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REPORT

Comparison between WBGT app prototype and WBGT monitor to assess heat stress risk in an eastern North Carolina outdoor setting

Bridget Angol[a], Sinan Sousan[b,c,d], and Jo Anne G. Balanay[a]

[a]Environmental Health Sciences Program, Department of Health Education and Promotion, East Carolina University, Greenville, North Carolina; [b]Department of Public Health, Brody School of Medicine, East Carolina University, Greenville, North Carolina; [c]North Carolina Agromedicine Institute, Greenville, North Carolina; [d]Center for Human Health and the Environment, NC State University, Raleigh, North Carolina

ABSTRACT

The wet bulb globe temperature (WBGT) index is the preferred environmental heat metric for occupational heat-related illness prevention but may not always be readily accessible in the workplace. Thus, there is a need for well-designed WBGT-based tools that are reliable, accessible, and inexpensive. A novel WBGT app prototype was developed to calculate the current and forecasted outdoor WBGT. The purpose of this study was to assess the reliability of the WBGT app prototype in providing accurate heat stress risk information for outdoor workplace settings in eastern North Carolina by comparing the WBGT indices and risk levels from the app ($WBGT_{app}$) with those derived from a heat stress monitor ($WBGT_{ins}$). Outdoor WBGT measurements were data logged at a university campus site using a heat stress monitor from March to August 2023 for 81 days and were assigned to risk levels by workload based on the ACGIH Threshold Limit Values. Hourly $WBGT_{app}$ values and their corresponding risk levels were obtained using the app prototype. Data analysis was conducted using a t-test, Pearson correlation test, and cross-tabulation. Results showed that the hourly mean $WBGT_{app}$ was significantly higher ($p < 0.01$) than the $WBGT_{ins}$, but there was no significant difference between the overall average of the daily mean ($p = 0.15$) and daily maximum ($p = 0.69$) $WBGT_{app}$ and $WBGT_{ins}$. There was a strong, positive correlation between the hourly mean ($r = 0.94$, $p < 0.01$), daily mean ($r = 0.97$, $p < 0.01$), and daily maximum ($r = 0.94$, $p < 0.01$) $WBGT_{app}$ and $WBGT_{ins}$. The app correctly identified 73–88% of minimal-risk conditions, depending on workload type, and was most reliable in correctly identifying extreme-risk conditions at 97%, 95%, and 93% for light, moderate, and heavy workloads, respectively. This demonstrates the app's capability of being protective of the workers, particularly in more severe heat stress risk conditions. Recommendations to improve the app's accuracy involved using accurate solar irradiance data and applying linear calibration. The WBGT app prototype shows good potential as an alternative risk assessment tool for heat stress risk among outdoor workers.

KEYWORDS
Groundskeeping; heat stress; landscaping; occupational exposure; outdoor workers; risk assessment

Introduction

Heat is the main cause of weather-related deaths in the United States, far exceeding the deaths caused by any other weather conditions, including floods, hurricanes, lightning, and tornadoes (Changnon et al. 1996), and is continually increasing due to global climate change (Lindsey and Dahlman 2024). More than 3,000 heat-related deaths occurred during 2018–2020 (CDC 2022), while a total of 1,600 deaths occurred in 2021 alone (CDC 2023). The overall burden of heat-related deaths at the community level is significantly influenced by outdoor work (Riley et al. 2018). Workers in outdoor settings are at high risk for heat-related illness (HRI) and death due to their prolonged exposure to high ambient temperature, high relative humidity, and direct sunlight (Bonauto et al. 2007; CDC 2008). Moreover, strenuous physical labor that increases metabolic heat production among outdoor workers contributes to occupational heat strain and increased HRI risks. Metabolic rate and labor productivity levels among outdoor workers were projected to remain higher than their physical work capacity (Ioannou et al. 2022). The highest fatality rates due to workplace heat exposure were particularly found among construction and agricultural workers

CONTACT Jo Anne G. Balanay balanayj@ecu.edu Environmental Health Sciences Program, Department of Health Education and Promotion, East Carolina University, Greenville, North Carolina.

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(Gubernot et al. 2015), but other outdoor workers were also found to be at high risk of extreme heat exposure, such as those in groundskeeping and municipal work (Beck et al. 2018; Uejio et al. 2018).

Wet bulb globe temperature (WBGT), typically measured by a heat stress monitor as a reference (i.e., gold standard) instrument, is the weighted average of dry bulb, wet bulb, and globe temperatures. WBGT is considered the preferred environmental heat metric as it incorporates the effects of air temperature, relative humidity, air movement, and radiant heat as key environmental heat determinants (Larranaga 2011). The National Institute for Occupational Safety and Health (NIOSH) and the American Conference of Governmental Industrial Hygienists (ACGIH®) advocate the use of WBGT as part of occupational heat stress prevention programs and have published their WBGT-based occupational exposure limits (i.e., Recommended Exposure Limit [REL] and Threshold Limit Value [TLV®], respectively) for heat stress (NIOSH 2016; ACGIH 2024). The Occupational Safety and Health Administration (OSHA) recognizes the advantages of WBGT over other environmental heat measurements (OSHA 2024a).

However, utilizing the WBGT method may not always be readily accessible in the worksite due to several factors, such as insufficient resources to purchase necessary equipment and/or to hire trained personnel to conduct heat stress monitoring (Dillane and Balanay 2020). Thus, an alternative method or tool such as a mobile app for heat stress assessment that is more accessible and inexpensive but reliable is an attractive concept. The heat index, known as the "apparent" or "feels like" temperature, is an alternative environmental heat metric that combines air temperature and relative humidity (Steadman 1979; NWS 2024). The OSHA-NIOSH Heat Safety Tool, a mobile app that provides the current and forecasted heat index and its corresponding risk level has been considered an alternative tool for occupational heat stress assessment (NIOSH 2022) and has been used as a mitigation and educational tool for agricultural workers (Luque et al. 2019a, 2019b). However, this heat index-based app was found to be inaccurate in assessing high and extreme heat stress risks at any workload when compared to WBGT-based heat stress risk data (Dillane and Balanay 2020). Thus, a reliable, well-designed, and easily available mobile app that delivers WBGT-based risk information was recommended as an alternative tool (Dillane and Balanay 2020). Moreover, OSHA recognizes that WBGT should be used to measure workplace environmental heat, and the use of heat index is a less desirable substitute (OSHA 2024a).

Weather stations are sources of readily available weather data that may be used to assess heat stress. Research has been conducted that assessed the accuracy of calculating WBGT using mathematical models that utilize weather data, particularly where there are no conventional measuring tools and direct data measurements (Liljegren et al. 2008; Gaspar and Quintela 2009; Lemke and Kjellstrom 2012; Patel et al. 2013; Maia et al. 2015; Grundstein and Cooper 2018; Carter et al. 2020). Liljegren et al. (2008) developed a heat and mass transfer algorithm that calculates WBGT using standard meteorological data, which was found to provide the most valid results among several published methods for calculating outdoor WBGT (Lemke and Kjellstrom 2012). The Liljegren algorithm is currently used by the OSHA Outdoor WBGT Calculator (OSHA 2024b).

Recognizing the need for a WBGT-based heat stress app, researchers at East Carolina University developed a WBGT web app prototype as a product of their app development training funded by the National Science Foundation (NSF) and financially supported by the ECU Office of Licensing and Commercialization. The app prototype, created as a proof of concept using limited funding, is capable of automatically calculating the current and forecasted WBGT index using the Liljegren et al. (2008) method and then converting the calculated WBGT into a corresponding heat stress risk level. The purpose of this study was to investigate the reliability of the WBGT app prototype in providing accurate heat stress risk information for outdoor workplace settings in eastern North Carolina by comparing it with WBGT data measured by an onsite heat stress monitor. The findings of this study have the potential to contribute to the development of an alternative tool for occupational heat stress assessment.

Methods

Heat stress monitoring

Area monitoring was conducted on one site located on a university campus in eastern North Carolina. The monitoring site was on a grassy area in front of a brick building intended to represent an outdoor workplace setting for groundskeeping workers. A heat stress monitor (QUESTemp34, 3 M, Oconomowoc, WI, United States) was placed at the monitoring site to collect heat stress data by setting it on a tripod at a height of 3.5 feet above the ground. The heat stress monitor was factory-calibrated within 6 months before data collection. On each monitoring day for 8–10 hr between 8:00 AM and 6:00 PM, the dry bulb, wet bulb, globe temperatures (°C), outdoor WBGT measurements (°C), and relative humidity (%) were data logged minute-by-minute. Monitoring was conducted for 81 days from March 1 to August 26, 2023, to represent days within the summer season.

Assignment of TLV-based risk levels to WBGT measurements

The hourly mean WBGT measurements acquired from heat stress monitoring were calculated and assigned to one of five heat stress risk levels (i.e., minimal, low, moderate, high, and extreme) according to criteria developed by Dillane and Balanay (2020) that defined the WBGT heat stress risk levels based on workload ranging from light to very heavy. The Dillane and Balanay (2020) criteria were derived from a graph adapted from the ACGIH TLV and action limit for heat stress (ACGIH 2024) and a study by Morris et al. (2019).

Use of WBGT app prototype

A WBGT web app prototype (i.e., WGBT app) developed by university researchers was used to collect estimated hourly WBGT indices. The app can instantaneously calculate the estimated current and forecasted WBGT indices using weather data collected from regional weather stations corresponding to the zip code provided by the user. The weather station data collected were air temperature (°F), relative humidity (%), wind speed (mph), and barometric pressure (inHg). The solar irradiance (W/m^2) was calculated using the date, time, latitude, and longitude, assuming direct sunlight (i.e., no clouds, clear sky). The app uses a free and readily accessible weather application programming interface (API) from OpenWeatherMap (https://openweathermap.org/api) to access current weather data and hourly forecasts for the next 12 hr. The collected weather data, latitude, longitude, date, and time of day were used by the app to estimate the outdoor WBGT index using the algorithm developed by Liljegren et al. (2008) via an open source-licensed software produced by UChicago Argonne, LLC under Contract No. DE-AC02-06CH11357 with the Department of Energy (downloadable at http://www.osha.gov/dts/osta/otm/otm_iii/wbgtutil.zip). The app-calculated WBGT indices were automatically assigned a corresponding heat stress risk level (minimal, low, moderate, high, extreme) depending on the selected workload level using the same criteria developed by Dillane and Balanay (2020). The WBGT app was used to collect data on the current hourly WBGT index (°C) and corresponding risk level based on three workload types (light, moderate, and heavy) that categorize the majority of the groundskeepers' tasks. App data were recorded at the start of every hour from 8:00 AM to 5:00 PM on each monitoring day.

Comparison between heat stress monitoring and app data

The estimated current WBGT index calculated by the app was compared to the WBGT measurements taken with the QUESTemp34 heat stress monitor at the monitoring site. Data from the WBGT app and heat stress monitoring were evaluated using two different comparison methods: (1) instrument-measured hourly mean, daily mean, and daily maximum WBGT ($WBGT_{ins}$) vs. app-calculated hourly, daily mean, and daily maximum WBGT ($WBGT_{app}$); and (2) hourly WBGT risk level derived from $WBGT_{ins}$ vs. hourly WBGT risk level derived from the $WBGT_{app}$. Only data pairs ($WBGT_{ins}$/$WBGT_{app}$) that were time-matched (i.e., same day, same hour) were used for comparison. The time-matched hours used were between "8:00 AM" and "5:00 PM," and the number of hours per day ranged from 8 to 10 hr. The reliability of the app in assessing occupational heat stress risk was determined by the percentage of hourly $WBGT_{ins}$ risk levels that had the same hourly $WBGT_{app}$ risk levels for different workloads. Determining such percentages aimed to compare the similarity between the assigned risk levels based on $WGBT_{ins}$ measurements and $WBGT_{app}$ calculated indices.

Data analysis

Time series plots were created to demonstrate hourly and daily trends of the WBGT indices. An independent sample t-test was completed to compare the hourly mean, daily mean, and daily maximum between the $WBGT_{ins}$ and $WBGT_{app}$ indices. The Pearson correlation test was used to assess the strength and direction of correlation between the $WBGT_{ins}$ and $WBGT_{app}$ indices and to derive the linear regression models. Cross tabulation was used to analyze the relationship between risk level categories based on the $WBGT_{ins}$ and $WBGT_{app}$ indices. The Statistical Package for Social Sciences (SPSS Statistics, version 29.0.1.0, IBM, Armonk, NY) was used to analyze the data. A p-value of <0.05 was considered statistically significant.

Results

Overall comparison and correlation between $WBGT_{ins}$ and $WBGT_{app}$ indices

The hourly mean $WBGT_{ins}$ for the entire monitoring period ranged from 8.4 to 33.0 °C, with an overall average of 24.6 ± 4.9 °C ($n = 790$), while the hourly mean $WBGT_{app}$ ranged from 6.1 to 37.8 °C, with an overall average hourly $WBGT_{app}$ of 25.7 ± 5.8 °C ($n = 790$). For $WBGT_{ins}$, the highest hourly mean $WBGT_{ins}$ (33.0 ± 0.3 °C) was measured on July 3, 2023, at 12:00 PM, while the highest daily mean (31.1 ± 1.0 °C) and daily maximum (34.2 °C) $WBGT_{ins}$ were recorded on July 28 and 3, respectively. For $WBGT_{app}$, the highest hourly $WBGT_{app}$ (37.8 °C) was measured on July 3, 2023, at 1:00 PM, while the highest daily mean (34.3 ± 3.5 °C) and daily maximum (37.8 °C) $WBGT_{app}$ were recorded on July 4 and 3, respectively.

Figure 1 compares the hourly mean $WBGT_{ins}$ and hourly $WBGT_{app}$ indices. Figure 1a compares the two WBGT indices for the entire monitoring period (March–August 2023), showing an increasing trend. Figure 1b compares the $WBGT_{ins}$ and $WBGT_{app}$ during July only to demonstrate a zoomed-in comparison of both indices. The $WBGT_{app}$ tended to be higher than the $WBGT_{ins}$ as particularly demonstrated in July (Figure 1b).

The overall average of the hourly $WBGT_{app}$ index (25.7 ± 5.7 °C, $n = 790$) was significantly higher ($t(1{,}578) = 4.04$, $p < 0.01$) than that of the hourly mean $WBGT_{ins}$ index (24.6 ± 4.9 °C, $n = 790$). However, the difference between the overall average of the daily mean $WBGT_{app}$ (25.7 ± 5.3 °C, $n = 81$) and $WBGT_{ins}$ (24.6 ± 4.6 °C, $n = 81$) was not statistically significant ($t(160)=1.44$, $p = 0.15$). Similarly, the difference between the overall average of the daily maximum $WBGT_{app}$ (28.4 ± 5.2 °C, $n = 81$) and $WBGT_{ins}$ (28.1 ± 4.4 °C, $n = 81$) was also not statistically significant ($t(160)=0.39$, $p = 0.69$).

The overall correlation between the $WBGT_{app}$ and $WBGT_{ins}$ indices was analyzed to determine the potential of the $WBGT_{app}$ to be used as a proxy for the $WBGT_{ins}$, and vice versa. Figure 2 shows strong, positive correlations ($r \geq 0.7$) between the hourly mean ($r = 0.94$, $p < 0.01$) (Figure 2a), between the daily mean ($r = 0.97$, $p < 0.01$) (Figure 2b) and between the daily maximum $WBGT_{app}$ and $WBGT_{ins}$ indices ($r = 0.94$, $p < 0.01$) (Figure 2c).

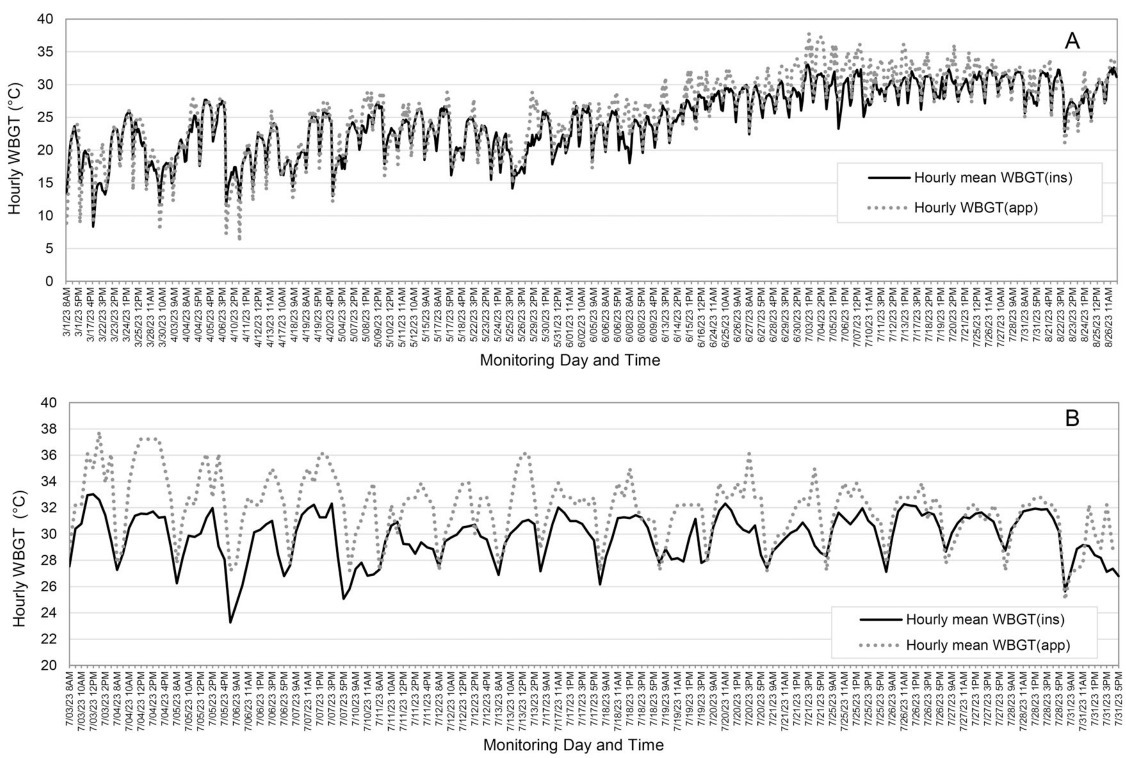

Figure 1. Hourly mean $WBGT_{ins}$ and hourly $WBGT_{app}$ indices by monitoring day and time for: (a) the entire study period (March to August 2023) and (b) the month of July 2023.

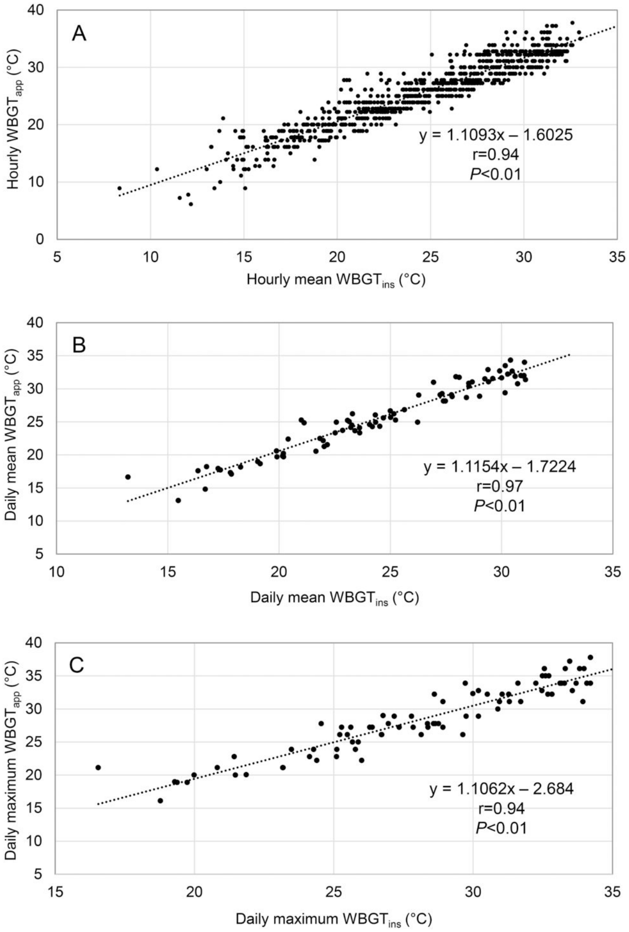

Figure 2. Overall correlation between (a) hourly mean, (b) daily mean, and (c) daily maximum WBGT$_{ins}$ and WBGT$_{app}$ indices.

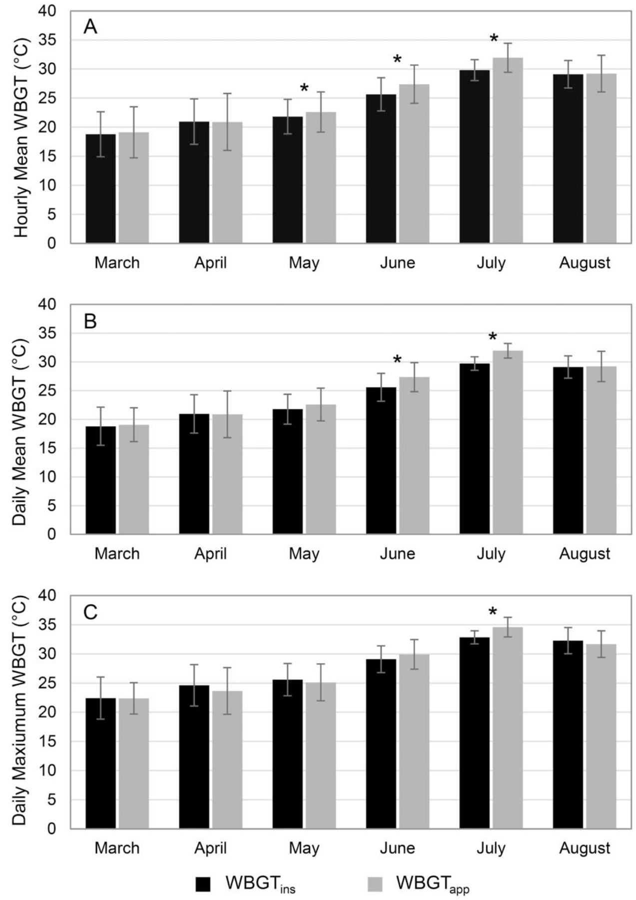

Figure 3. Comparison of hourly mean, daily mean, and daily maximum between WBGT$_{ins}$ and WBGT$_{app}$ indices by month. *statistically significant difference ($p < 0.05$).

Comparison and correlation between WBGT$_{ins}$ and WBGT$_{app}$ indices by month

Figure 3 shows a comparison of the hourly mean, daily mean, and daily maximum between the WBGT$_{ins}$ and WBGT$_{app}$ indices by month. For March, April, and August, the monthly average of the hourly mean, daily mean, and daily maximum WBGT$_{app}$ indices were not significantly different ($p = 0.54$–0.97) from those of the WBGT$_{ins}$ indices (Figure 3). For May, the monthly average of the hourly mean WBGT$_{app}$ (22.6 ± 3.4 °C) was significantly higher ($p = 0.02$) than that of the WBGT$_{ins}$ (21.8 ± 3.0 °C) (Figure 3a). However, the monthly average of the daily mean (22.6 ± 2.8 °C) and daily maximum (25.1 ± 3.1 °C) WBGT$_{app}$ indices were not significantly different ($p = 0.38$ and $p = 0.63$, respectively) from the monthly average of the daily mean (21.8 ± 2.6 °C) and daily maximum (25.6 ± 2.8 °C) WBGT$_{ins}$ indices (Figure 3b and c). For June, the monthly average of the hourly mean (27.4 ± 3.3 °C) and daily mean (27.4 ± 2.5 °C) WBGT$_{app}$ indices were significantly higher ($p < 0.01$ and $p = 0.04$, respectively) than the monthly average of the hourly mean (25.6 ± 2.8 °C) and daily mean (25.6 ± 2.4 °C) WBGT$_{ins}$ (Figure 3a and b). However, the monthly average of the daily maximum WBGT$_{app}$ (29.9 ± 2.5 °C) was not significantly different ($p = 0.31$) from that of the WBGT$_{ins}$ (29.1 ± 2.3 °C) (Figure 3c). For July, the monthly average of the hourly mean (31.9 ± 2.5 °C), daily mean (31.9 ± 1.3 °C) and daily maximum (34.6 ± 1.7 °C) WBGT$_{app}$ indices were significantly higher ($p < 0.01$) than the monthly average of the hourly mean (29.8 ± 1.8 °C), daily mean (29.7 ± 1.2 °C) and daily maximum (32.8 ± 1.1 °C) WBGT$_{ins}$ (Figure 3).

Table 1 summarizes the correlation data between the WBGT$_{ins}$ and WBGT$_{app}$ indices by month. For all months (except July), there is a strong, positive correlation ($r \geq 0.7$) between the hourly mean ($r = 0.83$–0.96, $p < 0.01$), daily mean ($r = 0.87$–0.98, $p < 0.01$) and daily maximum ($r = 0.71$–0.97, $p < 0.01$–0.04) WBGT$_{app}$ and WBGT$_{ins}$ indices. Figure 4

Table 1. Correlation parameters between $WBGT_{ins}$ and $WBGT_{app}$ indices by month.

	Hourly Mean				Daily Mean				Daily Max			
Month	n	r	*p*-value	Linear equation**	n	r	*p*-value	Linear equation	n	r	*p*-value	Linear equation**
March	80	0.83	<0.01*	$y = 0.939x + 1.489$	8	0.87	<0.01*	$y = 0.771x + 4.585$	8	0.85	<0.01*	$y = 0.634x + 8.153$
April	120	0.96	<0.01*	$y = 1.208x–4 .424$	12	0.98	<0.01*	$y = 1.192x–4.086$	12	0.97	<0.01*	$y = 1.094x–3.254$
May	175	0.84	<0.01*	$y = 0.974x + 1.369$	18	0.90	<0.01*	$y = 0.986x + 1.124$	18	0.85	<0.01*	$y = 0.964x + 0.449$
June	178	0.85	<0.01*	$y = 0.984x + 2.160$	18	0.92	<0.01*	$y = 0.955x + 2.928$	18	0.71	<0.01*	$y = 0.787x + 7.031$
July	177	0.63	<0.01*	$y = 0.876x + 5.824$	19	0.52	0.02*	$y = 0.563x + 15.220$	19	0.45	0.05	$y = 0.681x + 12.213$
August	60	0.89	<0.01*	$y = 1.184x–5.224$	6	0.95	<0.01*	$y = 1.285x–8.182$	6	0.83	0.04*	$y = 0.852x + 4.185$

*Statistically significant difference ($p < 0.05$).
**$y = WBGT_{ins}$ index, $x = WBGT_{app}$ index.

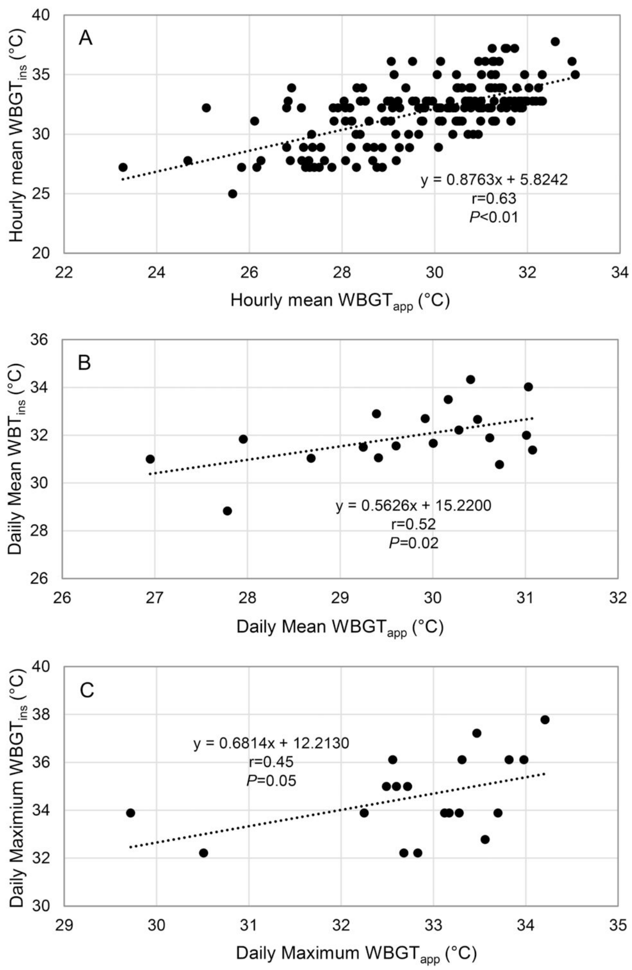

Figure 4. Monthly correlation for July between (a) hourly mean, (b) daily mean, and (c) daily maximum $WBGT_{ins}$ (C°) and $WBGT_{app}$ (C°).

demonstrates that the strength of correlation between $WBGT_{app}$ and $WBGT_{ins}$ for July was different from the other months, showing a moderate ($0.5<r<0.7$), positive correlation between the hourly mean ($r = 0.63$, $p < 0.01$) and between the daily mean ($r = 0.52$, $p = 0.02$) $WBGT_{app}$ and $WBGT_{ins}$, and a weak and marginally insignificant correlation ($r = 0.45$, $0.3<r<0.5$, $p = 0.05$) between the daily maximum $WBGT_{app}$ and $WBGT_{ins}$ indices.

Comparison between $WBGT_{ins}$ and $WBGT_{app}$ heat stress risks

Assigned heat stress risk levels for hourly mean $WBGT_{ins}$ indices ($n = 791$) were compared to corresponding risk levels for hourly mean $WBGT_{app}$ indices by workload. Figure 5 shows the percentage of each risk level category assigned to $WBGT_{ins}$ and $WBGT_{app}$ indices by workload. "Minimal risk" was the most commonly assigned risk level for $WBGT_{ins}$ under light (73.1%), moderate (51.2%), heavy (38.9%), and all workloads (54.4%), and for $WBGT_{app}$ under light (65.7%), moderate (39.6%) and all workloads (44.8%). "Extreme risk" was the most common risk level for $WBGT_{app}$ under heavy workloads (39.3%). Comparing the three workload types, either by $WBGT_{ins}$ or $WBGT_{app}$, the percentages for "minimal risk" (i.e., least severe risk level) decreased (e.g., from 73.1–38.9% for $WBGT_{ins}$; from 65.7 to 29.1% for $WBGT_{app}$) as the workload severity increased. In contrast, the percentages for "extreme risk" (i.e., most severe risk level) increased (e.g., from 7.8 to 34.6% for $WBGT_{ins}$; from 23.5 to 39.3% for $WBGT_{app}$) as the workload severity increased, which was also observed for "low risk" assignments (e.g., from 0.6 to 7.2% for $WBGT_{ins}$; from 0.0 to 17.1% for $WBGT_{app}$). The decreasing percentage of "minimal risk" assignments with increasing workload was observed in $WBGT_{ins}$ and $WBGT_{app}$, but these percentages tend to be higher for $WBGT_{ins}$ than $WBGT_{app}$. In contrast, the increasing percentage of "extreme risk" assignments with increasing workload was also observed in $WBGT_{ins}$ and $WBGT_{app}$, but these percentages tend to be higher for $WBGT_{app}$ than $WBGT_{ins}$ indices (Figure 5).

Figure 6 shows the percentage of hourly $WBGT_{ins}$-based risk level assignments that had the same hourly $WBGT_{app}$-based risk level assignment by workload and was used to determine the reliability of the app prototype in assessing heat stress risk. Among the $WBGT_{ins}$-based "minimal risk" assignments under the "light workload" assumption ($n = 578$), 87.5% were also assigned as "minimal risk" by the app, while the remaining 12.5% were assigned higher risk levels. As

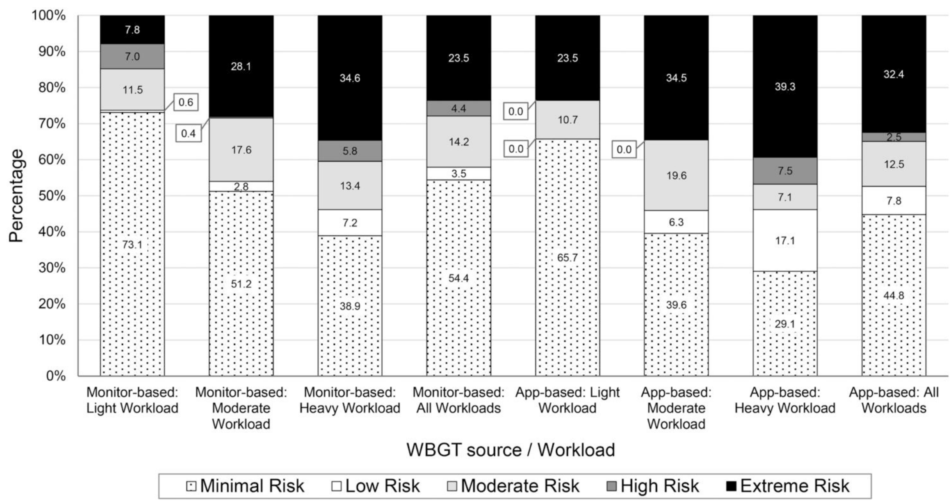

Figure 5. Percentage of assigned heat stress risk level ($n = 791$) for monitor-based $WBGT_{ins}$ and app-based $WBGT_{app}$ indices by workload.

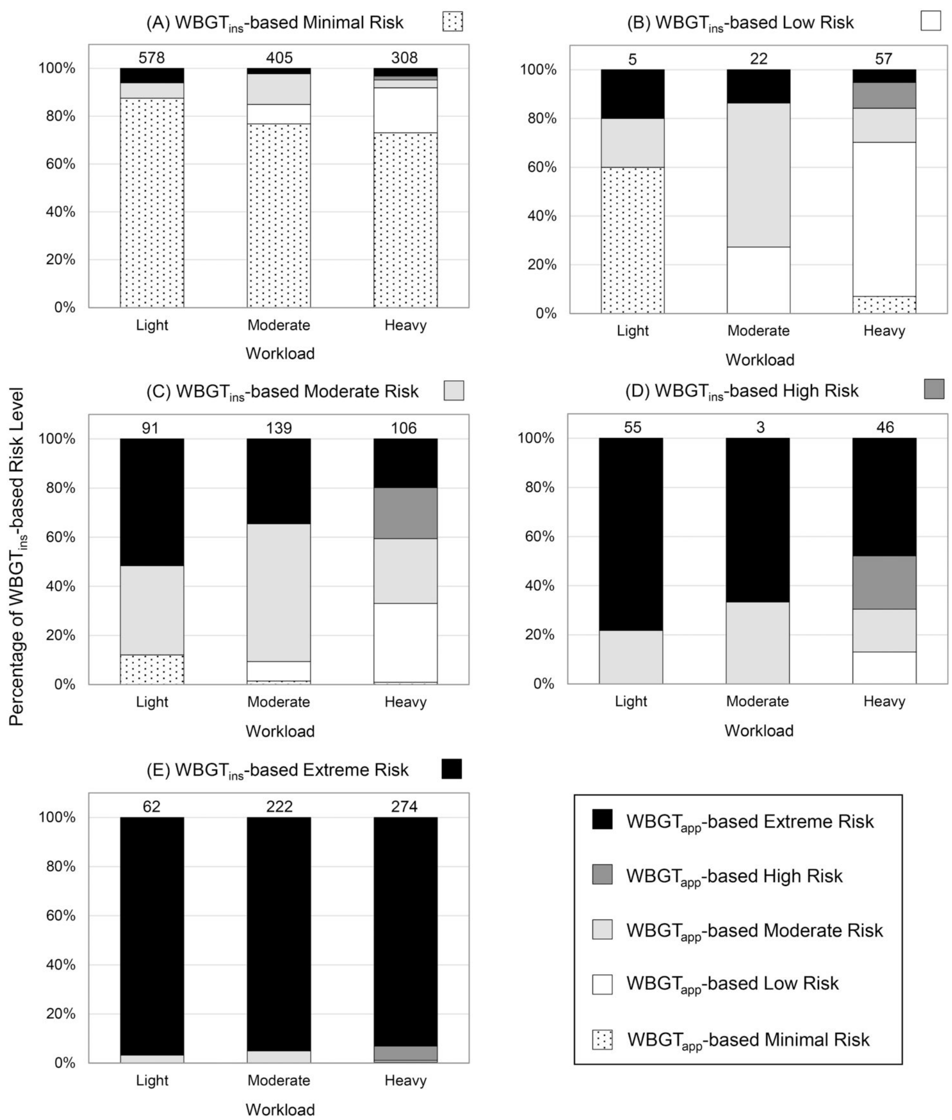

Figure 6. Percentage of hourly $WBGT_{ins}$-based risk level assignments with the same hourly $WBGT_{app}$-based risk level assignment by workload.

the workload increased, the percentage of "minimal risk" assignments by the app decreased from 87.5 to 73.1% for light to heavy workloads (Figure 6a).

Among the WBGT-based "moderate risk" assignments under the "light workload" ($n = 91$), 36.3% were also identified as "moderate risk" by the app while 51.6% were assigned a higher risk level of "extreme" (Figure 6c). Under "moderate workload," 56.1% of the WBGT-based "moderate risk" assignments ($n = 139$) were assigned the same risk level by the app. Under "heavy workload," 26.4% of the WBGT-based "moderate risk" assignments ($n = 106$) were assigned the same risk level by the app, while 40.6% were assigned to higher risk levels, and 33.0% were assigned to lower risk levels. Among the WBGT-based "high risk" assignments under light ($n = 55$) and moderate ($n = 3$), 0.0% were identified as "high risk" by the app while the majority (78.2% and 66.7%, respectively) were assigned to a higher risk level of "extreme" (Figure 6d).

Regarding the WBGT-based "extreme-risk" assignments, under "light workload" ($n = 62$), the majority (96.8%) were also identified as "extreme risk" by the app, indicating close alignment between the app and the $WBGT_{ins}$-based assessments. For "moderate workload" ($n = 222$), 95% were correctly categorized as "extreme risk," while 5% were assigned to a lower risk level of "moderate risk" by the app. Under "heavy workload" ($n = 274$), the app correctly classified 93.1% as "extreme risk," while the rest were assigned to lower risk levels. This pattern shows that the app performs best in identifying "extreme risk" conditions regardless of the workload (Figure 6e).

Table 2 summarizes the percentages of correct estimation, underestimation, and overestimation of heat stress risk assignments based on the $WBGT_{app}$ by workload type compared to those based on the $WBGT_{ins}$. The highest percentages of correct estimations of heat stress risk by the app were observed in "minimal risk" (73.1–87.5%) and "extreme risk" (93.1–96.8%) $WBGT_{ins}$-based risk assignments. With all risk levels combined, the app correctly estimated the heat stress risk for 75.7%, 76.6%, and 70.0% of the $WBGT_{ins}$-based risk assignments under light, moderate, and heavy workloads, respectively, while overestimating the risk at around 20%. Overall, the app correctly estimated the heat stress risk at 74.1%, overestimated at 20.6%, and underestimated at 5.3% of the $WBGT_{ins}$-based risk assignments (Table 2).

Discussion

Overall, the hourly mean $WBGT_{app}$ index was found to be higher than the $WBGT_{ins}$ index but the daily mean and daily maximum $WBGT_{app}$ index were similar to the $WBGT_{ins}$ index. When analyzed by month, the $WBGT_{app}$ index was similar to the $WBGT_{ins}$ index during the cooler months (e.g., March–May, August) but tends to be significantly higher than the $WBGT_{ins}$ index during the hottest months (e.g., June, July). These findings indicate that the app was more reliable in correctly estimating WBGT when the temperature was relatively cooler, and the app has reduced accuracy in hotter conditions due to WBGT overestimation.

The highest hourly mean, daily mean, and daily maximum WBGT index, whether measured by the heat stress monitor or calculated by the app prototyped, were found during July as supported by other published studies. Ghalhari et al. (2020) examined the changes in outdoor heat stress indices over 15 years and found that the highest average WBGT index occurred consistently in July. Moreover, Nakamura et al. (2022) analyzed trends in ambulance dispatches related to heat illness and found significant differences in WBGT across months, particularly identifying July as having one of the highest average maximum WBGT. Another study noted that in July and August, the WBGT was projected to increase by 3.2 °C across three cities, which highlights the trend of higher WBGT readings during these peak summer months (Nassiri et al. 2020). Lastly, a study by Dillane and Balanay (2020) in agricultural sites in eastern North Carolina found that July presented the highest daily mean WBGT and was one of the months with the highest percentages of hourly mean WBGT exceeding ACGIH TLV at any workload.

One potential reason for the app's overestimation of the WBGT index is the value of the solar irradiance used by the app's algorithm. The current algorithm estimates the WBGT from calculated solar irradiance in direct sunlight (i.e., assuming no clouds and a clear sky) using the date, time, and location (i.e., latitude, and longitude), which is the same method used by the OSHA WBGT calculator (OSHA 2024b) in calculating solar irradiance in direct sunlight. Solar irradiance can be significantly reduced depending on the cloud cover (Pfister et al. 2003; Ben Jemaa et al. 2013; OSHA 2017; Park et al. 2021). A study by Nevins and Apell (2021) found that solar irradiance decreased by about 67% at 100% cloud cover but was minimally impacted up to about 50% cloud cover. Thus, during times of the day when there is significant cloud cover, the actual solar irradiance may be much lower than the solar irradiance calculated by the app. This may explain why the $WBGT_{app}$ index was higher than the $WBGT_{ins}$ index, particularly since the estimated solar

Table 2. Accuracy of risk assignments estimated by $WBGT_{app}$ compared to $WBGT_{ins}$ indices.

			$WBGT_{app}$-based Risk Assignment					
			Underestimation		Correct Estimation		Overestimation	
$WBGT_{ins}$-based Risk Assignment	Workload	N	n	%	n	%	n	%
Minimal Risk	Light	578	–	–	506	87.5	72	12.5
	Moderate	405	–	–	311	76.8	94	23.2
	Heavy	308	–	–	225	73.1	83	26.9
Low Risk	Light	5	3	60.0	0	0.0	2	40.0
	Moderate	22	0	0.0	6	27.3	16	72.7
	Heavy	57	4	7.0	36	63.2	17	29.8
Moderate Risk	Light	91	11	12.1	33	36.3	47	51.6
	Moderate	139	13	9.3	78	56.1	48	34.5
	Heavy	106	35	33.0	28	26.4	43	40.6
High Risk	Light	55	12	21.8	0	0.0	43	78.2
	Moderate	3	1	33.3	0	0.0	2	66.7
	Heavy	46	14	30.4	10	21.7	22	47.8
Extreme Risk	Light	62	2	3.2	60	96.8	–	–
	Moderate	222	11	5.0	211	95.0	–	–
	Heavy	274	19	6.9	255	93.1	–	–
All Risks	Light	791	28	3.5	599	75.7	164	20.7
	Moderate	791	25	3.2	606	76.6	160	20.2
	Heavy	791	72	9.1	554	70.0	165	20.9
Total	All	2,373	125	5.3	1759	74.1	489	20.6

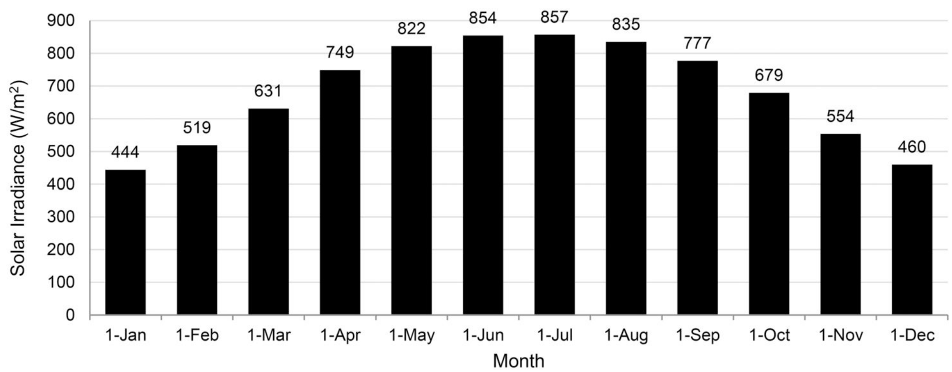

Figure 7. Solar irradiance (W/m^2) by first day of the month as calculated by the OSHA Outdoor WBGT Calculator at 12:00 PM, 35.6° latitude and 77.4° longitude.

irradiance was highest in July. To demonstrate this concept using the OSHA WBGT calculator (OSHA 2024b), given some constant parameters (i.e., time: 12:00; latitude: 35.6°; longitude: 77.4°), the solar irradiance for the 1st day of each month was calculated as shown in Figure 7, which demonstrates that the highest solar irradiance was calculated for July 1st (857 W/m^2).

The findings indicate that there is a need to adjust the app's algorithm to improve its estimation of the WBGT index in hot conditions. However, despite its overestimation of the WBGT index, the app may still provide sufficient worker protection against heat stress given its more conservative advice on heat stress risk reduction, particularly for resource-limited occupational settings, such as small-scale businesses. The app will be vital when appropriate instrumentation and/or trained occupational health and safety professionals may not be available to conduct heat stress monitoring. Similarly, Yorio and Wachter (2014) noted that small businesses may not have sufficient resources to develop and implement effective safety practices. Moreover, Gubernot et al. (2015) found that workplace heat-related fatality rates were the highest among small establishments and concluded that prevention efforts need to be directed at them. The app may serve as a beneficial tool in these occupational settings. Work supervisors or managers may use the app for work planning which may involve decreasing the workload when certain heat stress risk levels are reached. For example, tasks involving heavy workloads may be scheduled during times of the day when the heat stress risk is forecasted to be minimal or low, while light workloads may be scheduled when the forecasted heat stress risk is high or extreme. Although the app is a simpler tool than the heat stress monitor, training of app users to ensure accurate input of certain parameters (e.g., workload type) and correct interpretation of the app's output, and investigation on app user experience to gather data for app improvement will be beneficial.

If used without modification as a heat stress assessment tool, the app can serve as an early warning system since it tends to calculate higher WBGT levels. However, caution needs to be exercised, and app users must be advised that the estimated WBGT is for a "worst-case" outdoor scenario with the assumption of direct sunlight exposure. Overestimation of risk by the app may lead to the implementation of more stringent heat stress preventive measures than necessary, such as more frequent breaks, reduced working hours in hot conditions, or the use of additional cooling facilities, which can potentially decrease worker productivity. On the other hand, the app user may anticipate and, consequently, assume that the WBGT and associated heat stress risk are consistently overestimated and may disregard the app's advisories on heat stress risk and its corresponding recommended preventive measures, perceiving them as unnecessary. Such a scenario may lead to the app users' underestimation of their own risk, potentially putting the exposed workers in danger when heat stress is high.

The current algorithm of the app prototype can be adjusted to improve its estimation of the WBGT index in hot conditions by two methods: (1) using more accurate values for solar irradiation in the WBGT calculation, and (2) using linear regression calibration values based on the correlation between $WBGT_{app}$ and $WBGT_{ins}$ indices, from Table 1.

For the first adjustment method, two recommendation options are proposed regarding the solar irradiance values to use by the app for WBGT calculation. The first recommendation is to use solar irradiance values based on cloud cover. Instead of using an automatically calculated solar irradiance in direct sunlight, the app user will provide input on the cloud cover, which will then be converted into a corresponding solar irradiance value. Examples of solar irradiance values that can be used are 990 W/m^2 when sunny, 980 W/m^2 when mostly/partly sunny, 710 W/m^2 when mostly cloudy, and 250 W/m^2 when cloudy, as stated in the OSHA Technical Manual (OSHA 2017). Using the input on the actual cloud cover in the work site, the overestimation of the WBGT index by the app will be less likely. However, a disadvantage of this approach is that the app user would have to input this information into the app, which can be underestimated or overestimated during weather conditions when cloud cover is constantly changing (e.g., from cloudy to sunny and vice versa). Although the increase in cloud cover tends to decrease solar irradiation, sunlight penetration may depend not only on the cloud cover ratio but also on the cloud type and thickness (Park et al. 2021). The second recommendation is to automatically pull the solar irradiance data from weather stations, together with the other weather parameters used to calculate the WBGT index. The advantage of this approach is that the app will not have to rely on user input for solar irradiance information. However, a disadvantage is that solar irradiance data may not always be available from weather stations. If available, there is a possibility that the cloud cover at the weather station site is different from the cloud cover at the monitored worksite, which may either result in the under- or overestimation of the calculated WBGT index. Dillane and Balanay (2021) similarly attributed the potential differences in cloud cover between the local worksite and the regional weather station to the differences in solar ultraviolet radiation exposure between locations.

The second adjustment method for the app's algorithm involves the use of a linear regression calibration method to adjust the $WBGT_{app}$ estimations by determining the best linear equation for the calibration curve. This method has been used by previously published occupational health (Hallman et al. 2019) and environmental health (Yamamoto et al. 2017) studies to adjust the accuracy of predicting dependent variables. This present study showed a positive correlation, which is mostly strong, between the $WBGT_{app}$ calculated by the app and the $WBGT_{ins}$ measured by the reference heat stress monitor across all WBGT measures (hourly mean, daily mean, and daily maximum) for all months except in July (i.e., hottest month). The linear equations for use in the calibration of $WBGT_{app}$ were determined and presented in Figure 4 and Table 1.

Future directions

A partnership has been established with American Industrial Hygiene Association (AIHA) and the software development company, Dualboot Partners to develop an improved WBGT-based mobile app in iOS and Android platforms, which is the AIHA Heat Stress App (Rutkowski 2024). At the time of writing, the mobile app has been released and is undergoing the beta testing phase. The AIHA app uses the algorithm utilized in the ECU web app prototype but is modified to improve output by incorporating contributing factors, such as cloud cover and worker clothing. Some of the features of the newly released mobile app include the current and forecasted WBGT index and its translation to a heat stress risk level, and WBGT adjustments according to app user input on cloud cover and worker clothing.

Another future direction of the web app prototype is its integration in stand-alone WBGT devices that will combine the current and/or forecasted WBGT index with wearable sensors that provide physiological parameters (e.g., core body temperature, heart rate, sweat rate) that indicate heat strain responses. Such application is promising since wearable sensors continue to advance in technology and are becoming increasingly more popular in heat stress exposure assessment, as demonstrated in several recently published studies (MacLean et al. 2021; Sharma et al. 2022; Kim and Yoo 2023; Yaldiz et al. 2023; Tan et al. 2024). These real-time wearable sensors will allow a personal heat-stress exposure evaluation that is specific to each individual. The wealth of data provided by these sensors could be used with machine learning models to establish prediction models that evolve based on seasonality and improve the feedback provided to the users in real time. However, such sensors could also present privacy issues and researchers must ensure the anonymity of the data and restrict access to individuals wearing the sensors.

Limitations

A limitation of this study is that it was conducted at only one monitoring site in eastern North Carolina. This limited geographical coverage may restrict the generalizability of the findings to other regions. While the study covered the summer months with peak heat stress, it may not fully capture the variability in heat stress conditions throughout the year, particularly in regions with significant seasonal temperature fluctuations. The effects of weather parameters, such as cloud cover, wind, and rain, were not directly considered in assessing the accuracy of the app. The weather patterns during the study period may also not be representative of long-term trends. Moreover, conducting the study in a university campus environment, wherein certain factors (e.g., shade from buildings) may influence the microclimate, may not fully represent the diverse range of outdoor work settings that may have different microclimates and heat stress risks. To address this limitation, it is recommended that future research be conducted in other states or regions with different geographical features (e.g., rural vs. urban, plain vs. mountainous) and weather conditions, and in other outdoor workplaces (e.g., construction, agriculture) to determine potential factors that may affect the performance and accuracy of the app prototype. The app should also be continuously tested as long-term weather patterns change and in various weather conditions (e.g., rainy, cloudy, windy). Lastly, a sensitivity analysis is recommended in future studies to determine the effects of varying input meteorological parameters on the calculated WBGT by the app and the corresponding risk levels.

Conclusions

While the WBGT indices from the app prototype and the heat stress monitor generally followed similar daily patterns, the $WBGT_{app}$ indices were found to be significantly higher than the $WBGT_{ins}$ indices during hotter months but were similar to the $WBGT_{ins}$ during cooler conditions. The app prototype was found to be most reliable in identifying minimal and extreme risk conditions, demonstrating its capability of protecting outdoor workers in hazardous scenarios. However, the app tends to overestimate the corresponding heat stress risks derived from the WBGT indices in other risk conditions depending on the workload. Given its tendency to overestimate risk, the app prototype still shows promise in heat stress risk assessment as it has demonstrated to be more conservative in protecting outdoor workers from heat exposure. Although the app prototype may be useful as a heat stress assessment tool, caution must be exercised when using the information provided by the app as it may advise for preventive measures that may be more than necessary. Both the app and the monitor as exposure assessment methods are useful for monitoring heat stress but the differences between them should be considered when making decisions on exposure prevention and risk mitigation based on the measurements.

Given the significant differences between the WBGT indices from the app and the monitor during hotter conditions, there is a need to adjust the app's algorithm to improve its accuracy in estimating the WBGT indices from the reference heat stress monitor. This can be accomplished by using more accurate values for solar irradiation in the WBGT calculation by the app. Moreover, given the strong correlation between the $WBGT_{ins}$ measurements and $WBGT_{app}$ calculated indices during most months, the app's estimation of the WBGT index can be improved by linear regression calibration. Future improvements to the app may also involve WBGT adjustments according to factors affecting heat stress, such as cloud cover and worker clothing. Considering its many advantages, such as its portability, accessibility, affordability, and less complexity, the WBGT app prototype is a promising tool for occupational heat stress assessment and prevention of heat-related illnesses and deaths among outdoor workers. Future research may involve field validation with human participants to assess the impact of the app on worker behavior associated with heat-related illness prevention measures, to investigate the need for training and education on the proper use, accurate output interpretation, and limitations of the app, and to obtain feedback on the user interface from target occupational groups as end users. Moreover, the benefits of the app may be extended to its application on the public health and safety of vulnerable populations, including the elderly, athletes, and others who spend a significant amount of time outdoors for leisure. With the widespread usage of smartphones, tablets, and other portable technology, the app will make it easier to stay informed about heat stress risks.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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