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Novel Analytic Methods Needed for Real-Time Continuous Core Body Temperature Data

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Abstract

Affordable measurement of core body temperature (T_c) in a continuous, real-time fashion is now possible. With this advance comes a new data analysis paradigm for occupational epidemiology. We characterize issues arising after obtaining T_c data over 188 workdays for 83 participating farmworkers, a population vulnerable to effects of rising temperatures due to climate change. We describe a novel approach to these data using smoothing and functional data analysis. This approach highlights different data aspects compared with describing T_c at a single time point or summaries of the time course into an indicator function (e.g., did T_c ever exceed 38 °C, the threshold limit value for occupational heat exposure). Participants working in ferneries had significantly higher T_c at some point during the workday compared with those working in nurseries, despite a shorter workday for fernery participants. Our results typify the challenges and opportunities in analyzing Big Data streams from real-time physiologic monitoring.

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With climate change models projecting increasing frequency and severity of heat waves, heat-related illness (HRI) due to environmental exposure is of increasing public health concern (Spector & Sheffield, 2014). One population at increased risk is that of farmworkers, whose heat-related mortality rate is nearly 20 times that of the U.S. civilian population (Jackson & Rosenberg, 2010). We have undertaken a community-based participatory research project among farmworkers to better understand the effects of occupational heat exposure on body core temperature, as well as the association of body core temperature with other physiological measures of heat stress, enabling us to identify the workers at highest risk for HRI.

The current workplace recommendation for core body temperature (T_c) set by the American Congress of Government and Industrial Hygienists (ACGIH; 1995) is a threshold limit value of 38 °C; it is recommended that a worker's T_c not be permitted to exceed this threshold to avoid progression to heat exhaustion and heat stroke. Understanding the interplay of workplace environmental temperature, physical exertion, and T_c in real time requires collecting and analyzing copious quantities of complex physiologic data over extended periods. Although affordable technology now exists to measure T_c in a non-laboratory setting continuously over the course of a workday, new technical challenges and a new data paradigm have arisen with this advance, necessitating novel analytic approaches. With these challenges also lie opportunities to analyze data in novel ways that can more fully explain the underlying phenomena.

Ultimately, we wish to determine if symptoms of heat stress are related to T_c in a dose–response fashion, as well as understand patterns of correlation between T_c, environmental temperature, physical exertion, and physiologic strain. We will take advantage of the new power of continuous T_c measurements by analyzing these data with functional data analysis (FDA; Ramsay & Silverman, 2005), a set of techniques that allows relationships to be tested based on smoothed data curves of T_c rather than simple per-person summary measures of T_c.

Purpose

In this article, we describe the technical issues related to capturing real-time T_c and the analytic issues arising when large amounts of such data points are generated, detailing how we responded to these issues. We use the data collected from 88 participants enrolled in our summer 2015 data collection period as exemplars of these issues as well as to illustrate our analytic approaches.

Method

Setting and Design

In a community-based participatory research project among farmworkers, we enrolled 88 workers in a longitudinal cohort study and assessed 86 of them over the course of up to 3 working days.

Participants

Community health workers recruited participants. Each week, the health workers consented and enrolled a cohort of no more than 14 participants. Exclusion criteria (based on recommendations of the manufacturer of the sensor) are as follows:

- Weight less than 80 pounds;
- Type 1 diabetes;
- History of disease of the esophagus, stomach, or intestine;
- Previous surgery of the esophagus, stomach, or intestine;
- Dysphagia;
- Presence of a pacemaker;
- Pregnancy.

Measuring core body temperature is part of a broader collection of data that includes baseline and daily questionnaires capturing work habits, health, and heat stress symptoms; clinical measurements focusing on signs of dehydration; and environmental conditions. Results based on the interrelationship of those data will be addressed in future papers. This protocol was reviewed and approved by our institutional review board.

Physiological Data Collection

The CorTemp® Sensor (HQInc., Palmetto, FL; “the pill”) is an ingestible device about the size of a large vitamin pill that wirelessly transmits T_c as it moves through the digestive tract. The gold standard for measuring core body temperature is rectal temperature. Intestinal temperature via the CorTemp ingestible thermistor has been shown to be an equally valid, less invasive method that is highly correlated to rectal temperature (r = .86), with an intraclass correlation coefficient (ICC) of .87, mean bias of −0.19 °F, and low coefficient of variation (CV; 1.99 °C) as compared with rectal temperature in a validation study (Becker et al., 2007).

The pill transmits readings to a sensor worn by the participant. We set the system to measure T_c every 30 s. Based on pilot testing, this interval best allowed us to capture multiple streams of physiological data that eventually will be combined; for example, the physiologic strain index (Moran, Shitzer, & Pandolf, 1998), a function of T_c and heart rate, will be explored in a future analysis as a predictor of HRI. The pill continues to produce readings until it is excreted from the body.

Each participant wore a neoprene belt with the CorTemp® data recorder secured in an attached pocket; participants wore the belt on the waist underneath clothing. In addition, each participant wore a heart rate monitor around the torso and, at the hip, an elastic belt with an activity monitor. The three belts were worn securely underneath clothing, so as not to interfere with daily activities. At baseline, participants ingested the pill. In the mornings of the next 3 days, participants reported to the study field office where they donned the equipment; subsequently, they went to their work sites. After their shifts, they returned to the field office where we removed the measurement devices. Before and after each shift, we used the recorder to determine if the pill had been excreted since the last determination; if so, we gave the participant another pill to ingest. Data were downloaded from the recorder at the end of each workday.

Technical Issues

Several technical issues had to be surmounted before data analysis could commence. These issues can be grouped as personal aspects, system issues, and outcome definitions, which we discuss in further detail below.

Personal aspects. The first of the personal aspects was that of the acceptability of the pill. This arose first in subject recruitment. There were 160 people that came to our field sites to learn more about the study; of these, 88 (55%) people consented to participate and completed the baseline evaluation. Of the 72 people who did not consent, seven (10%) refused because of concerns about ingesting such a large pill.

Another issue was worker compliance with the measurement protocol. Although 88 workers were recruited, only 86 reported prior to the first shift. The two who did not return were concerned about time commitment. Of the

86, 81 completed all three shifts. Of the five who did not, two did not have work on the third day, two did not show at the field office on the third day, and one started data collection later in the week, and the field office was not open on that participant's third observation day.

Another issue related to the pill was that of pill excretion. For each participant, we determined before and after each shift if the pill was present; if not, they were given a new pill to ingest. In addition, there are a number of individuals who excreted the pill during a shift. We could determine this occurrence by examining the time-stamped temperatures in comparison with the time-stamped heart rate data—if there were no temperature data after a certain point in the day, but heart rate data continued to accrue, we inferred that the pill had been excreted. In the 81 workers with 3 days of observation (prior to data cleaning), 15 excreted the pill during at least one work period. Ten (12%) workers retained the pill over 3 days and nights, while another worker excreted the pill during each work period. To limit analysis to fully monitored workdays, if pill excretion was more than a brief period (20 min) before the assumed workday stop time, that observation was excluded.

Noncompliance with the monitoring protocol was another issue. Five observation days were unusable due to wearing the monitor improperly, taking it off, or turning it off, possibly due to worker manipulation of the belts to relieve discomfort.

Finally, there was the issue of how to define a "working day." For purposes of data registration for the planned FDA (described below), we need to have a common Time 0 on each day for each worker to serve as the time that she or he started work. Workers reported to the study field office in the morning before starting their shifts, at which time they were equipped with their individual monitors. They then drove to their work sites, possibly stopping along the way to drop children off for day care or to pick up food and/or beverages. At the end of the shift, they returned to the field offices where their monitors were removed. Once there, they also answered a short questionnaire that included questions about start and stop times of their work periods. We found that the responses to the questionnaire about shift start and stop times were highly variable and often nonsensical, and therefore were not useful for establishing a common definition of a working day. We decided instead to restrict analyses to the times between the time of first concurrent temperature and heart rate detection plus 30 min (start time or time = 0) and the time of last concurrent temperature and heart rate detection minus 30 min (stop time). This was done in an attempt to exclude periods expected to be associated with travel to and from the worksite.

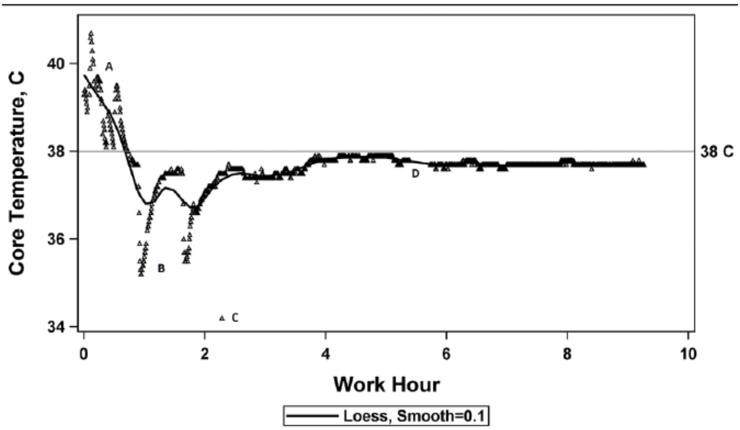

Figure 1. Examples of data issues and LOESS estimates.
Note. This graph shows several issues that commonly arise in our data. The bouncing ball effect is seen on the left side, where there are two initial rapid rises in T_c followed by recovery (A), followed by two rapid declines followed by recovery (B). There is an extreme value of 34.2 °C at Work Hour 2.28 (C). Finally, there is a substantial gap in the temperature data between work hours 5.39 and 5.73 (D). Overlaying the observations (triangles) is the LOESS estimated curve for these data (solid line). LOESS = local regression; T_c = core body temperature.

System issues. Among the system issues was that periods of seemingly random missing temperature data, sometimes occurred throughout the observation period. An example is shown in Figure 1, where all observations between 12:56 and 1:16 p.m. are missing. We examined the distribution of the percentage of values for which interim temperature values were missing, and decided to eliminate any worker's observation day on which more than 20% of values were missing. Our rationale was that days with 20% or more missing were more likely to be due to faulty devices. We also excluded data from any worker whose monitor failed during the day ($n = 11$). Finally, we excluded data from participants who excreted the pill more than 20 min before the stop time.

A second technical issue occurred when the pill was ingested in the morning, after which the recordings rose quickly from a low start. Occasionally, there was a quick peak likely due to drinking a hot beverage. By censoring observations in the first 30 min, we generally were able to remove the effects of the early morning consumption of hot beverages (see Figure 1); this would also allow temperature recordings to stabilize.

A related issue was that our initial cursory observations revealed an unexpected but common data pattern that we term the "bouncing ball" effect (i.e., a rapid temperature decline with rapid recovery or a rapid increase with rapid recovery). This is also illustrated in Figure 1. After subsequent evaluation by our field staff, we believe that these occurrences were associated with consumption of cold beverages while the pill was still in the stomach or the proximal portion of the small intestine. Again, this is illustrated in Figure 1. As beverage consumption throughout the workday is likely to be associated with the body's reaction to exertion and to environmental temperature, this is an important feature to capture.

Another system issue is that the data occasionally included implausible changes in temperature between 30-s readings. An example is shown in Figure 1, in which there is a single temperature value of 32 °C occurring 2.3 hr into the measurement period (Figure 1, Point C); the proximal and distal values close to this extreme reading were between 37 °C and 38 °C. From conversations with the technical support engineers in HQInc., we attribute these periodic implausible values to interference from another monitor or electromagnetic (EM) fields generated by large electric motors, such as fans. To avoid removing data that may be involved in the "bouncing ball" effect, only the most extreme singleton readings (≥5 degree difference between nearest neighbors) are set to missing; remaining values are realigned by the FDA, which smooths out extreme values such as in this example.

Finally, mishandling of files during the download process (mislabeling, duplication, overlooked) is a potential problem arising from the large number of biomonitoring data files that must be handled on-site in the field, under strict time constraints at the end of a day of data collection that may start at 5 a.m. and end in the early evening. Extensive and varied checks are required to flag files that should be examined for possible mislabeling and identify those that are missing.

The effects of these cleaning decisions are detailed in Tables 1 and 2. We began with 88 participants, of which 86 reported for the temperature measurements. We gathered 253 workdays of data from these participants. After these exclusions, there were 189 workdays from 83 participants with usable data in our final data set for analysis.

Outcome definitions. Our analytic approach used both summary measures per person and functional data as outcomes. Summary measures for each workday included whether the worker's T_c ever reached or exceeded 38 °C (defined as at least two consecutive values ≥38 °C within 1 min, to eliminate any implausible changes previously mentioned) and duration of time $T_c \geq 38$ °C. A summary for each worker included the number of workdays with any

Table 1. Issues Affecting the Quality of Core Temperature Data and the Impact on the Quantity of Data Available for Analysis.

	Subjects	No. of Workdays Removed	Workdays Remaining
Number of participants, N = 88			
Participated on ≥1 workday	86		253
Reasons workday data was unusable			
Noncompliance			
Did not wear monitor	86	2	251
Wore monitor in pocket	86	1	250
Monitor switched off	86	2	248
Monitor battery failed[a]	86	11	237
Pill expelled during workday[b]	85	16	221
>20% missing values	83	33	189

a. Included one in which pill was expelled.
b. Three pill expulsions occurred within 30 min of morning field office visit. We did not exclude 3 days when pill expulsion was within 20 min of end of the workday.

elevated T_c. These data points condensed the information from many hundreds of data points into a single measure.

An alternative approach is FDA, the foundational assumption of which is that the data reflect the smooth functional curves that generated them. In FDA, the datum associated with replication i is a finite set of measurements, $y_{i1},\ldots,y_{in}$ that occur at n distinct points of some dependent variable, which is typically, but not always, time. Thus, FDA takes advantage of all data by treating the individual's temperature time course *curve* as an outcome. This functional object can then be modeled in similar ways to a simple point response—an example of a simple point response being "T_c at precisely 8:00 am in the first observation period." By using functional analysis, we can capture important features of T_c over the course of the workday that are lost when using a single summary measure as the response, such as when T_c is more likely to exceed 38 °C during the workday. These functions may also be used as predictors of health outcomes.

Because our functional observations had occasional data gaps, missing values, and other noise, it is desirable to smooth the functions for each workday prior to further analysis. There are many ways to smooth a functional response. For these data, we have chosen the LOESS method (Cleveland, 1979; Cleveland & Devlin, 1988). The name LOESS is derived from "LOcal regrESSion," and it refers to a locally weighted scatterplot smoothing technique based on non-parametric regression. Consider a two-dimensional

Table 2. The Impact of Data Issues on Per Day and Per Person Core Temperature Data Available for Analysis, Pre-Cleaning Versus After Cleaning.

	Pre-Cleaning	Post-Cleaning
No. of participants each day		
Workday 1	86	68
Workday 2	86	61
Workday 3	81	60
No. of workdays available per participant		
3 workdays	81	37
2 workdays	5	32
1 workday	0	14

scatterplot of T_c versus time, t, with n points. The LOESS method builds up a functional estimate by fitting a low-degree polynomial using weighted least squares to a subset of the data at each data point. By using weighted least squares, this method gives more weight to points near the data point whose response is being estimated. There are two choices of parameters necessary for application: λ, the degree of the local polynomial, and α, the proportion of the overall data set used for each local fit. Other terms for α include bandwidth and smoothing parameter. At each data point, the method uses the $n\alpha$ points (rounded to the nearest integer) that are closest to the point at which the response is being estimated. The range for α is between $(\lambda + 1) / n$ and 1. The estimated curve becomes smoother as α increases. Conversely, as α becomes smaller, more of the features of the functional responses are retained. However, this comes at a cost of increased computational time as well as more wiggles in the estimator in response to fluctuations in the data. Figure 1 shows the LOESS estimator overlaid on the data. In this case, we used $\alpha = .10$, and $\lambda = 1$.

After smoothing the T_c time curve for each workday, we can apply FDA. FDA works as follows: Let $Y_{ij}(t)$ denote the response variable (e.g., the smoothed estimator for T_c at time t) for subject i on day j at time t. In our case, $i = 1, \ldots, 83; j = 1, \ldots, n_i; t \in [0, T_{ij}^S]$, where n_i is the number of days for which subject i is observed, $n = 1, 2, 3$, and T_{ij}^S is the length of time between the start of work and a timepoint 30 min before the end of the observation period for subject i on day j. We can estimate the average curve for subject i as

$$Y_{i.}(t) = \sum_{j=1}^{n_i} \frac{Y_{ij}(t)}{n_i},$$

and the overall sample mean as

$$Y_{..}(t)=\sum_{i=1}^{n}\frac{Y_{i.}(t)}{n}.$$

An alternative strategy is to use an alternative, non-parametric, definition for central tendency. In our case, due to the skewed distribution of T_c, we used the median as the summary measure for $Y_{i.}(t)$. Thus, we defined the overall median curve, $Y_m(t)$, for t in some interval $[t_{start}, t_{end}]$, as

$$Y_m(t)=median\left\{Y_{ij}(t), j=1,\ldots,n_i, i=1,\ldots,n\right\}.$$

In a similar manner, we can define the overall percentile curves. After derivation of these functional estimates, we can apply LOESS again to smooth out minor fluctuations.

Although these examples may seem simplistic, they allow great flexibility. Suppose we want to determine if two groups of workers had different relationships between temperature and time. At each time point, we evaluate the results of a statistical test, then create an inferential curve of p values, $p(t)$. In addition, we address the issue of multiple comparisons (i.e., 60 [5%] of the ~1200 time-point wise statistical tests we conduct will be significant just by chance) by conducting an omnibus test (Nichols & Holmes, 2002) for significance tests at a fixed overall significance level. The omnibus test is a permutation test of group assignments of the maximal test statistic over the interval of interest in which we reject the omnibus hypothesis at level α, if the maximal statistic for the actual realization of the group assignments is in the top 100α% of the permutation distribution for the maximal statistic.

Results

In Table 3, we describe the demographic and occupational characteristics of our usable sample. The majority of participants were female (63%), and the average age was 37.7 years. During this recruitment season, participants worked in two different segments of the agriculture industry—fernery (81%) and nursery (19%). The median duration of observation was 6.0 hr (interquartile range [IQR] = 4.9-8.3) for the group as a whole; for fernery participants, it was 5.5 hr (IQR = 4.7-7.1), whereas for nursery participants, it was 9.5 hr (IQR = 8.8-10.6).

We found readings of T_c exceeding 38 °C at some point on 61% of workdays, and 83% of participants had at least 1 workday on which $T_c \geq 38$ °C at some point (Table 4). Among the 37 participants with 3 days of usable data, 32% had 1 day, 16% had 2 days, and 41% had all 3 days on which $T_c \geq 38$ °C

Table 3. Characteristics of 83 Participants With 189 Workdays of Usable Data.

Characteristic	*n* (%) of Participants	*M* (Minimum-Maximum)
Type of agricultural work		
Fernery	67 (81%)	
Nursery	16 (19%)	
Gender		
Female	52 (63%)	
Age, years		37.7 (19-54)

Table 4. Distribution of Per Workday and Per Person Summaries of Continuously Measured Core Temperature.

	n/*N* (%)	Median (1st and 3rd quartile)
No. of days with core temperature ≥38 °C	116/189 (61%)	
No. of participants with core temperature ≥38 °C on at least 1 day	69/83 (83%)	
No. of days with core temperature ≥38 °C, per participant (among those with 3 days data)[a]		
0 days	4/37 (11%)	
1 day	12/37 (32%)	
2 days	6/37 (16%)	
3 days	15/37 (41%)	
On those days with core temperature ≥38 °C		
Average time until ≥38 °C, min		193 (109-257)
Average duration ≥38 °C, min		49 (21-109)

a. Among those with 2 days of data (*n* = 32), 34% had 2 days and 53% 1 day ≥38 °C; among those with 1 day of data (*n* = 14), 57% reached core temperatures ≥38 °C on that day.

at some point. Among those with 2 days of data ($n = 32$), 53% had 1 day and 34% had 2 days on which $T_c \geq 38$ °C at some point on that day; among those with 1 day of data ($n = 14$), 57% had $T_c \geq 38$ °C at some point on that day. For these workdays, the median time to reach $T_c \geq 38$ °C was 193 min (IQR = 109-257 min), and the average duration of $T_c \geq 38$ °C was 49 min (IQR = 21-109 min).

We plotted the LOESS estimates overlaid on the observed data for each workday, using $\lambda = 1$ and $\alpha = .1$, .15, and .5. We found that $\alpha = .1$ struck an appropriate balance between smoothing out fluctuations in the data and maintaining the features of the T_c–time relationship, hence all further work

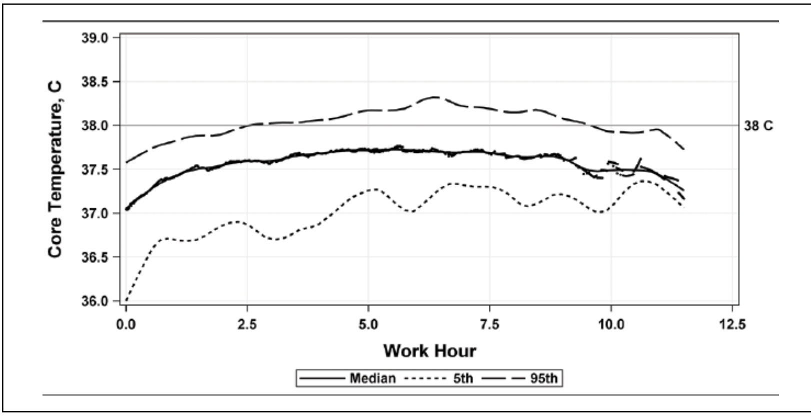

Figure 2. FDA median estimates for T_c versus time (closed circles) are overlaid with the smoothed curve (solid line). Also shown are smoothed curves for the 5th (short dash) and 95th (long dash) percentile values of these curve estimates.
Note. FDA = functional data analysis.

used $\lambda = 1$ and $\alpha = .1$. We also examined the mean and median functional curves and found that the median was less noisy, smoothing over noisy phenomena such as the bouncing ball effect without totally dampening this important feature. In Figure 2, we plot the median values of the LOESS estimates at each time point, as well as smoothed curves for the 5th and 95th percentile values. Note the noise occurring after Hour 10, when only a few participants remained working.

Figure 3 shows smoothed median and upper and lower percentile LOESS estimated curves for fernery (left-hand side) and nursery participants (right-hand side). Although the median curve never exceeds the threshold limit value, the 90th percentile curve does so for part of the day, indicating that at least 10% of fernery workdays have $T_c \geq 38$ °C sometime between the end of the fourth hr to the end of the 9th hr after starting work. While the median curve for nursery participants similarly never exceeds the threshold limit value, the 90th percentile curve also never exceeds it.

Figure 4 shows smoothed median curves for fernery and nursery participants superimposed with a rug plot of the results of the permutation test conducted at each time point comparing the two groups. The median T_c for fernery participants exceeds that for nursery participants throughout the day, significantly so around the end of the first work hour, and again between Hours 5 and 8. Larger stars on the figure's lower significance bar ("the rug") indicate statistical significance using the omnibus critical value.

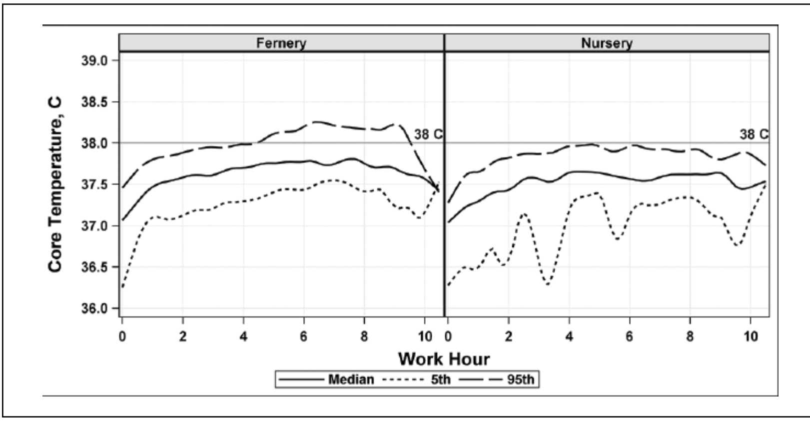

Figure 3. Smoothed FDA estimates for median (solid line), 10th (short dash), and 90th (long dash) percentile values for T_c in fernery (left) and nursery (right) workers.

Note. FDA = functional data analysis; T_c = core body temperature.

Figure 4. Rug plot of results of significance tests for differences in core temperature between fernery (solid line) and nursery workers (dashed line) at each 30-s time interval.

Note. Point-wise significant times are marked with open circle, whereas the triangles indicate points that meet the omnibus significance test. Both types of tests were carried out at the .05 significance level.

Discussion

We have deployed an innovative technology—ingestible temperature sensors—in a field setting for an epidemiological study of environmental heat exposure. These sensors produce vast amounts of real-time data on physiologic conditions; as such these data present a new data paradigm that has both challenges and rewards.

The primary challenge is in managing and examining the tremendous quantity of data to assure data quality. We discovered unexpected wrinkles as part of our data wrangling (the process of data cleaning and merging data from disparate sources) in preparation for analysis. For instance, we found that a quarter of the days observed had participant or technical issues that prevented their use in analysis. There are two implications. First, researchers should anticipate such data loss when considering sample size requirements during study planning stages. Second, the issues that we encountered and describe above illustrate the importance of graphing data, participant by participant, prior to analysis to understand what problems have arisen.

However, the "Big Data" collected by continuous monitoring provides new opportunities for in-depth understanding of the interplay between environmental and work inputs and physiologic responses. By using several methods of summarizing the abundant data monitored in real time, we were able to highlight different aspects of the information. For example, using simple per day and per person summaries, we observed that on a majority of days, participants developed T_c values exceeding the threshold limit value at some point during the workday, and four fifths of participants exceeded the threshold limit value on at least 1 workday. With the use of FDA, we gained additional insight into the time course of the physiologic response beyond that culled from the summary statistics, determining that fernery participants were significantly hotter than nursery participants during some portions of the day.

Our finding that fernery participants have higher T_c values was not surprising, based on previous data research with these communities. In both industries, much of the work occurs in hot enclosed environments and workers are under pressure to meet certain production quotas, requiring rapid work and limited breaks. Yet there are differences in the physical structure of the two work environments and the nature of work tasks performed that may account for the differences in measurements. Fernery work takes place in fields that are open on four sides, but are covered by porous black shadecloth ("saran") or, less commonly, under natural tree cover. Ventilation in ferneries is limited, and although there is usually a packing shed with toilet and sink somewhere on the property, it is often not close to workers in the field.

Harvesting ferns requires a lot of bending, carrying, and rushing down fields. Workers bend over repeatedly to thrust their arms into masses of ferns, cut the fronds at their base, and secure them into bunches of 20 to 25 fronds. They leave the frond bunches on the ground until they have a particular quantity, then they gather up all the frond bunches into an armload, which they quickly carry to a trailer waiting at the edge of the field. Nursery work involves the production of potted flowers and foliage mainly in more permanent structures enclosed by nonporous plastic, and there are often fans and ventilation within these structures. There are usually permanent outbuildings close to workers that have toilets and sinks. Work tasks are variable, but often require standing at a particular station for extended periods of time to plant at conveyor belts or load pots of plants into trays (Flocks et al., 2013; Mayer, Flocks, & Monaghan, 2010).

We collected the data reported here in summer 2015, during which we were only able to recruit a portion of the nursery workers that we had planned. To allow for more accurate comparison, additional nursery workers and other field crop workers will be recruited in future seasons as a means to minimize the discrepancies between the numbers of workers in each industry.

LOESS smoothing and FDA techniques cannot overcome the noise present in the data when sample sizes are small, as seen in later times in Figure 3, as many fewer participants had shifts longer than 10 hr. Although we accomplished part of the process of data registration by starting all workdays from a common Time 0, our inference suffers at later times as the sample size decreases for longer workdays. Therefore, a future direction is to explore the process of data warping, where we transform each workday to begin at a common Time 0 and end at a common Time 1—each interval on the *x* axis will then represent a proportion of workday.

Another future direction is to formalize and automate smoothing parameter selection. For these data, we used visual inspection, but in 2017, when we reach our targeted sample size of 400 participants, each with up to 3 workdays, visual inspection will not be possible. One possible approach is to summarize the parameter estimates of noise reduction and parameter retention across a space of smoothing parameters, and to identify the point at which a minimax is found.

Communication of these findings to the community partner in a way that will allow for workers to understand their risk for HRI and generate appropriate action toward attenuating these risks will also be challenging. Our next analytical efforts will be directed at integrating T_c with the simultaneous heart rate and actigraphy data into predictive models of HRI.

The results of this work illustrate analytical techniques used when sensors generate large amounts of data that are often messy or not easily interpretable.

Sophisticated smoothing and FDA techniques allow us to discover patterns in the data, testing these patterns as independent or dependent variables, rather than only looking at more simplified outcome measures. These approaches have direct applicability to other large data generating devices outside of agricultural heat stress monitoring, including physiologic readings from patient monitoring devices in the intensive care unit.

Although the challenges of analyzing large real-time data sets are substantial, the importance of this work cannot be minimized. Rising temperatures are a real threat to human life and the frequency at which workers exceed the core body temperature that is safe to continue to work is of great concern. The graphs depicted in this article illustrate what is happening physiologically in groups of workers over time and can be used to develop compelling messages advocating for policy to protect vulnerable working populations.

Declaration of Conflicting Interests

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