Statistical Learning – Replacement for Expert Judgement in Occupational Risk Assessment?

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Abstract. The objective of this paper was to verify the applicability of statistical learning (SL) compared to human reasoning with respect to the Universal Thermal Climate Index (UTCI), a complex tool for the assessment of outdoor thermal stress. UTCI is an equivalent temperature index based on the 48-dimensional output of an advanced model of human thermoregulation formed by 12 variables at four time steps, which were calculated for 105642 thermal conditions from extreme cold to extreme heat. Comparing the performance of SL algorithms to the results accomplished by an international endeavor involving more than 40 experts from 23 countries, we found that random forests closely predicted UTCI values, but that clustering applied after dimension reduction algorithms (principal component and t-distributed stochastic neighbor embedding) were inadequate for risk assessment in relation to the UTCI stress categories. This indicates the potential supportive role for SL, although it will not (yet) fully replace the knowledgeable occupational health expert.

Keywords: artificial intelligence, machine learning, simulation, cold stress, heat stress, risk assessment

1. Introduction

Statistical or machine learning (SL) is central to artificial intelligence (AI) applications (Berk 2020; Hastie et al. 2009; James et al. 2013) with potential relevance to occupational risk assessment in settings with high dimensional input, where they may assist or even replace the occupational health expert.

The objective of this paper was to verify the applicability of SL compared to human reasoning with respect to the Universal Thermal Climate Index (UTCI), a complex assessment tool for the physiological strain related to the outdoor thermal environment (Bröde et al. 2013b; Bröde et al. 2009; Bröde et al. 2008).

The development of UTCI was accomplished by an international endeavor involving more than 40 experts from 23 countries (Jendritzky et al. 2012). Figure 1 visualizes the concept of UTCI (Bröde et al. 2012) as an equivalent temperature (in °C) defined as air temperature of the reference condition with the same dynamic physiological response as the actual condition derived from the output of an advanced human model of thermoregulation (Fiala et al. 2012) coupled with a clothing model (Havenith et al.

2012). For risk assessment, a scale classifying the UTCI values into ten categories of thermal stress was added to the operational procedure (Bröde et al. 2012).

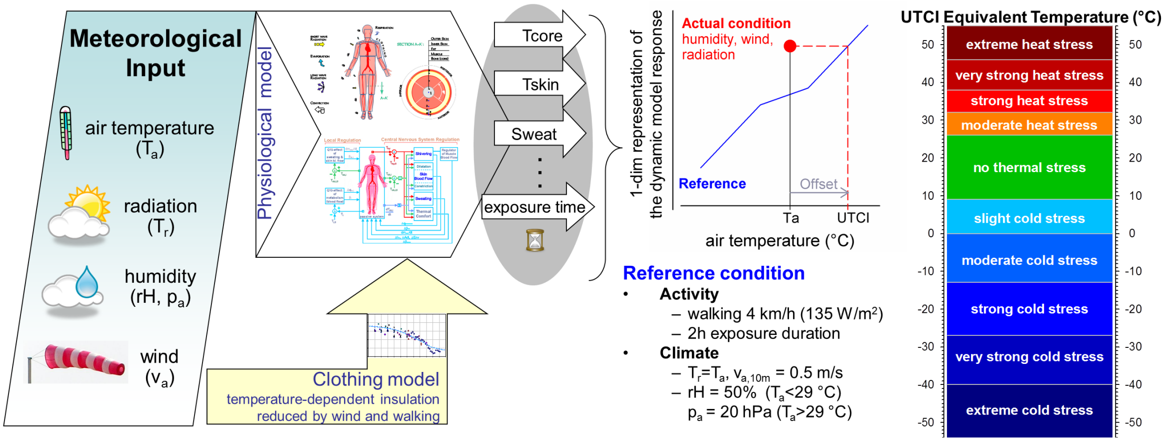

Figure 1. *Elements of UTCI equivalent temperature with thermal stress assessment scale, modified from Bröde et al. (2012).*

2. Material and Methods

We compared the performance of SL algorithms to the results provided by the international expert group, who developed the UTCI values using a multivariate approach (Bröde et al. 2012; Bröde et al. 2009) involving a dimension reduction step of the multidimensional model output to a one-dimensional strain indicator followed by searching the reference condition with the same indicator value (Figure 1).

The assessment scale was developed from comparing the values of variables describing the thermal state and regulation of the human body to established ergonomic limit criteria (Bröde et al. 2013a; Bröde et al. 2012).

2.1 UTCI data

The operational procedure was based on the dynamic physiological response characterized by the 48-dimensional model output formed by 12 variables at 4 time steps. This output was generated for 1051 reference conditions covering the whole relevant climatic range with known UTCI values set equal to air temperature.

Another set of 104591 non-reference conditions with varying levels of wind speed, humidity and solar radiation had to be valued in UTCI °C and classified in 10 stress categories ranging from extreme cold to extreme heat as indicated by Figure 1.

2.2 Data analysis

Splitting the reference conditions in 840 training and 211 test data and using the non-reference conditions as additional test data, we compared the results of the UTCI expert group to SL methods comprising multiple linear regression, classification and regression trees (CART) and random forests (RF) predicting UTCI values from the 48 predictors (Breiman 2001; Genuer and Poggi 2020), using mean prediction error (bias) and root-mean squared error (rmse) as performance metrics.

For comparison to the UTCI assessment scale, UTCI values were then categorized by hierarchical and k-means clustering (Berk 2020) after applying principal component analysis (PCA) and t-distributed stochastic neighbor embedding t-SNE (van der Maaten and Hinton 2008), respectively, to the high-dimensional UTCI model output for dimensionality reduction. In accordance with the UTCI approach (Bröde et al. 2012), we searched for ten categories using the UTCI reference data set.

3. Results

3.1 UTCI values

Table 1 compares bias and rmse obtained by the diverse algorithms for the three sets of training and test data, respectively.

While multiple linear regression worked well for UTCI reference conditions, rmse, indicating the typical prediction error, increased to more than 7 °C for the non-reference data, approximately corresponding to one heat stress category deviation (Figure 1).

UTCI predictions by RF fitted the reference data well (rmse<0.1 °C) and closely agreed with non-reference UTCI (bias 0.6 °C, rmse=3.5 °C, correlation coefficient r=0.98). CART performance was inferior to RF in all cases in accordance with earlier observations (Genuer and Poggi 2020).

Table 1. *Bias ± rmse for UTCI predictions from different datasets by diverse algorithms.*

	Reference – training data	**Reference – test data**	**Non-reference Test data**
Linear regression	0.00 ± 0.07 °C	0.00 ± 0.07 °C	0.27 ± 7.27 °C
CART	0.00 ± 7.58 °C	-0.06 ± 7.62 °C	0.19 ± 8.13 °C
Random Forest	0.00 ± 0.07 °C	-0.01 ± 0.08 °C	0.57 ± 3.45 °C

3.2 UTCI assessment scale

As illustrated by Figure 2, the UTCI model output projected to the first two principal components, which explained more than 90% of total variance, exhibited a one-dimensional structure along the UTCI categories from extreme cold to extreme heat.

The groups formed by hierarchical or k-means clustering identified extreme heat and cold, but did show discrepancies concerning the intermediate UTCI categories.

As shown by Figure 3, the results were only marginally different when using non-linear t-SNE for dimensionality reduction compared to the linear PCA in Figure 2.

4. Discussion

Our results concerning the thermal risk assessment index UTCI indicate that recent machine learning algorithms like random forests may be helpful tools to derive summarizing metrics for complex occupational hazards characterized by high dimensional input describing stress and strain.

Though clustering identified extreme heat and cold, it did not reliably discriminate between the intermediate categories, with only marginal differences between the diverse algorithms. This demonstrates the discrepancy between clustering algorithms searching for patterns in the data and forming groups of data of comparable size on one hand (Härdle and Simar 2007) and the definition of UTCI stress categories based on ergonomic reasoning on the other hand (Bröde et al. 2013a; Bröde et al. 2012).

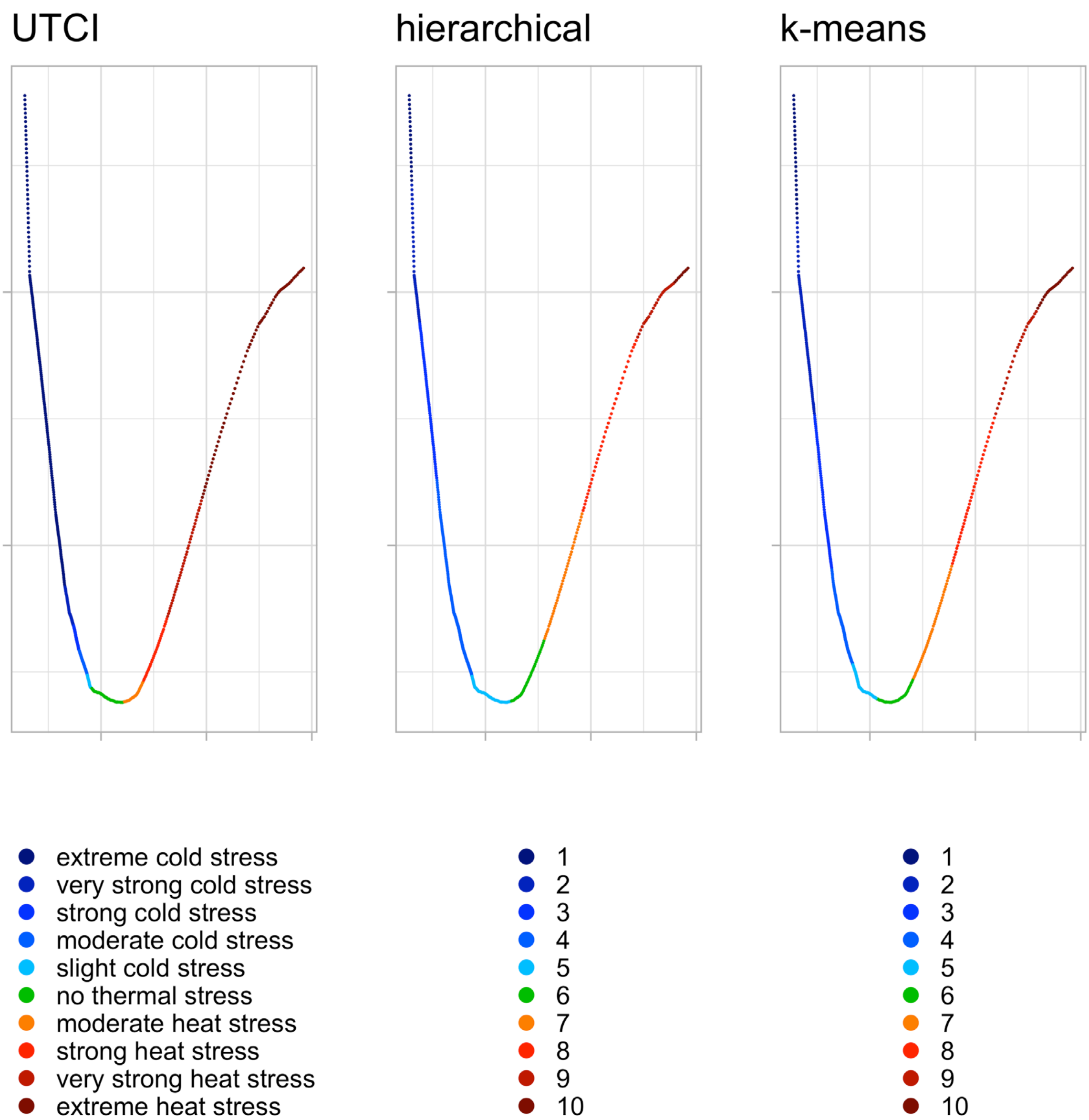

Figure 2. *Two-dimensional projections of the reference data (48 physiological variables plus 4 calculated dynamic thermal sensations) computed by principal component analysis and coloured by the ten UTCI categories (left panel) and the corresponding numbers of groups found by hierarchical (mid panel) and k-means-clustering (right panel), respectively.*

5. Conclusion

In summary, our results indicate the potential supportive role for AI when analyzing high dimensional input in occupational risk assessment, although it will not (yet) fully replace the knowledgeable occupational health expert.

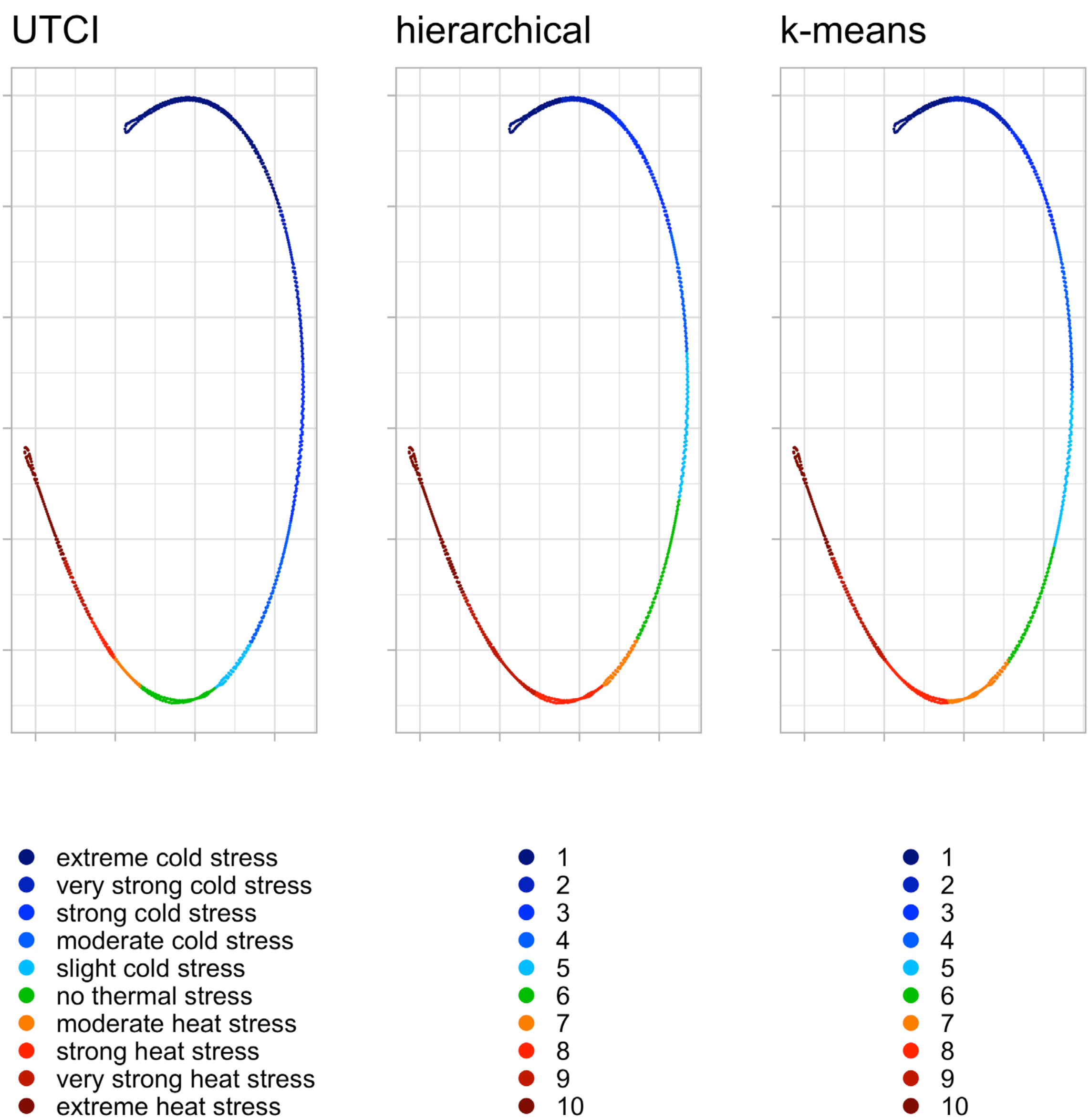

Figure 3. *Two-dimensional projections from t-distributed stochastic neighbor embedding of the reference data (48 physiological variables plus 4 calculated dynamic thermal sensations) coloured by the ten UTCI categories (left panel) and the corresponding numbers of groups found by hierarchical (mid panel) and k-means-clustering (right panel), respectively.*

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