calculated Bias of -0.02, MAE of 0.40, and RMSD of 0.45 °C for the three classes combined. These analyses showed HSDA predictions were able to meet many of the accuracy criterions used to determine acceptability. Additionally, this work highlights areas for potential improvement of the HSDA modeling method.

Keywords: biophysics, modeling, load carriage, Ranger training, thermophysiology

INTRODUCTION

Modern dismounted Soldiers are often at increased risk of thermal injuries, as they regularly work at high intensities for prolonged periods of time; while operating in a complex range of environments (1). These risks are further complicated by the requirements for carrying heavy loads and wearing cumbersome clothing and individual equipment (2-4). It is critical to their missions and individual safety to effectively manage these physiological and environmental threats. The US military has worked extensively on providing guidance as well as computer-based decision aids to help provide tools for mission planning and risk mitigation strategies (5-11)

Goldman (12) eloquently simplified the thermal problem for humans based on the interaction of three main elements: 1) environment, 2) clothing, and 3) metabolic heat production (activity rate). Understanding and predicting responses to these challenges are particularly complex for warfighters, as they work in a variety of environmental conditions (e.g., hot, cold, high altitude, subterranean) (11), they are required to wear occlusive and/or heavy personal protective equipment (13-17), and they work at high or varied demands for extended periods of time. Soldiers in contrast to athletes, work at unpredictable and varying levels of metabolic demand, operate in a wide range of climatic conditions, and these activities and exposures can last for protracted and unpredictable periods of time.

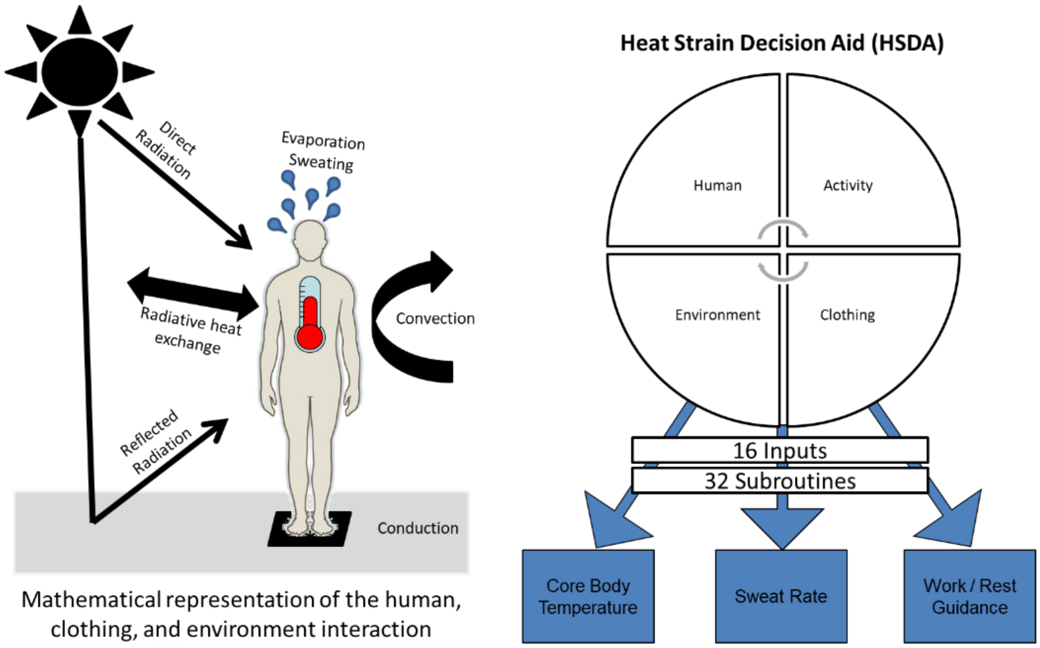
The U.S. Army's Heat Strain Decision Aid (HSDA) is a widely-used thermoregulatory model that makes predictions of core body temperature (Tc) and sweat rate based on inputs related to an individual (or group), clothing biophysical properties, environmental conditions, and metabolic rate (7, 18, 19). The HSDA has been developed and refined based on three main equations developed by Givoni and Goldman (20, 21) that were created to predict Tc at rest, rise in Tc during exercise, and the decrease in Tc following exercise. From these equations, a final equilibrium model was generated that predicts Tc trajectory or rate of rise based on inputs of the biophysical conditions (e.g., human, environment). The model in its current embodiment is designed with several modular components to allow for incremental improvements to component subroutine equations (18, 19).

The HSDA method relies on the heat balance equation (Eq. 1), where in order to predict heat rise or fall in humans, heat storage (S) is calculated from the sum of heat produced, heat gained, and via heat dissipation to the four pathways of heat exchange:

$$S = M \pm W \pm R \pm C \pm K - E \ [\mathrm{W/m^2}] \quad \text{Eq.1}$$

where M and W represent metabolism and work rate; R is radiation transferred via electromagnetic waves (e.g., solar or infrared); C is convective heat transfer with fluid contact (e.g., air or water); K is conductive heat transfer from direct contact with solid objects (e.g., touching a cold surface); E is evaporative heat loss to the environment of water changing from liquid to vapor (e.g., sweat and respiratory evaporative water loss). The HSDA requires ~16 inputs that are passed into a series of approximately 32 subroutine equations that collectively make predictions of Tc and sweating rates (S_{wt}), which can then be used to produce maximal safe (uninterrupted one-time) work times, optimal work rest cycles for prolonged work, estimation of water requirements, and establish cooling requirements (Figure 1).

Figure 1. Heat exchange and the Heat Strain Decision Aid (HSDA)



METHODS

This study was conducted to assess the predictive accuracy of the HSDA model for mission planning and heat stress mitigation during self-paced load carriage exercise in the field. US Army Ranger students from the Ranger Traning Brigade (RTB) (Fort Benning, GA) volunteered to be monitored during a load carriage event of their training. Biophysical assessments were made for the clothing worn by the students. Collectively, the data obtained from the students were compared to modeled predictions from HSDA.

Volunteers

Eighty-three US Army Ranger students during three classes were studied (Spring Class: n = 28; age, 24.4 ± 3.9 years, height 175.3 ± 7.4 cm, body mass, 79.0 ± 8.4 kg; body fat 15.2 ± 3.2 %; 2-mile run time, 12:58 ± 0:50 min:sec. Summer Class: n = 25; age, 25.6 ± 4.7 years; height, 177.8 ± 5.3 cm; body mass, 79.3 ± 9.6 kg; body fat, 14.2 ± 3.6 %; 2-mile run time, 12:52 ± 0:52 min:sec. Winter Class: n = 30; age, 24.7 ± 4.2 years; height, 178.6 ± 6.4 cm; body mass, 83.6 ± 9.0 kg; body fat, 16.6 ± 4.0 %; 2-mile run time, 12:56 ± 0:58 min:sec). The three classes were studied to examine the efficacy of the range of applying HSDA across different environmental conditions, as it has not historically been used in cool or cold conditions

Of these 83 enrolled, 65 participants had complete datasets and were used for the analyses (Spring, n = 15; Summer, n = 20; Winter, n = 30).

Volunteers were briefed on the purposes, risks, and benefits of the study and gave their written informed consent prior to study participation. Study approval was granted by the Scientific and Human Use Review Committees at the U.S. Army Research Institute of Environmental Medicine, Natick, MA.

Baseline demographics data were collected from each volunteer, along with measures of body mass, height, and body fat estimates, made based on circumfrerence measures (AR 600-9 (22). Each volunteer was fitted with a physiological status monitoring device (EQ-01 Equivital™, Swavesey, Cambridge, UK, www.equivital.co.uk) to collect heart rate, respiration rate, body motion, body position, and skin temperature (Ts). Additionally, each volunteer ingested a thermometer pill (MiniMitter, Inc., Bend, OR) approximately 18 hours prior to their measured activities, to obtain continuous measures of Tc.

Environmental Conditions

Air temperature (Ta, °C), percent of relative humidity (RH, %), solar radiation (Tmr, °C), and wind speed (Vw, m/s) were measured along the road-march course using a combination of three different data collection instruments; the Campbell Scientific, Inc. (Logan, UT) CR-10x weather station, the ADA Weather Pod (ADA Technologies Inc.; Littleton Colorado), and the HOBO® Pro v2 Ta/RH logger (Onset Computer Corporation; Pocasset MA).

Clothing Assessments

Standard biophysical assessments for the thermal and evaporative resistances (R_t and R_{et}) were conducted (ASTM F1291-16 & ASTM F2370-16) (23, 24) for the worn ensembles. Assessments were conducted using a 20-zone sweating thermal manikin (‘Newton’, Thermetrics, Seattle, WA http://www.thermetrics.com/) located in a controlled environmental chamber.

Values of (R_t and R_{et}) were converted to total insulation (clo), a permeability index (i_m). A ratio of clo and i_m (i_m/clo) is used as a measure of the ensembles evaporative potential (25, 26). Testing for R_t and R_{et} measurements were conducted at three wind velocities (*V*) to enable the calculation of exponent (gamma) value (^{g}) to describe the change in insulation and evaporative potential with increasing wind speeds (27-29).

Exercise Conditions

Students from the Spring and Winter courses each marched 19.3 km (12 miles); while students in the Summer class marched for 12.9 km (8 miles). The course grade was mostly flat (0%), with some uphill and downhill sections within ± 6% grade. Each of the students carried military equipment on their body and in a rucksack. The load was similar between students but sligthly different between classes (Spring: 34.1 ± 1.9, Summer: 31.6 ± 1.2, and Winter: 30.8 ± 1.6 kg). The students all walked/ran at their own self-pace; however, a mimum qualifying time was required in order to graduate from the course.

Predictive Modeling

Modeling with HSDA requires inputs related to the human, their activity (metabolic rate), environmental conditions and clothing biophysics.

Inputs for each individual were based on direct measures of initial Tc, Ts, and calculated body surface area (BSA) from height and body mass measurements (30). Individuals were assumed to be fully hydrated (0% dehydrated) and heat acclimatized (more than 12 days in the heat).

Metabolic rate was calculated for each individual based on their body size, average pace speed, load carried, and terrain features (3, 31-33). As each individual traveled at a varied self-pace, for practical purposes the cacluations were done based on a single grade (G%) and terrain factor (η) combination (G = 0%; η =1.1). Part of the predictive modeling challenge is the fact that student pace varied for different reasons. For example, some of the variations were easily explainable (e.g., uphill or downhill sections); while some were less predictable (e.g., individuals trying to pace one-another, onset of fatigue). While this is a challenge from a scientific design perspective, this is also more realistic to real-world activities.

Inputs of the environment (Ta, RH, Vw) were used for each class based on the average during the march periods. Inputs for each class were set as: Spring: 15.5 °C, 92.6

%, 0.21 m/s, Summer: 23.6 °C, 99.9 %, 0.48 m/s,, and Winter: -11.1 °C, 83.7 %, 0.08 m/s). Additionally, calculations for were set to Tmr = Ta; while for each individual Vw = measured from the environment + individual movement speed.

Clothing input properties were based on measured values for the Advanced Combat Uniform (ACU), where clo = 1.08, i_m/clo = 0.47, clo^g= -0.24, and i_m/clo^g = 0.35.

Statistical analysis

Statistical analyses were performed using a combination of Microsoft Excel (Microsoft Corporation, Redmond, WA, 2016) and MATLAB (2019b, The MathWorks, Inc., Natick, MA). Descriptive statistics are presented as means ± SD. Criterion for acceptable accuracies were based on bias, mean absolute error (MAE), root mean square error (RMSE), and calculated limits of agreement (LoA). A direct measurement accuracy criterion of mean bias ± 0.27 °C was used, as well as MAE and RMSE within observed SD values (34-36). Additionally, a non-parametric comparison method (similar to Bland-Altman (37)) was used for comparisons between observed and modeled data.

Bias is used to indicate whether the model over- or under-predicted Tc, calculated as the mean difference between predictions and measurements. The MAE, average of the absolute prediction errors, is calculated with as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i|$$

where f_i is the predicted value, y_i is the actual value, and e_i is the absolute error.

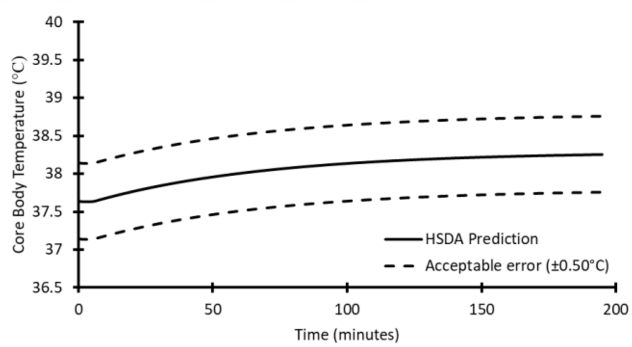
The use of RMSE is helpful, as it applies a greater penalty to larger errors, calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} d_i^2}$$

where d_i is the difference between observed and predicted T_c and n is the number of data points, in this case being the number of measurements for each minute. This represents the mean absolute difference between predicted values and measured values (38). One advantage of RMSE is that the value calculated is in the same units as the original data, i.e., degrees Celsius. Overall RMSE was compared to a variation of 0.50 °C, criteria used by Gunga et al. (39).

The area between the HSDA prediction line and the band (0.50 °C) lines shown in Figure 2 would be considered acceptable model performance. If the model's prediction fell above or below these band lines (the dashed lines) then the model would be determined to be inaccurate.

Figure 2. Example of 0.50 °C acceptable error bands surrounding Heat Strain Decision Aid (HSDA) prediction curve



RESULTS

Calculated Bias, MAE, and RMSE between predicted and actual Tc showed a calculated Bias of -0.02 °C, MAE of 0.40 °C, and RMSE of 0.45 °C for the three classes combined (Table 1). Each class and the aggregate met the Bias criterion of being within ± 0.27 °C. Using the comparison to the observed data SD, each of the classes and the aggregate MAE was within the observed SD.

The aggregate of the classes RSME was within the aggregate of the overall observed SD; while each individual class was within their respective observed SD with the exception of the Spring class being slightly over but less than 1.5·SD (0.41 to 0.49 °C). For the RMSE, if ± 0.50 °C is used as the acceptable error, each class was within this criterion.

Figure 3 shows the actual and predicted Tc for all classes; while Figures 4-6 show the same comparisons for each class (Spring, Summer, Winter). These figures show there are errors in predicted Tc, especially after the first hour of the road march.

Table 1. Error estimates (°C) of Bias, mean absolute error (MAE), root mean square deviation (RMSE), and Limits of Agreement (LoA) for predicted vs. observed core temperature by class

Class	Observed SD	*n*	Bias	*MAE*	*RMSE*	*LoA*
Spring	± 0.41	15	-0.22	0.40	0.49 ± 0.3	-1.09 to 0.65
Summer	± 0.63	20	0.22	0.53	0.50 ± 0.3	-0.68 to 1.12
Winter	± 0.36	30	0.05	0.26	0.35 ± 0.2	-0.62 to 0.73
Overall	± 0.47	65	0.02	0.40	0.45 ± 0.3	

Figure 3. Comparison of predicted (HSDA) to observed (Obs) core temperature during the road march for all classes averaged together (n = 65)

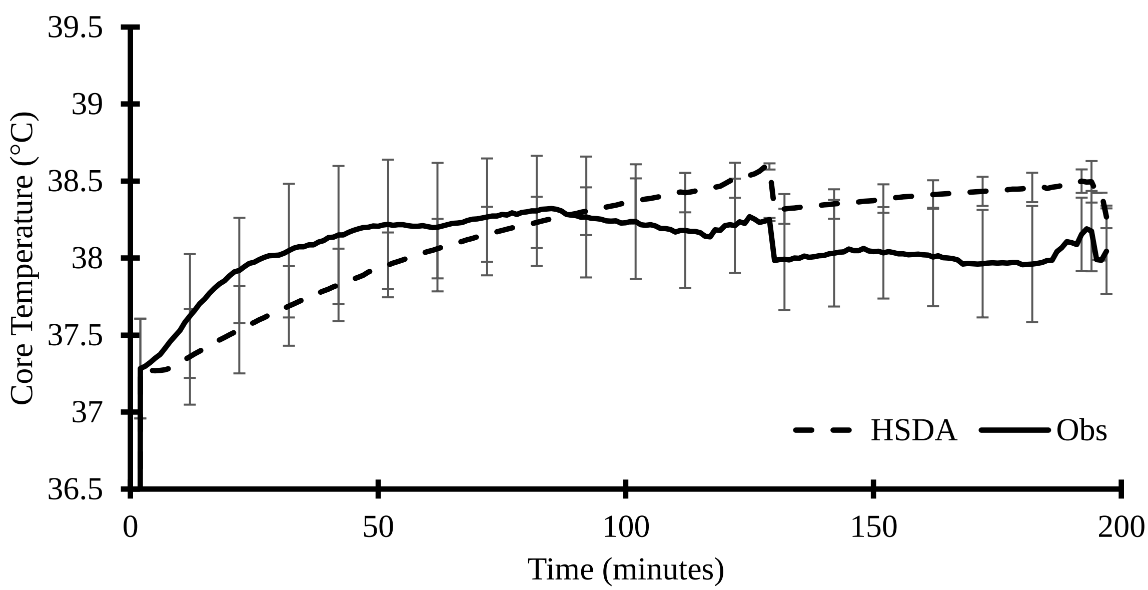


Figure 4. Comparison of predicted (HSDA) to observed (Obs) core temperature during the road march for the Spring class (n = 15)

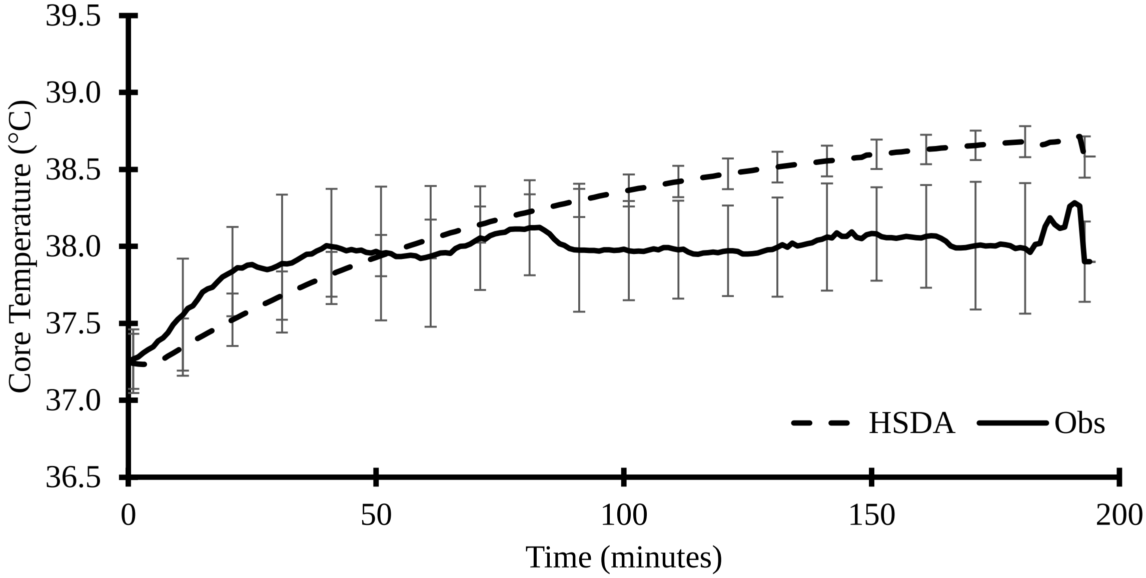


Figure 5. Comparison of predicted (HSDA) to observed (Obs) core temperature during the road march for the Summer class (n = 20)

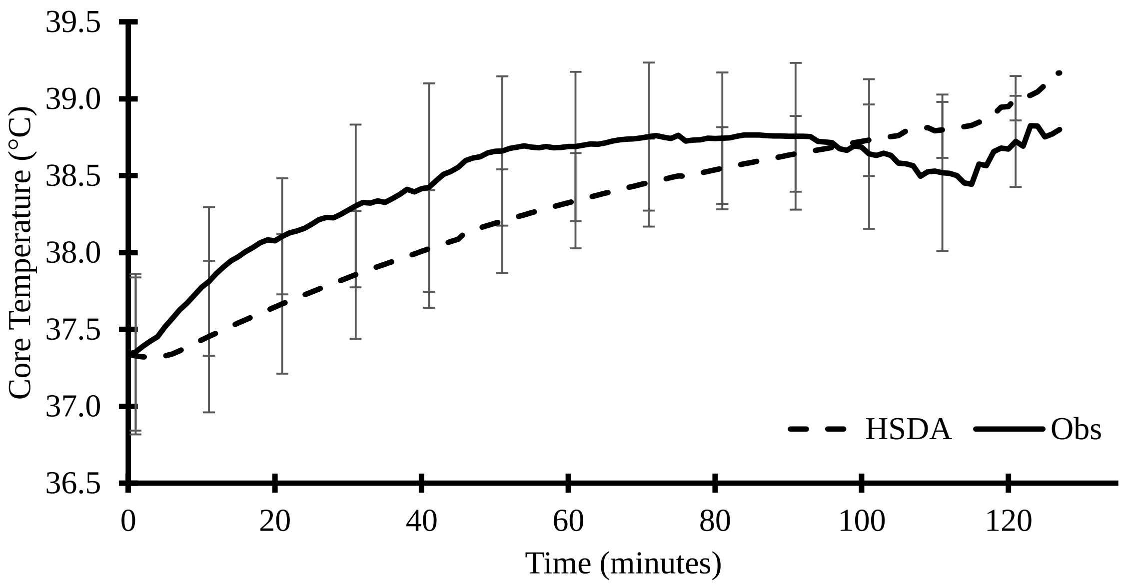
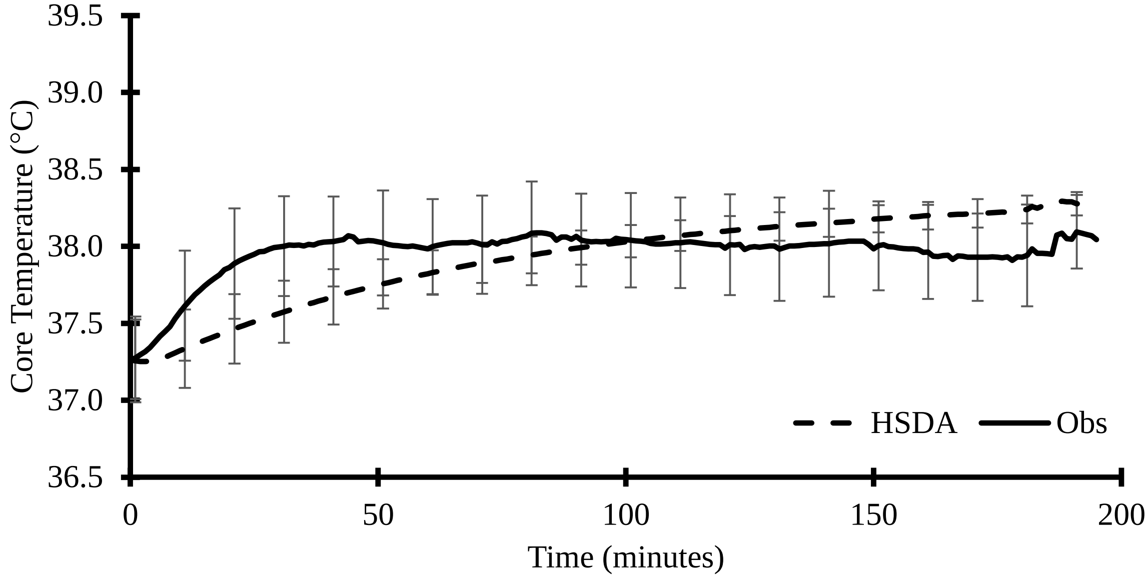


Figure 6. Comparison of predicted (HSDA) to observed (Obs) core temperature during the road march for the Winter class (n = 30)



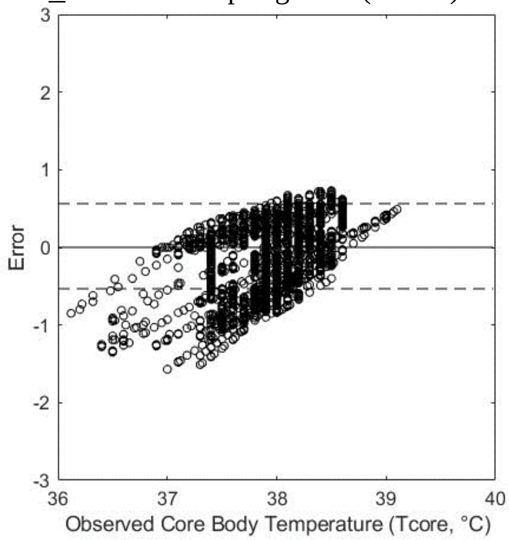
Non-parametric comparisons

Non-Parametric comparison method was used to show the deviations between the predicted and actual observed Tc. The percentage of Tc values for all individuals outside the accepted error criteria of 0.50 °C was 24% of all predicted values. Table 2 shows the percent of the time HSDA under- and over-predicted Tc relative to the acceptable error criteria by class. Additionally, the amount of over- and under-predicted values (error) based on the criterion measure of 0.50 °C is shown in Figures 7-9 for each class.

Table 2. Percent under-predicted and over-predicted core temperature by Heat Strain Decision Aid (HSDA) using error acceptance criterion of 0.50 ºC

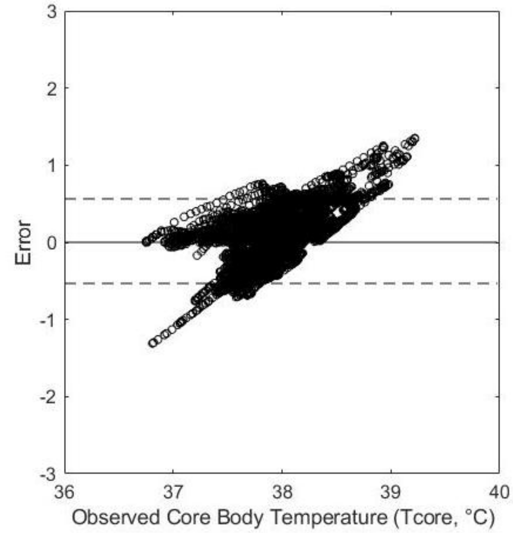
Class	% Under Predictions < -0.50 °C	% Over Predictions > +0.50 °C
Spring	29	3
Summer	5	29
Winter	5	10
Overall	12	12

Figure 7. Comparison of predicted vs. actual core temperature (error) with criterion measure of + 0.50 °C for Spring class (*n* = 15)



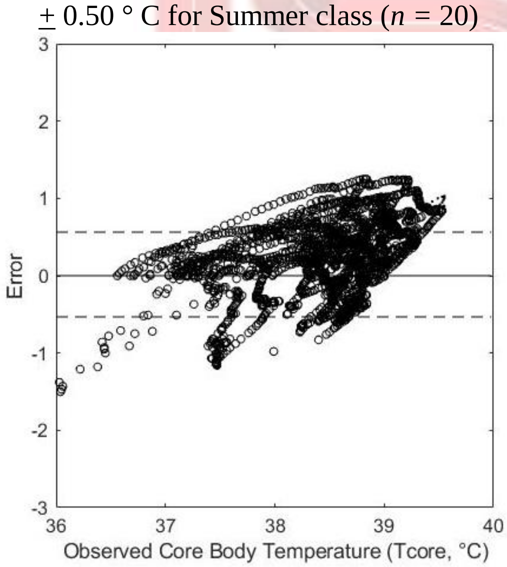
Note: Dashed lines represent the + 0.50 °C criterion

Figure 8. Comparison of predicted vs. actual core temperature (error) with criterion measure of + 0.50 ° C for Winter class (*n* = 30)



Note: Dashed lines represent the + 0.50 °C criterion

Figure 9. Comparison of predicted vs. actual core temperature (error) with criterion measure of + 0.50 ° C for Summer class (*n* = 20)



Note: Dashed lines represent the + 0.50 °C criterion

DISCUSSION

The HSDA model was chosen because it is easy to use and has been relied on to help guide the recommendations made in TB-MED 507 (5). Additionally, HSDA was being sought as a potential tool to use by the RTB, so it needed to be user-freiendly and designed for the operational users. Results of the present study show that averaged inputs to HSDA predictions were within the pre-established statistical criterion. While some of the individual assessments showed inaccuracies over time, the model outcomes still fell within acceptable criterion limits and the outcomes were similar to other assessments for both individual (40) and group mean data (41). Some variance was expected, as many variables that affect heat production and heat loss were dynamically changing (i.e., pace, terrain grade and ground type, weather, clothing wetness, and hydration), whereas the predictions used time averaged pace, grade and terrain. In addition, variables that did not change over the mission did vary between individuals, or varied over time, such as percent body fat, fitness level and clothing wetness. Both these dynamic and static variables will influence the magnitude and time dynamics of the Tc observed during exercise.

Individual Variability: The ability of HSDA to accurately model observed Tc responses varied by individual. A published government technical report by Tharion et al., (10) includes figures of plots for each individual. While it is also important to note the variable (self paced) speed of movement by the student over the course poses some challenges for the accuracy of the predictions. Tharion et al. (8) reported from this same data on the variability of these paces. From that Table 2 of this work (8), the list of the average per mile pace by class is shown. Students, in general, began the march at a brisk pace, slowed during the middle miles, and increased their pace near the end of the march. To compound this challenge to the modeled accuracy, is that when students were nearing the end of the march many used different types of strategies (i.e., some sped up, some kept their pace, and some slowed down). Unlike a civilian road race, where maximum performance is the goal of those running competitively, the goal of the march is to meet the qualifying standard. These students had other tasks to complete in that same training day and almost two more months of training to undergo after this qualification road march. While the event was self-paced it was not an event where maximum performance of all students was expected.

It should be noted there were great individual differences in the successful predictions from the model. While HSDA was not designed nor intended to predict individual responses to thermal stress, the large differences observed among individuals illustrates the problems HSDA will have in accurately predicting the thermal strain of a group of individuals that may have various individual differences in their physiology and behavioral histories. Previous research has shown that individual differences can affect prediction accuracy of thermal strain (42, 43).

The acceptability of HSDA group average predictions suggest that it could be used by the RTB to give a conservative rough estimate of the likely thermal strain the event will impose on the students. Moreover, the results from this study confirm that historical use of HSDA and TB-MED 507 (2) are meeting their intent (i.e., protect most Soldiers from heat injuries and provide a conservative estimates of work duration, before a rest break is required). In the scenario modeled, RTB students will have a low risk of experiencing a heat-related illness if they maintain an average pace, carry similar loads, and wear clothing that falls within the safe zone as predicted by HSDA for a given set of ambient conditions.

HSDA relies on several input variables and then uses a combination of equations to make the output predictions. The more accurate these inputs are to the observed data, the more closely the predictions should be to what is observed. However, in dynamic and real-world conditions, like these field based load carriage efforts, there are many elements that change in reality but are not easily captured within the model (e.g., non-steady-state pace, weather conditions, or changes to clothing properties overtime). These elements highlight both limitations and areas for potential improvement. For example, in the current study we used an average metabolic rate for each individual based on the distance and their individual time to complete the activity. While this is the more practical use model, it does create a higher predicted Tc initially and then a lower later Tc compared to the observed data (as students typically started at a higher pace and then slowed down). An example of this can be seen in Figure 10. Using Volunteer 1 during the Spring class, we can see the original prediction based on the average metabolic rate (~700 W) for the course (Fig. 10a). However, if we started with a higher metabolic rate (1200 W) to meet the higher initial pace for the first 30 minutes and then dropped it to a lower rate (400 W) for the remainder of the exercise (~160 minutes) we would see a much more accurate prediction comparison (Fig. 10 b). The challenge in this approach, as mentioned above, is that these patterns of work rate are not easily known at the beginning of the timed road march. Similarly, changes to the environmental conditions or clothing properties (e.g., wetted) that occur over the course of time are not easily accounted for in the model; while if available could be used to make time point corrections similar to the example shown in Figure 10. Wetted clothing in this study was a particular issue due to the high humidly, preventing evaporation of sweat and many students would dump water over their heads during various points of the march further wetting their clothing.

Despite the confounding factors and limitations, HSDA predictions met many of the accuracy criterions used to determine acceptability. Table 3 presents a subjective evaluation (authors of this report) of model performance as evaluated by the various methods by class. If predicted values were within 5% of the criteria values classified for either under- or over-predicted, the model was deemed acceptable; otherwise it was considered unacceptable. The prevalence of acceptable markings suggest that the HSDA was reasonable for predicting the observed class average responses.

Figure 10. Example of differences in predictions based on average inputs (A) and mid-exercise adjustments (B) to metabolic rate

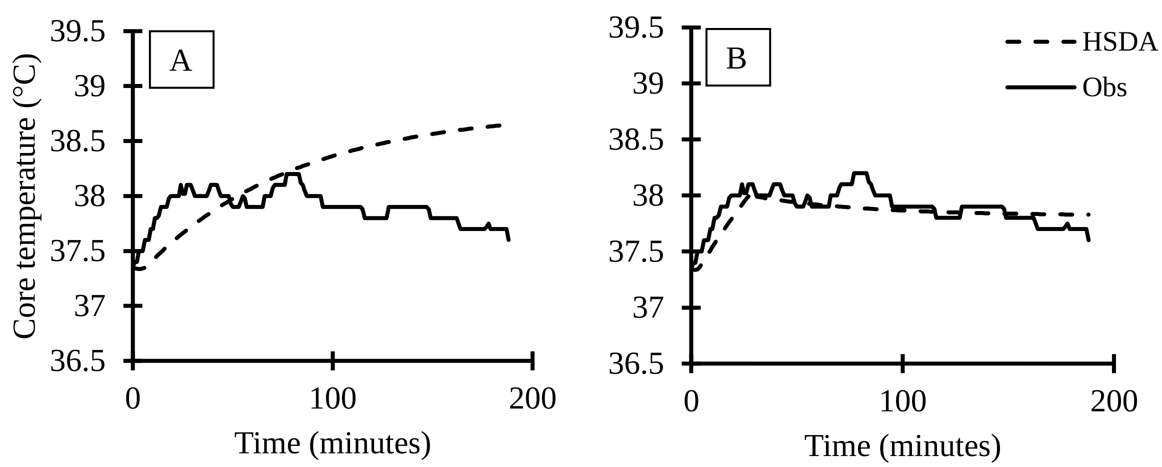


Table 10. Summary of Heat Strain Decision Aid (HSDA) performance assessed by the various methods and pre-established criteria by class

Class	**Bias**	***MAE***		***RMSD***		**Non-Parametric Comparison**	
	± 0.27 °C	± Obs SD	± 0.50 °C	± Obs SD	± 0.50 °C	Under Predicted	Over Predicted
Spring	+	+	+	-	+	-	+
Summer	+	+	-	+	+	+	-
Winter	+	+	+	+	+	-	+
Total	+	+	+	+	+	+	-

(+) Equals acceptable performance and (–) equals unacceptable performance of the model

Future work

Trying to improve the HSDA model itself was beyond the scope of this research. However, it may be possible to improve the performance of HSDA by improving estimates for the metabolic cost of activities (*M*). This work used legacy metabolic cost predictive equations (31); while recent work has been done to improve upon these methods (3, 4, 32) specific to military activities. Additionally, work is underway to incorporate all of these newer elements into one platform for modular updates and to further improve and evaluate the HSDA performance across a range of clothing configurations (19).

The use of non-direct measures are often ideal but can come with some significant limitations. This is especially true with respect to metabolic rates, as they have the greatest influence on heat gain for an individual. This influence is mathematically reflected in HSDA. For practical reasons, this study used the average movement speed for each individual as an input for predicting their individual metabolic rates. While the accuracy of HSDA was shown to be within the established statistical criterion; there are still areas that could be improved upon. Recent work has shown these predictions to be accurate within similar self-paced field conditions (44); while additional research has shown that adjustments could be made to correct predictions of metabolic rates during dynamic activities by using GPS sensors (45). This type of adjustment could be used to correctly account for more dynamic self-paced and complex movement activities.

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Conflict of interest declaration

The authors have no conflicts of interests.

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. 1. 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. 2. 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.

Ethics

This study was approved by the Scientific and Human Use Review Committees at the U.S. Army Research Institute of Environmental Medicine. The study conformed to the provisions of the Declaration of Helsinki.

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