A Novel Multi-Domain Model for Thermal Comfort which Includes Building Indoor CO\textsubscript{2} Concentrations

Sarah Crosby\textsuperscript{1}, Adam Rysanek\textsuperscript{2}

\textsuperscript{1} Department of Mechanical Engineering, University of British Columbia, Vancouver, Canada
\textsuperscript{2} School of Architecture and Landscape Architecture, University of British Columbia, Canada

Abstract

In a prior work, we applied Bayesian logistic regression to investigate possible quantifiable correlations between occupant’s perceived thermal comfort, thermal indoor conditions, and non-thermal metrics of indoor environmental quality (IEQ). This study updates the findings of the prior work by adding IEQ data collected from a recent field study carried out at the University of British Columbia. Bayesian logistic regression of the expanded dataset reinforces observations made in our first paper that thermal comfort is correlated to measured values of indoor CO\textsubscript{2} concentrations. Cross-validation and posterior checks revealed that it is possible to increase the prediction accuracy of thermal satisfaction in open-plan offices by including measurements of CO\textsubscript{2} concentration. This paper formulates a new predictive model of thermal comfort which can be used by building modellers to predict thermal comfort in office settings based on thermal conditions and ventilation rates.

Key Innovations

- This paper presents a novel predictive model for thermal comfort that uses Bayesian inference to quantitatively predict perceived thermal satisfaction given psychrometric IEQ metrics and measured values of CO\textsubscript{2} concentrations.
- This work is one of few studies to evaluate the multi-domain relationships of thermal comfort quantitatively and in a manner that supports future thermal comfort prediction.
- This is the first known work to apply Bayesian inference on a large multi-domain field dataset to quantify, with uncertainty bounds, the independent effect of indoor CO\textsubscript{2} concentrations on perceived thermal comfort and to suggest that including measurement of CO\textsubscript{2} can improve the prediction accuracy of thermal satisfaction.
- The new model can be used by building performance simulation experts to predict thermal comfort in office spaces based on thermal conditions and ventilation rates, which may result in energy savings while not sacrificing indoor air quality and well-being, an important challenge to building modellers, particularly now in a post-COVID-19 world.

Practical Implications

This research suggests that an open-plan office with high amounts of fresh air can provide the same level of thermal comfort at higher/lower temperatures than an office with ‘typical’ ventilation rates. Additional monitoring of CO\textsubscript{2} concentrations can further improve thermal comfort compliance estimates and may result in energy savings.

Introduction

Occupants’ thermal dissatisfaction and its implications on cognitive performance, health, well-being, productivity, and workplace satisfaction have been the focus of many recent research studies (Ferreira et al., 2012; Vischer, 2011; Jamrozik et al., 2018; Crosby et al., 2019; Jensen et al., 2009; Int-Hout, July 2013; Jokl and Kabele, 2006; Al Horr et al., 2017; Kamaruzzaman et al., 2011). Thermal comfort, defined as “the condition of the mind in which satisfaction is expressed with the thermal environment” (ASHRAE, 2013), is a state of mind, rather than a state of condition, where its judgment is a cognitive process influenced by the occupant’s well-being and overall satisfaction (Djongyang et al., 2010; Lin and Deng, 2008). Previous studies have shown that compromising occupants’ thermal comfort to reduce energy consumption in buildings costs more than providing comfortable indoor thermal conditions in the workplace (Int-Hout, July 2013; Jensen et al., 2009). Previous studies have shown that occupant’s thermal comfort can be influenced by individual differences in mood, culture, and well-being (Djongyang et al., 2010; Huang et al., 2012; Jamrozik et al., 2018; Jokl and Kabele, 2006; Pellerin and Candas, 2004; Schweiker et al., 2018). It has been argued that, if it is accepted that occupant’s judgment of thermal comfort is a cognitive process, then perceived thermal comfort may be affected by the psychological effect of many physical conditions that occupants encounter in the built environment (Djongyang et al., 2010), Jamrozik et al. (2018); Wagner et al. (2007) showed that the occupant’s perception of thermal comfort and other indoor environmental conditions is holistic, which implies that the dissatisfaction with one type of environmental conditions affects the occupant’s perception of the whole environment and leads to dissatisfaction with the thermal environment and other...
unrelated metrics of IEQ.

In recent years, evidence in support of the multidomain nature of thermal comfort and IEQ as well as the existing correlations between occupants’ perception of thermal comfort and other indices of IEQ is growing (Schweiker et al., 2020). For instance, recent works that studied the cross-modal effects of acoustical and thermal conditions on occupant’s perception have suggested that perceived thermal dissatisfaction increases with increased noise levels (Pelletier and Candas, 2004; Yang and Moon, 2018; Huang et al., 2012). Further, Gauthier et al. (2015) have found a modest correlation between increased CO₂ concentrations levels and occupant’s thermal dissatisfaction. The authors suggested that the relationship is not strong as a result of the small sample size of 80 participants in their climate chamber-based experiments.

Crosby and Rysanek (2021) investigated the independent relationships between non-thermal metrics of IEQ, such as CO₂ concentrations, noise levels, and light levels and perceived thermal comfort. Bayesian logistic regression was applied to the COPE field study dataset, a prior dataset of objective and subjective IEQ measurements collected from about 800 occupants of open-plan offices in nine buildings across Canada and the United States (Veitch et al., 2007; Newsham et al., 2008). The COPE, or the cost-effective open-plan study, is a field dataset collected by the National Research Council of Canada (NRC) between 2000 and 2002. The dataset contains instantaneous physical measurements of IEQ, taken using a cart-and-chair system for each visited workstation, as well as data from occupant’s satisfaction survey responses (Newsham et al., 2008). The results revealed that there is evidence to suggest that indoor CO₂ concentrations and indoor speech intelligibility are correlated with perceived thermal satisfaction, at least in the open-plan offices of the COPE dataset. One of the important findings of that study is that, under the same psychrometric conditions, a modest increase in indoor CO₂ concentration levels from 500 ppm to 900 ppm is found to be correlated with a decrease in perceived thermal satisfaction by about 30 ± 8%. Model checks and statistical validation techniques revealed that there is evidence to suggest that including CO₂ levels into thermal comfort modelling provides improved predictive accuracy over the Null hypothesis for thermal satisfaction. This observation is consistent across all of the performed model comparison and validation techniques (Crosby and Rysanek, 2021).

The current study aims to 1-update and verify these findings by adding over 100 new samples of IEQ measurements collected from a recent IEQ field study of open-plan offices. 2- Investigate and test the significance and statistical robustness of the correlations between perceived thermal satisfaction and non-thermal IEQ metrics. 3- Formulate a new predictive model of thermal comfort, derived from the Bayesian logistic regression of both datasets, which can be used by building modellers to predict thermal comfort in office settings based on thermal conditions and ventilation rates.

Methodologies

A Bayesian Framework for Thermal Comfort

Bayesian inference techniques have been applied effectively in many recent studies to improve predictions of thermal comfort using new observational data (Jensen et al., 2009; Langevin and Gurban, 2013). Adopting Bayesian statistical modelling in thermal comfort predictions has several benefits. In particular, Bayesian framework provides a mechanism that is able to incorporate different IEQ datasets into one single thermal comfort model. This is done by updating prior knowledge on thermal comfort distributions from past research into the current estimation of model parameters, which also provides a robust manner of updating these parameters as more data becomes available. This use of the Bayesian framework reflects the scientific “learning cycle,” where prior estimates are updated as new data becomes available (Choy et al., 2009).

Crosby and Rysanek (2021) have recently developed a Bayesian framework that evaluates the correlations between non-thermal IEQ conditions, such as indoor lighting levels and CO₂, and perceived thermal comfort. The Bayesian framework is configured so that it estimates the probability of an occupant feeling thermally satisfied, $p(S)$, as a function of not only psychrometric/thermal IEQ parameters, but also to several non-thermal IEQ parameters. A Bayesian logistic process was firstly undertaken on a large field study of about 800 participants to infer the correlations between perceived thermal comfort and thermal and non-thermal metrics of IEQ. Then, model validation techniques were applied to identify the independence, and potentially the universality of observing a quantifiable effect of non-thermal IEQ metrics on perceived thermal comfort. In the following sections, we present our recent field IEQ dataset that is used to investigate the significance and robustness of the previous findings using the Bayesian framework.

UBC field IEQ study

A large field study has been conducted at the University of British Columbia to determine whether the evidence base for the prior findings is improved upon the addition of new data. The new IEQ study utilises modernized instrumentation under the auspices of more modern indoor building environments and building systems compared to the COPE field study of the early 2000s.
The UBC dataset consists of instantaneous physical measurement of IEQ, spatial, and manual measurements coupled with responses from an IEQ questionnaire collected from 150 workstations in five buildings between 2019 and 2020 from open-plan offices. Each building is visited twice, in summer and wintertime. A satisfaction survey questionnaire is developed to collect “right-here-right-now” occupant’s satisfaction responses. Participants are mostly University staff and faculty members from different schools and disciplines.

Participants completed a 41-questions survey at their workstations while the physical IEQ measurements are collected. Questions about IEQ satisfaction included 3 different perception categories for each IEQ parameter: perceived levels, satisfaction with perceived levels, and preference to perceived levels. These questions were answered on a 7-point Likert scale. The survey covered satisfaction with the thermal environment, long term satisfaction with the air temperature, satisfaction with job and workplace, background noise levels, lighting levels, daylight availability, glare, view to the outside, quality and quantity of artificial lighting, air quality, olfactory comfort, air movement, humidity, IEQ controllability, and other individual features of the workspace. These questions follow the same methodology adopted in the survey data collection of the COPE study.

A high precision IEQ sensors cart, ESTEBAN (Exceptional Sensing Testbed for Environment, Biophilia, Air-quality, and Nippiness), is designed and built for this study. The cart carries all the IEQ sensors required for the local micro-climate measurement conducted at each workstation. For each participant, the occupant’s office chair is removed and replaced with the measurement cart. ESTEBAN, as shown in Figure 1, holds a variety of sensors and measurement tools to record indoor air temperature, relative humidity, mean radiant temperature, CO₂ concentrations, CO concentrations, Total Volatile Organic Compounds (TVOCs), air velocity, A-weighted noise levels, and desktop illuminance levels.

**Sampling of posterior distributions**

The UBC IEQ dataset is added to the COPE dataset and the Bayesian framework developed by Crosby and Rysanek (2021) is used to predict correlations between occupant’s perceived thermal satisfaction, \( p(S) \), and thermal and non-thermal parameters of IEQ. As this paper seeks to determine whether, based on the updated dataset, the previous observations of the relationships between thermal satisfaction and non-thermal metrics of IEQ are reinforced, an initial investigation of the effect of three non-thermal variables of IEQ on perceived thermal satisfaction is carried out. The three non-thermal IEQ metrics included in the initial investigation are: CO₂ levels, light intensity, and noise levels. The Bayesian statistics Python library, PyMC3, is used to infer posterior distributions of logistic regression model coefficients for the investigated models. For each model, 5000 samples are drawn from the posteriors using the Sequential Monte Carlo (SMC) method, a type of Markov Chain Monte Carlo (MCMC) sampling method. Weakly informative priors for each of the models’ regression parameters \( \beta \) are used, as recommended by Gelman et al. (2008).

**Results**

Posterior predictions of the probability of thermal satisfaction, \( p(S) \), inferred from the Bayesian logistic regression of the COPE and UBC expanded dataset revealed that the non-thermal IEQ parameter that showed a significant correlation with thermal satisfaction is indoor CO₂ levels. The noise levels showed only a modest correlation with \( p(S) \), while light intensity showed no correlation with \( p(S) \). This finding reinforces the observations made in the prior study. The relationship between occupant’s thermal satisfaction and indoor CO₂ concentrations will be then the focus of this study.

Figure 2 displays the posterior results of the Bayesian regression process that predicts the correlation between occupant thermal satisfaction, \( p(S) \), and measured values of indoor CO₂ concentrations levels, C, assuming a fixed set of values for all other parameters. The attributed notation of the model is \( p(S | T, M, C) \), which predicts the probability of an occupant feeling thermally satisfied, \( p(S) \), as a function of indoor air temperature, \( T \), mean radiant temperature, \( M \), and CO₂ concentrations levels, C. Unless otherwise specified, the fixed set of parameters are: indoor air temperature, \( T = 23.3 \, ^\circ C \), and mean radiant temperature, \( M = 23.4 \, ^\circ C \). These are the observed mean values for each parameter, taken at the moment of the survey, out of the COPE and the UBC.
datasets. As the regression coefficients of the model, $\beta$, are probabilistic, there is a range of fit of the model. In Figure 2, the mean predictive value of $p(S)$ is denoted by a solid black line. The standard error of predictions is denoted by the upper and lower dotted black lines around the mean. These initial results suggest a relationship between surveyed thermal satisfaction and indoor $\text{CO}_2$ levels, which supports previous findings. In the following sections, model comparison and cross validation techniques are performed to compare these results with the previous results drawn from the COPE dataset and verify whether these findings are statistically robust and significant.

Model checks and comparison

Visualization of odds ratios

In Bayesian inference, and particularly for Bayesian regression models, when determining the significance of conclusions drawn from statistical analyses, metrics that evaluate the predictive accuracy of a proposed model are used to compare individual models against one other in the process of determining the models of best fit to observable data (Vehtari and Ojanen, 2012).

One of the common methods of model validation, that is widely used in Bayesian logistic regression, is the visualization of the odds ratio. It aims to measure the effect of predictor variables on binary responses and validate the correlations between each independent variable and the posterior outcome of the model (Cooper et al., 2009). Here, we are interested to validate the significance of the relationship between thermal satisfaction, $p(S)$, and $\text{CO}_2$ levels inferred from the expanded dataset.

The log odds ratio for the $p(S)$ model’s $\text{CO}_2$ regression parameter inferred from the UBC and COPE datasets are produced and illustrated in Figure 3. The odds ratio inferred from the expanded dataset is compared against the $\text{CO}_2$ odds ratio inferred from the COPE dataset as shown in Figure 3. Variables that are more likely to affect a logistic regression model in a statistically significant manner are those with odds ratios that deviate from 1. We observe that the odds ratio of the posterior traces of the $\beta_{\text{CO}_2}$ comply with this for the $p(S)$ model, which suggests that $\text{CO}_2$ levels have a significant attributable independent effect on the $p(S)$ model’s outcome. Comparing the new odds ratio with that of the COPE dataset, it is clear that adding the UBC data made the correlations between thermal satisfaction $p(S)$ and $\text{CO}_2$ more robust and statistically significant.

Quantitative model comparison and selection

Two different model validation and comparison approaches are performed to evaluate the developed model: the Watanabe-Akaike Information Criteria (WAIC) and Leave-one-out Cross-Validation (LOO-CV). WAIC and LOO scores are performed to determine the best-performing model and compare their expected predictive accuracy. When comparing the fit and appropriateness of two different models to a dataset, models with lower WAIC and LOO scores are suggested to be a better fit to data.

A Null hypothesis is selected for this process to establish our comparison, which is selected to be the model that most closely fits the observed data but only includes thermal IEQ parameters. This first step reveals that the best representation of $p(S)$ as a function of only thermal parameters, as inferred from the COPE and UBC datasets, is the model that includes indoor air temperature, $T$, and mean radiant temperature, $M$, as independent variables i.e. $p(S | T, M)$.

The WAIC and LOO scores for the developed Bayesian model are calculated and the difference between the WAIC and LOO scores of the Null hypothesis and that of the $\text{CO}_2$ Bayesian model, $\Delta$ WAIC and $\Delta$ LOO respectively, are summarized in Table 1. The sign of the difference in WAIC scores compared...
to the Null hypothesis indicates the significance of the model: if the difference is positive, it means the model shows improvement in prediction accuracy of \( p(S) \) over the Null the hypothesis, and the absolute value of the difference reflect the degree of which the model provides an improvement in prediction accuracy over the Null hypothesis.

The difference in WAIC scores compared to the Null hypothesis for each model is evaluated for the COPE+UBC dataset and compared to the COPE results, as shown in Table 1. The results indicate that \( p(S | T, M, C) \) model provides improved predictive accuracy over the Null hypothesis for thermal satisfaction. This observation is consistent with the odds ratio analysis visualized in Figure 3. The results also reveal that adding the UBC dataset makes the previous findings more significant and robust. This suggests that by including measurement of CO\(_2\) concentration levels, it is possible to improve the prediction accuracy of thermal satisfaction in open-plan offices, as inferred from both the COPE and UBC datasets.

**Drawing posterior predictions from the model**

Figure 4 represents a visualization of posterior predictions of thermal satisfaction against both operative temperature and indoor CO\(_2\) levels. The standard deviation of posterior predictions is denoted by the translucent band around the median. Operative temperature is assumed to be the average indoor air temperature and mean radiant temperature. As observed from Figure 4, the independent negative correlation between CO\(_2\) levels and perceived thermal comfort is notable and observable. This finding is robust and supported by model selection criteria. Specifically, between an indoor air CO\(_2\) concentration of 500 ppm and 900 ppm, and at an operative temperature of 23 °C, the mean likelihood of an occupant feeling thermally satisfied decreases from 0.58 to 0.46. These are not trivial ranges for the indoor CO\(_2\) levels and predicted effects on thermal satisfaction; for instance, 900 ppm is still well within historically prescribed CO\(_2\) limits for good indoor air quality in buildings (Ng et al., 2011).

The subjective element of comfort consists of physiological, psychological and behavioural factors. As discussed in the paper, the argument is that occupant’s perception of thermal comfort is holistic and may be affected by the psychological effect of many physical conditions that occupants encounter in the built environment. Our work only finds some evidence to support a statement that measurements of

| \( p(S | T, M, C) \) | COPE | COPE+UBC |
|-----------------|------|----------|
| \( \Delta \text{WAIC} \) | 1.82 | 3.83     |
| \( \Delta \text{LOO} \)   | 1.82 | 3.83     |

**Proposing a New Predictive Model of Thermal Comfort**

After updating and verifying the prior study’s findings using the recently developed field dataset, indoor CO\(_2\) levels appear to be significantly correlated with occupant’s thermal satisfaction. Model checks and validation techniques revealed and reinforced the previous findings, that including measurements of CO\(_2\) levels is proved to increase the prediction accuracy of thermal satisfaction modelling in open-plan offices. In this section, we propose and formulate a new predictive model, derived from the Bayesian logistic regression of the COPE and UBC datasets, which takes into account thermal environmental conditions, as well as indoor CO\(_2\) concentrations levels. The proposed thermal satisfaction model evaluates the probability of occupant’s thermal satisfaction, \( p(S | T, M, C) \) as follows:

\[
p(S | T, M, C) = \frac{1}{1 + e^{-\zeta}}
\]

\[
\zeta = [(\beta_T \cdot T) + (\beta_M \cdot M) + (\beta_{T^2} \cdot T^2) + (\beta_{M^2} \cdot M^2) + (\beta_C \cdot C) + \beta_o] \tag{1}
\]

Where \( T \) = air temperature (°C), \( M \) = mean radiant temperature (°C), \( C \) = indoor CO\(_2\) levels (ppm), \( \beta_C, \beta_T, \beta_{T^2}, \beta_M, \beta_{M^2} \) are the model regression parameters for \( C, T, T^2, M, M^2 \) respectively, and \( \beta_o \) is the constant model coefficient. Based on the initial trial and error undertaken prior to this paper, the following model coefficients are modelled as having a first-order linear relationship with \( p(S); C \). The following parameters are modelled as having a quadratic relationship with \( p(S); T, M \). The choice of these re-
The thermal comfort predictive model that we are proposing is a probabilistic model which predicts the occupant’s thermal satisfaction as a probabilistic distribution with model parameters’ uncertainty bounds presented above. For future use of the model, we recommend sampling from our model, presented in Eq.(1), instead of using the deterministic formula for more accurate predictions. We suggest using MCMC or other sampling methods to sample from the model an adequate number of times until the predicted outcomes are well-converged. In this study, we have used 5000 draws to infer the posterior predictions of the logistic regression model parameters. It is recommended, for observational studies that involve logistic regression in the analysis, to have a minimum sample size of 500 to sufficiently derive the statistics that represent the parameters (Bujang et al., 2018). If using PyMC3, the recommended default number of draws in logistic regression is 1000 draws.

### Model Validation

Model validation is an essential part of the model development process. It aims to validate the model’s robustness and accuracy, to verify that the model is not over-fitting or under-fitting the data, and to prove it is not an ungeneralized model (i.e. model’s predictions can’t be generalized on other data). In statistics and machine learning, model validation is usually done by splitting the data into two subsets: training data and testing data. The model is first fit on the training data to make predictions on the test data (Tipping, 2003).

To validate our model, we first trained the model by fitting it to the COPE dataset to infer predictions for the model parameters. Using the UBC dataset as the testing data, we inferred predictions of thermal satisfaction and then compared these predictions against true observations drawn from the test data. The probability distribution of the predicted thermal satisfaction, \( p(S) \), inferred from the training data is shown in Figure 6. The maximum likely predicted \( p(S) \), displayed as a blue dashed vertical line, is compared against the mean of the true \( p(S) \), observed typical operating indoor conditions of office setups, with ranges of IEQ parameters as follows: \( T = (18.7 \degree C - 29 \degree C); M = (19.4 \degree C - 27.3 \degree C); C = (469.5 \text{ ppm} - 1356 \text{ ppm}) \)

<table>
<thead>
<tr>
<th>Model Parameter(( \beta ))</th>
<th>MAPE</th>
<th>95% CrI</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_0 )</td>
<td>-0.11</td>
<td>-0.72 : 0.55</td>
</tr>
<tr>
<td>( \beta_T )</td>
<td>1.1</td>
<td>-0.51 : 2.6</td>
</tr>
<tr>
<td>( \beta_M )</td>
<td>0.088</td>
<td>-1.4 : 1.5</td>
</tr>
<tr>
<td>( \beta_T^2 )</td>
<td>-0.0004</td>
<td>-1.5 : 1.8</td>
</tr>
<tr>
<td>( \beta_M^2 )</td>
<td>-0.67</td>
<td>-2.1 : 0.99</td>
</tr>
<tr>
<td>( \beta_{CO_2} )</td>
<td>-0.92</td>
<td>-1.8 : -0.037</td>
</tr>
</tbody>
</table>

The probability distribution of the predicted thermal satisfaction, \( p(S) \), inferred from the training data is shown in Figure 6. The maximum likely predicted \( p(S) \), displayed as a blue dashed vertical line, is compared against the mean of the true \( p(S) \), observed
from the test data and displayed as an orange dashed vertical line. The 95% credible interval of the predicted \( p(S) \) is shown in Figure 6 as a grey shaded area. The model validation process, displayed in Figure 6, reveals that the true value of \( p(S) \) lies within the 95% credible interval of predictions of thermal satisfaction with maximum likely predicted \( p(S) \) equals 0.578 and mean observed \( p(S) \) equals 0.56 (percentage prediction error = 3.2%). As more IEQ data is gathered in future, the model will become more accurate and more universal. The Bayesian approach, we adopted here, is grounded for assessing the incremental change in the evidence base upon the addition of future data.

**Conclusion**

This paper updated the findings of a prior study that examined the correlations between non-thermal indoor environmental conditions and perceived thermal comfort in open-plan offices. A new IEQ field study conducted at the University of British Columbia is presented in this paper. A Bayesian framework that estimates the probability of an occupant feeling thermally satisfied as a function of not only psychrometric IEQ parameters but also to non-thermal metrics of IEQ was applied on the expanded dataset to infer relationships between perceived thermal satisfaction and non-thermal parameters of IEQ. Posterior prediction results revealed stronger evidence that there exists a statistically significant independent correlation between thermal comfort and indoor \( \text{CO}_2 \) concentration. Model comparison, cross-validation, and posterior checks revealed that it is possible to increase the prediction accuracy of thermal satisfaction in open-plan offices by including measurements of \( \text{CO}_2 \) concentration levels. These findings validate the robustness and significance of the prior results.

This paper proposed a new predictive model of thermal comfort that predicts the occupant’s thermal satisfaction given measured values of \( \text{CO}_2 \) concentration, indoor air temperature, and mean radiant temperature. The new model was validated by fitting it to a training set and comparing the predictions against true observations drawn from a test dataset. The validation process revealed that the true observation lies within the 95% credible interval of predictions of thermal satisfaction with percentage prediction error equals 3.2%. This new model could be used by building performance simulation experts to predict occupants’ thermal comfort in office spaces based on thermal conditions and ventilation rates.

While many recent studies have identified the multi-domain nature of thermal comfort - that thermal comfort may be related to other indices of IEQ, this work is one of few studies to evaluate these relationships quantitatively and in a manner that can support future thermal comfort prediction. The buildings sector is facing several conflated challenges, particularly now in a post-COVID-19 world. Energy use should be minimized to support climate change objectives, but indoor air quality and well-being cannot be sacrificed - if anything, it should be improved as well.

**References**


S. Crosby, G. Newsham, J. Veitch, S. Rogak, and A. Rysanek. Bayesian inference of thermal comfort:


