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PREDICTING WHOLE ENSEMBLE (3D) THERMAL AND VAPOR RESISTANCES FROM SWATCH TEXTILE MEASURES (2D)

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PREDICTING WHOLE ENSEMBLE (3D) THERMAL AND VAPOR RESISTANCES FROM SWATCH TEXTILE MEASURES (2D)

Adam W. Potter
Julio A. Gonzalez

Thermal and Mountain Medicine Division

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U.S. Army Research Institute of Environmental Medicine
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14. ABSTRACT
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The thermal resistances of ensembles are influenced by a number of complex variables that are not fully understood and quantifying each of these variables (textile, the air gap between the skin and ensemble, and the boundary layer air outside the ensemble) is technically challenging. This report outlined a multi-step analysis to estimate total three-dimensional (3D) ensemble thermal and vapor resistances from two-dimensional (2D) textile measurements. Data from this analysis used 30 paired sets of measured values from both sweating guarded hot plate (SGHP) (i.e., 2D) and whole human thermal manikins (i.e., 3D). These paired data were then used to develop estimation methods based on two predictive approaches: 1) generally applied simple machine learning methods and 2) a multiplicative solver function. Calculated bias and errors were compared between methods and usable equations were proposed as initial approaches for functionally estimating 3D values from 2D-obtained data.

15. SUBJECT TERMS
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EXECUTIVE SUMMARY

This report has been prepared to support the Personalized Protective Biosystem (PPB) project, managed at the project level by Dr. Natalie Pomerantz (DEVCOM Soldier Center) and at the program level by Dr. Chris Bettingers (Program Manager, DARPA/BTO).

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INTRODUCTION

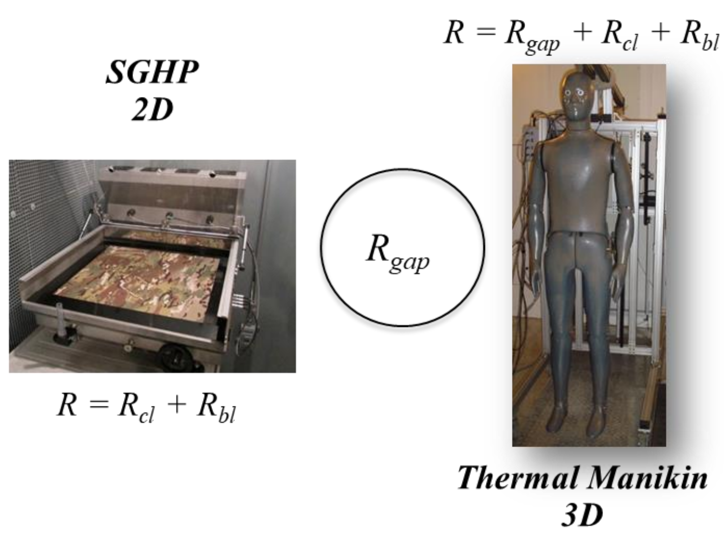
Developing of a new method for estimation of thermal/vapor resistance utilizing hotplate measurements will be a more readily available, cost effective, and timely approach to testing materials. Increased understanding of thermal resistance will ultimately impact materials, designs, and combat load impose on the thermal burden of the Soldier. Several organizations will benefit from this work, to include government chemical protective ensemble communities, material and textile developers, ensemble designers, as well as similar organizations in public and private industries.

Thermal and evaporative resistances of ensembles are influenced by a number of complex variables that are not fully understood. Quantifying each of these variables (textile, the air gap between the skin and ensemble, and the boundary layer air outside the ensemble) is technically challenging. While the concept is fairly straightforward, there are many complexities within various textiles that make extrapolation of a simple mathematical estimate complex (1). However, at the simplest level these resistances (R) of an ensemble consist of three main parts: an air gap (R_{gap}), the clothing textile (R_{cl}), and the boundary layer (R_{bl}), mathematically seen as:

$$R = R_{gap} + R_{cl} + R_{bl}$$

Measures from a total ensemble (e.g., via a human thermal manikin, three dimensional (3D)) can be used to measure the total of these variables inclusively; while textile swatches are typically measured without the geometry of the human shape (i.e., two dimensional (2D)) and therefore exclude the air layer (e.g., R_{gap}) (Figure 1). While several methods have been developed to estimate this air layer specifically; this effort seeks to develop a simple method for estimating the inclusion of this air layer from simple textile measures only.

Figure 1. General difference between Sweating Guarded Hot Plate (SGHP) and thermal manikin calculation (2D vs. 3D)



METHODS

A multi-step analysis was conducted to estimate total three-dimensional (3D) ensemble thermal and vapor resistances from two-dimensional (2D) textile measurements. This approach used data collected from both sweating guarded hot plate (SGHP) (i.e., 2D) and whole human thermal manikins (i.e., 3D). These data were paired together to develop estimation methods. Two predictive approaches were used to develop estimation methods: generally applied simple machine learning methods (with down selection of those with lowest error) and a multiplicative solver function calculated based on usability and tuned for low bias.

2D Sweating Guarded Hot Plate (SGHP) Biophysics

Thermal and evaporative resistances (R_{ct} and R_{et}) were measured using a Sweating Guarded Hot Plate (SGHP) (Model 306-200/400, Thermetrics, Seattle, WA) based on ASTM F1868-17 (2) conditions (Table 1).

Table 1. ASTM F1868-17 test conditions.

Test	SGHP	Chamber			Comments
	Temperature (T; °C)	Temperature (Ta; °C)	Relative Humidity (RH; %)	Wind Velocity (V; m/s)	Tests conducted with the manufacturer specified outward face of the fabric facing up towards the environment; inward (skin) facing side against the SGHP
Thermal Resistance (R_{ct})	35 °C	20 °C	50 %	1.0 m/s	"Dry" conditions.
Evaporative Resistance (R_{et})	35 °C	35 °C	40 %	1.0 m/s	"Wet" conditions.

Thermal resistance (R_{ct}) was calculated in SI units from:

$$R_{ct} = \frac{(T_s - T_a)}{Q/A}\,[\mathrm{m^2K/W}]$$

where R_{ct} is the total thermal resistance (m^2K/W) of the fabric and boundary air layer, T_s is the SGHP average temperature, T_a is ambient chamber air temperature, and Q/A is the heat flux (W/m^2). Intrinsic thermal resistance (R_{cf}) of the fabric is the calculated by subtracting the bare SGHP resistance (R_{cbp}) from the R_{ct}, seen as:

$$R_{cf} = R_{ct} - R_{cbp}\ [\mathrm{m^2{}^\circ C/W}]$$

Total evaporative resistance (R_{et}) of the fabric and the boundary air layer was calculated in SI units using:

$$R_{et} = \frac{(P_{sat} - P_{amb})}{Q/A}\,[\mathrm{m^2Pa/W}]$$

where P_{sat} is the saturation vapor pressure (Pa) at the SGHP surface temperature, P_{amb} is the ambient vapor pressure (Pa). The intrinsic evaporative resistance (R_{ef}) of the fabric was calculated by subtracting the bare SGHP evaporative resistance (R_{ebp}) from the measured R_{et}, seen as:

$$R_{ef} = R_{et} - R_{ebp} \text{ [m}^2\text{Pa/W]}$$

SGHP Fabric Thickness and Density

Fabric thickness was measured using a dial thickness gauge (MTG-DX2 Digital Contact Material Thickness Gauge, Electromatic Equipment Co., Cedarhurst, NY) according to ASTM D1777-96 standards (3).

3D Thermal Manikin Biophysics

Whole human / ensemble biophysical measures using sweating thermal manikins requires two fundamental measures at a single wind velocity of 0.4 m/s (0.89 mph). The ASTM International have two defined standards for testing both thermal resistance (R_{ct}) (4) and evaporative resistance (R_{et}) (5). These measures represent the dry (convection, conduction, and radiation) and wet heat exchange (evaporation). Both R_{ct} and R_{et} are often converted into units of clo and i_m (6-7), then a ratio of these two is often used to describe an ensemble's evaporative potential (i_m/clo) (8). These testing conditions are shown in Table 2.

Table 2. ASTM F1291 and F2370 test conditions.

Test	Manikin	Chamber			Comments
	'Skin' Temperature (Ts; °C)	Temperature (Ta; °C)	Relative Humidity (RH; %)	Wind Velocity (V; m/s)	
Thermal Resistance (R_{ct})	35 °C	20 °C	50 %	0.4 m/s	**ASTM F1291** "Dry" conditions. Manikin not sweating.
Evaporative Resistance (R_{et})	35 °C	35 °C	40 %	0.4 m/s	**ASTM F2370** "Wet" conditions. Manikin sweating, surface set to 100% saturation.

Thermal resistance (R_{ct}), is measured dry heat transfer from the surface of the manikin through the clothing and into the environment, mainly from convection, described as:

$$R_{ct} = \frac{(T_s - T_a)}{Q/A} \text{ [m}^2\text{K/W]}$$

where T_s is surface temperature and T_a is the air temperature, both in °C or °K. Q is power input (W) to maintain the surface (skin) temperature (T_s) of the manikin at a given set point; A is the surface area of the measurement in m^2. These measures of R_{ct} can then be converted to units of clo:

$$1\ clo = 6.45(I_T)$$

where I_T is the total insulation including boundary air layers. Evaporative resistance (R_{et}) is heat loss from the body in isothermal conditions ($T_s \approx T_a$), described as:

$$R_{et} = \frac{(P_{sat} - P_a)}{Q/A} [\mathrm{m^2Pa/W}]$$

where P_{sat} is vapor pressure in Pascal at the surface of the manikin (assumed to be fully saturated), and P_a is vapor pressure, in Pascals, of the chamber environment. Measures of R_{et} can then be converted to a vapor permeability index (i_m), a non-dimensional measure of water vapor resistance of materials defined as:

$$i_m = \frac{60.6515\ \frac{Pa}{°C}\ R_{ct}}{R_{et}}$$

Biophysical Testing Wind Velocity Differences

Typically, 3D ensemble values are used for thermoregulatory modeling and therefore require estimates for the effects of wind velocity on the ensemble's biophysical characteristics (i.e., how differences in wind affect clo and i_m values). These effects are typically referred to as wind velocity coefficients or gamma values (^{g}) (9-10). Historically, obtaining these coefficients consisted of collecting measurements of both R_{ct} and R_{et} at multiple wind velocities, above the ASTM standard of 0.4 m/s. However, recent work suggests estimating these coefficient values can be estimated from single wind velocity tests (11). This adjustment for wind velocity is particularly important for the current work, as the two measurement standard methods are different (SGHP 1.0 m/s and manikins 0.4 m/s), and still generally require balancing for use in thermoregulatory modeling (i.e., thermal tests typically need to be converted to 1.0 m/s for thermal models).

Materials

Data from these analyses included 25 layered textile systems measured from SGHP and 30 full uniform systems measured from thermal manikins (11-12). Of this data, a total of 25 SGHP measured systems have 30 complementary full ensembles. For the purposes of this analyses, 2D textiles have been number alphanumerically and 3D ensembles have been numbered 1-30.

Data Analyses

Predictive and statistical analyses were conducted using a combination of Microsoft Excel (Microsoft Corporation, Redmond, WA, 2016) and machine learning methods using MATLAB (2019b, MathWorks, Inc., Natick, MA).

RESULTS

Biophysical values for the set of 30 test systems, 2D assessments (via SGHP) and the complimentary 3D assessments (via thermal manikin), are shown in Table 3. Plotted comparisons of 2D values and associated 3D values are shown in Figure 2. Difference between the two unadjusted values of 2D to 3D is shown clearly in Figure 2, with calculated bias between the values are (understandably) large. Bias between 2D and 3D values directly are functionally non-comparable, for both R_t and R_{et} (-0.20 and -42.99 respectively); while for reference the root mean square error (RMSE) is also understandably large for both R_t and R_{et} (0.21 and 44.82). Calculated bias and RMSE are shown in Table 4, for the unadjusted comparison, machine learning approaches, and multiplicative solver function.

Table 3. Paired fabric (2D) and full ensemble (3D) dry total and intrinsic (R_t, R_{cf}) and evaporative total and intrinsic (R_{et}, R_{ef}) resistances.

2D-3D Pair	Fabric				Ensemble			
	Rt	Rcf	Ret	Ref	Rt	Rcf	Ret	Ref
1	0.087	0.017	9.66	3.84	0.25	0.17	37.7	28.1
2	0.087	0.017	9.66	3.84	0.31	0.24	46.7	38.0
3	0.098	0.029	11.7	5.9	0.32	0.25	60.6	52.0
4	0.098	0.029	11.7	5.9	0.31	0.24	60.4	51.7
5	0.086	0.016	14.4	8.6	0.32	0.25	67.4	58.8
6	0.099	0.029	13.6	7.8	0.35	0.28	69.6	61.3
7	0.083	0.013	15.3	9.5	0.30	0.23	64.7	55.9
8	0.089	0.020	13.1	7.2	0.30	0.23	64.7	55.9
9	0.100	0.030	14.8	9	0.32	0.25	62.3	53.7
10	0.117	0.048	18.6	12.8	0.38	0.31	75.8	67.8
11	0.087	0.017	9.66	3.84	0.28	0.21	40.9	31.8
12	0.098	0.029	11.7	5.9	0.29	0.22	50.8	41.9
13	0.098	0.029	11.7	5.9	0.32	0.22	58.8	49.9
14	0.086	0.016	14.4	8.6	0.29	0.25	57.6	49.0
15	0.070	-	5.82	-	0.10	-	12.7	-
16	0.099	0.029	13.6	7.81	0.35	0.26	69.6	59.0
17	0.086	0.016	14.4	8.59	0.32	0.23	67.4	56.8
18	0.089	0.020	13.1	7.24	0.30	0.22	64.7	54.1
19	0.083	0.013	15.3	9.47	0.30	0.22	64.7	54.1
20	0.100	0.030	14.8	8.98	0.32	0.23	62.2	51.7
21	0.120	0.048	18.6	12.8	0.38	0.29	75.7	65.1
22	0.098	0.029	11.7	5.92	0.32	0.23	60.6	50.0
23	0.098	0.029	11.7	5.92	0.31	0.23	60.4	49.8
24	0.087	0.017	9.66	3.84	0.25	0.16	37.7	27.1
25	0.087	0.017	9.66	3.84	0.31	0.22	46.7	36.1
26	0.070	-	5.82	-	0.10	-	12.72	-
27	0.086	0.016	14.4	8.59	0.29	0.21	57.62	47.02
28	0.100	0.029	11.7	5.92	0.29	0.20	50.82	40.22
29	0.100	0.029	11.7	5.92	0.32	0.23	58.82	48.23
30	0.087	0.017	9.66	3.84	0.28	0.20	40.9	30.31

Figure 2. Plotted paired fabric (2D) and full ensemble (3D) dry total (R_t) and evaporative total (R_{et}) resistances.

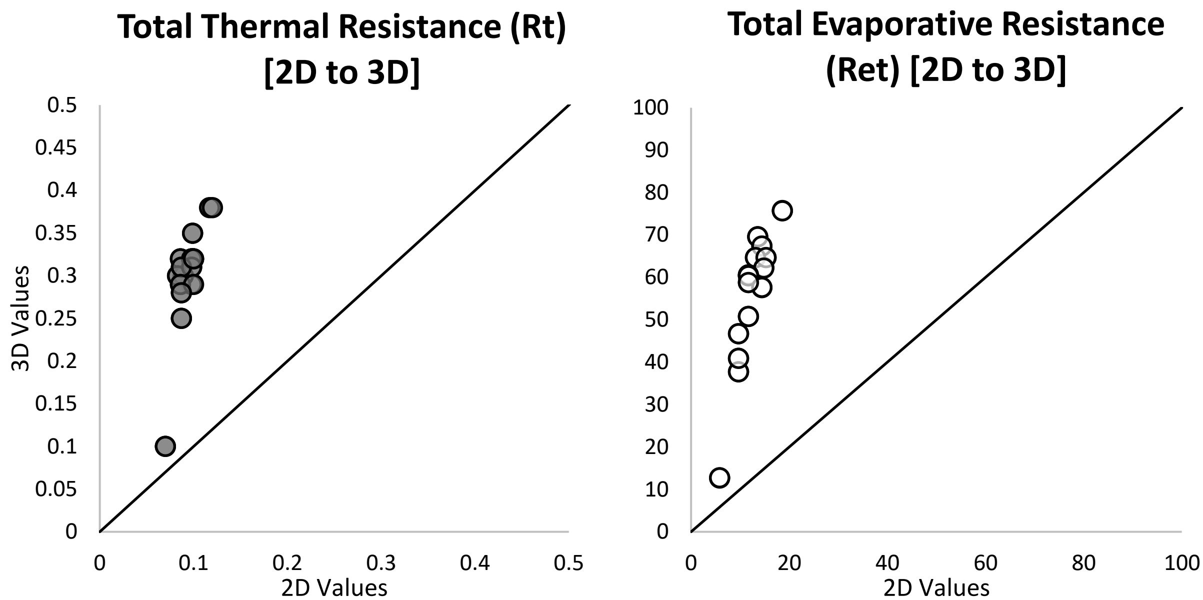


Table 4. Compared bias and RMSE for unadjusted and prediction methods

Predicted value	Method	Bias	RMSE	Comments
Total (dry) thermal resistance (R_t)	Unadjusted comparison between 2D and 3D values	-0.20	0.21	Not functionally usable.
	2 Feature prediction: Exponential Gaussian Process Regression (GPR)	~0.0	0.02	Lower error, but more complicated to implement.
	4 Feature prediction: Quadratic support vector machine (SVM)	~0.0	0.02	Lower error, but more complicated to implement.
	Solver function multiplier: 2D value * 3.2 = estimate	~0.0	0.04	Slightly higher error than machine learning methods. Functionally usable.
Total (wet) evaporative resistance (R_{et})	Unadjusted comparison between 2D and 3D values	-42.99	44.82	Not functionally usable.
	2 Feature prediction: Exponential Gaussian Process Regression (GPR)	~0.0	4.68	Lower error, but more complicated to implement.
	4 Feature prediction: Rational Gaussian Process Regression (GPR)	~0.0	4.91	Lower error, but more complicated to implement.
	Solver function multiplier: 2D value * 4.5 = estimate	0.36	6.62	Slightly higher error than machine learning methods. Functionally usable.

An array of machine learning methods was applied using two features (2D measured R_t and R_{et}) and four features (2D measured R_t, R_{cf}, R_{et}, and R_{ef}), and then down selected to those with the lowest calculated errors. For prediction of R_t using two features, the lowest error approach was found using an Exponential Gaussian Process Regression (GPR); while using four features it was found and using a Quadratic support vector machine (SVM) approach (Figure 3), where both approaches were both calculated to an averaged bias of zero with RMSE of ~0.02 (Table 4). For prediction of R_{et} using two features, the lowest error approach was found using an Exponential GPR (RMSE = 4.68); while using four features it was found and using a Rational GPR approach (RMSE = 4.91) (Figure 4) (Table 4).

Figure 3. Two feature Exponential GPR (left) and four feature Quadratic SVM (right) for predicting full ensemble (3D) dry total (R_t) resistance from swatch (2D) values.

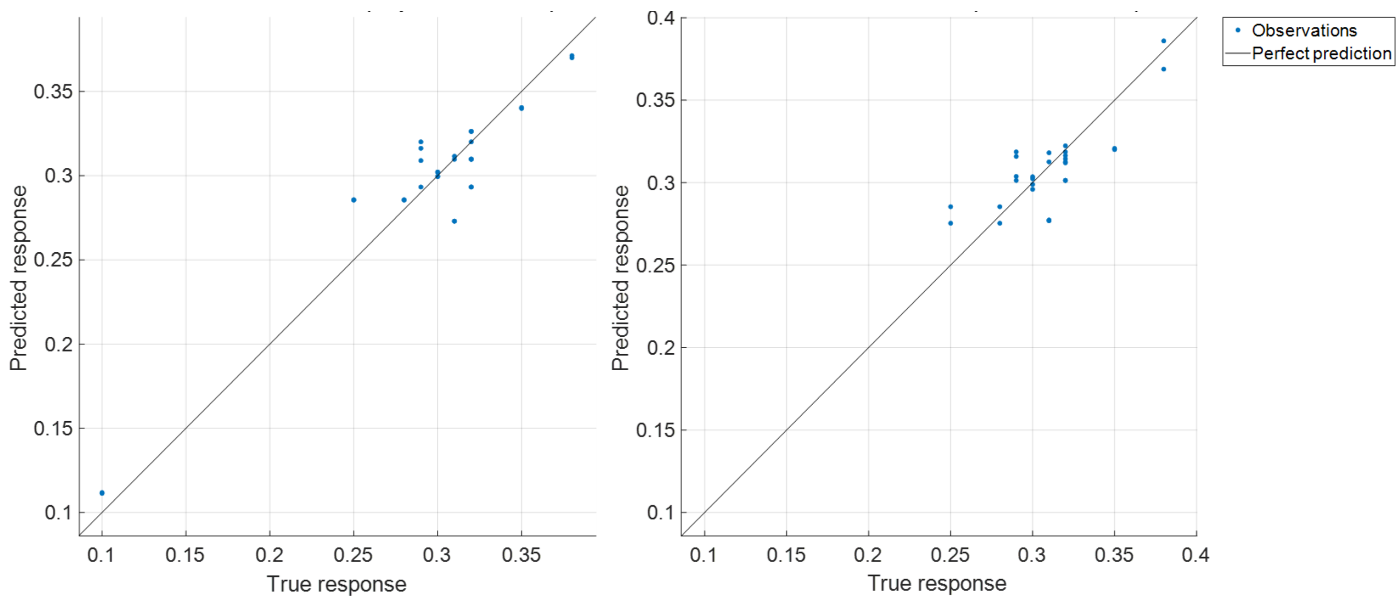
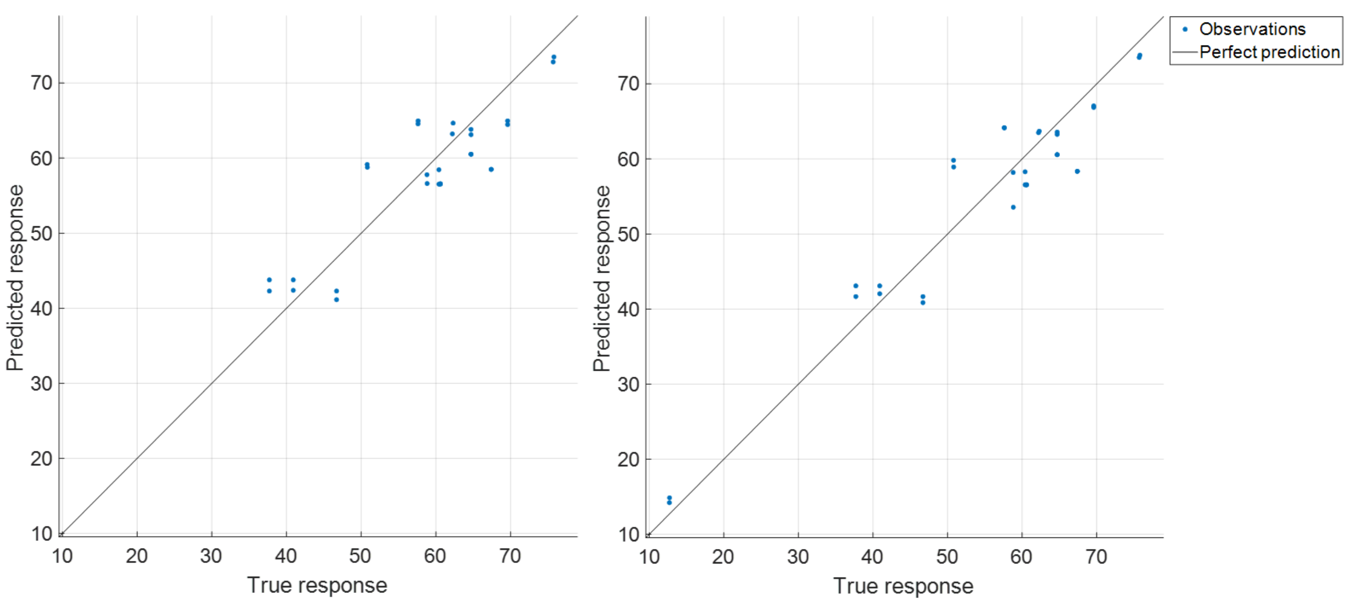
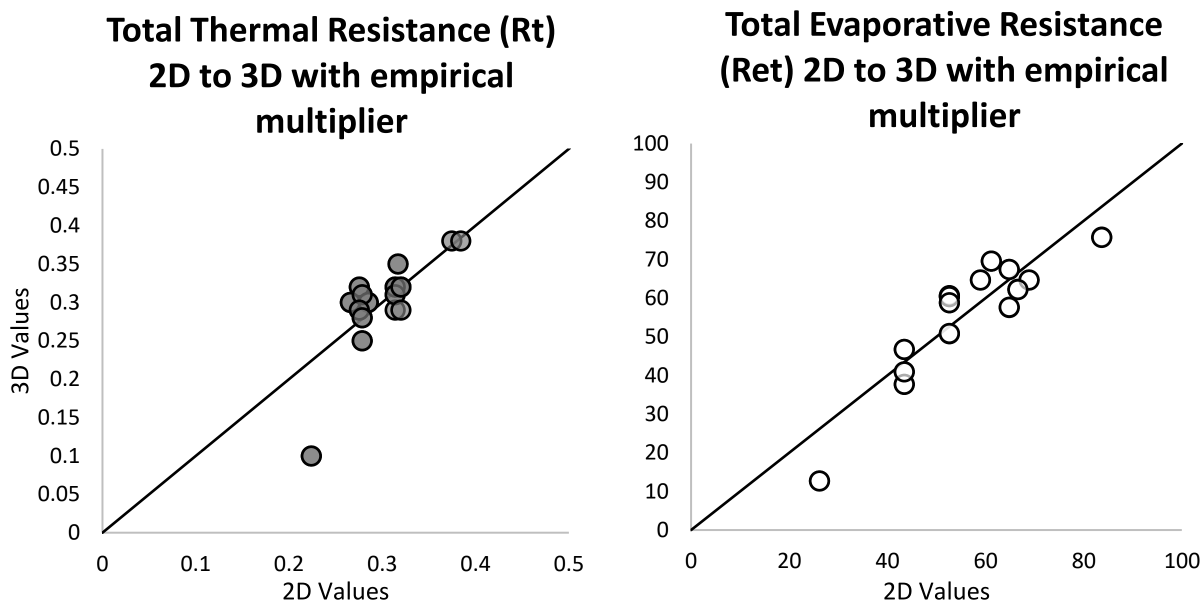


Figure 4. Two feature Exponential GPR (left) and four feature Rational GPR (right) for predicting full ensemble (3D) evaporative total (R_{et}) resistance from swatch (2D) values.



A solver function was used to empirically calculate, a weighted value multiplier to the initial 2D measurements to align them to their paired full ensemble 3D values (Figure 5). Weighted values calculated were fitted to multipliers of 3.2 for R_t and 4.5 for R_{et} to result in lower (functionally usable) calculated total biases (0.00 and 0.36) and acceptable RMSE (0.04 and 0.36) (Table 4).

Figure 5. Plotted paired fabric (2D) and full ensemble (3D) dry total (R_t) and evaporative total (R_{et}) resistances adjusted by empirical multipliers (3.2 and 4.5).



Observed solver function equations for functional use seen below, based on SGHP values of R_t and R_{et}:

Predicted 3D total thermal (dry) resistance (R_t):

$$R_t = [SGHP]R_t * 3.2 \quad [\mathrm{m^2K/W}]$$

Predicted 3D total evaporative (wet) resistance (R_{et}):

$$R_{et} = [SGHP]R_{et} * 4.5 \quad [\mathrm{m^2Pa/W}]$$

DISCUSSION

The work outlined in this report describes an initial approach towards making predictions of whole body (3D) biophysical values based on measures from a 2D textile. While these two measures (from sweating guarded hot plate (SGHP) and thermal manikin) are generally considered as not interchangeable; there is reason to believe that with enough data and the appropriate representation of inputs, that predicting between these two can be acceptably accurate. From this work we showed that modeling using machine learning methods can be used to obtain low error empirical predictions (e.g., Table 4, Figures 3-4). However, these more 'sophisticated' methods often require more complicated functions or complex equations for using them, making their use less practical. Herein, we described a simple and functionally useable method of creating multipliers to the SGHP values that can be more readily applied with reasonable errors (Table 4, Figure 5).

Ultimately, the value in the full ensemble biophysical properties is useful as inputs into thermoregulatory models to interpret and predict human responses (13-16). However, even in this human-centric thermal modeling approach, there is often some assumed inherent variability and uncertainty, making the use of an initial estimate both reasonable and a challenge at the same time. That is to say, minor errors may only impose minor consequences, but may still add to errors non-the-less. Recent assessments have proposed that a level of differences in an ensembles' evaporative potential (i_m/clo) of ≤ 0.1 may be considered generally similar in their impact on the human (i.e., values differing in ≥ 0.1 may be significant) (17-18). Additional work has show that while there is a general increase in thermal insulation (clo, R_t) and decrease in i_m/clo, there is the potential for a shift in this response due to increasing layers and the compression of air space within the ensemble (e.g., reducing the air gap, R_{gap}) (19).

Significant work investigating, characterizing the air gaps of various clothing systems conducted (20-23) provides important steps towards better being able to predict how the differences between 2D and 3D clothing systems. While proactive work has shown promise in the concept of applying 3D scanner technologies to estimate these air gaps within full ensembles (24-25). Future work should be conducted that leverages information from this current report and novel technologies to provide more comprehensive and validated methods for making predictive methods that are both easy to use and acceptably accurate.

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