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ORIGINAL PAPER

Validation of a Temperature Prediction Model for Heat Deaths in Undocumented Border Crossers

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Abstract Heat exposure is a leading cause of death in undocumented border crossers along the Arizona–Mexico border. We performed a validation study of a weather prediction model that predicts the probability of heat related deaths among undocumented border crossers. We analyzed a medical examiner registry cohort of undocumented border crosser heat- related deaths from January 1, 2002 to August 31, 2009 and used logistic regression to model the probability of one or more heat deaths on a given day using daily high temperature (DHT) as the predictor. At a critical threshold DHT of 40 °C, the probability of at least one heat death was 50 %. The probability of a heat death along the Arizona–Mexico border for suspected undocumented border crossers is strongly associated with ambient temperature. These results can be used in prevention and response efforts to assess the daily risk of deaths among undocumented border crossers in the region.

Keywords Heat stroke · Epidemiology · Undocumented immigrant · Border crosser

Introduction

The Arizona portion of the United States–Mexico border is the most frequently used section of the border by undocumented border crossers (UBC), with approximately 500,000 UBCs apprehended by the United States Border Patrol (USBP) per year. Beginning in the 1990s, border crossing routes began to shift from populated areas towards more remote regions of the border [1]. As a result of this shift, environmental heat exposure emerged as the leading cause of death among undocumented border crossers, with 61 % of deaths attributable to heat-related causes [3]. By the summer of 2010, record numbers of border crosser heat deaths were recorded along the border despite decreases in the estimates of the volume of undocumented crossings. The risk of heat deaths along the Arizona–Mexico border was in fact highest when the volume of border crossings was lowest, which happened to be the summer months. As widespread media reports have indicated, it has become apparent that summer is an extremely hazardous time for border crossers to attempt to cross the Arizona desert [4–8].

While the precise definition varies, heat stroke is a highly lethal clinical condition that involves multi-organ failure and central nervous system dysfunction in the setting of hyperthermia [9–16]. Thermally stressed individuals are thought to be at significant risk for heat stroke when the body's core temperature exceeds 40 °C [13]. Medical co-morbidities and other conditions such as acclimatization play a significant role in an individual's susceptibility to heat stroke and death [16–25]. Heat stroke is traditionally thought of as a disease associated with environmental heat waves. Heat waves are usually defined as three or more consecutive days with high temperatures that exceed 90°F (32.2 °C) [13, 24]. Arizona deserts consistently record summer daily high temperatures in excess of 100°F (37.8 °C) for 30 days or more. While these conditions place residents and visitors to the state at seemingly increased risk of heat stroke compared to other climates, very few heat deaths were noted in the state prior to the emergence of

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increased heat deaths among UBCs about 10 years ago [4, 26].

Previous work evaluating heat related deaths in UBCs in Southern Arizona demonstrated a relationship between the daily high temperature (DHT) and heat deaths, with a 35 % increase in the risk of a death occurrence for each 1 °C increase in the DHT [5]. A limitation of this work, however, was that it did not test if the association between the log odds of death and DHT was linear. The current study seeks to further validate and refine the association between death and DHT and build a prediction model of heat deaths among undocumented border crossers in the region based on more than 8 years of data linking individual dates of death, confirmed heat death occurrences, and ambient DHTs. The long-term goal of this work is to help foster the development of public health interventions and data driven medical system responses to decrease mortality and morbidity from heat illness along the Arizona border.

Methods

Data Source

We conducted a retrospective cohort study of death data from the Pima and Cochise County Medical Examiner's (ME) case records from January 1, 2002 through August 31, 2009 in which the units of study were days of the year in the border region. These two ME offices have responsibility for death investigations of UBC death cases from the three Southern Arizona border counties of Pima, Cochise and Santa Cruz, which encompass the majority of the approximately 360 mile Arizona–Mexico border region (Fig. 1). The geographical region encompassing these three counties was considered the case study site for every 24-hour period during the study. A heat death was only attributed to a date in the region if forensic case files documented it. Case records were collected from the ME in electronic format that included age, gender, cause of death, date of death (if known), and nationality (if known). Cause and date of death determinations were performed by board certified forensic pathologists as a part of routine case analyses. These were typically those with dates of death estimated within 72-hours of the date the body was found as longer post-mortem intervals made accurate cause of death decisions less accurate.

Ambient temperature data for the study period was obtained from the National Oceanic and Atmospheric Administration's (NOAA) National Weather Service to obtain the daily high temperature (DHT). Data from the Tucson main reporting station at Tucson International Airport was used as previous work has shown very high correlation between the Tucson station and other weather stations in the border region [4]. Moreover, although the heat index is often used to reflect thermal stress, the arid nature of Southern Arizona renders the use of the heat index less valuable, so the unadjusted DHT was used to measure the level of heat exposure on each given day [5].

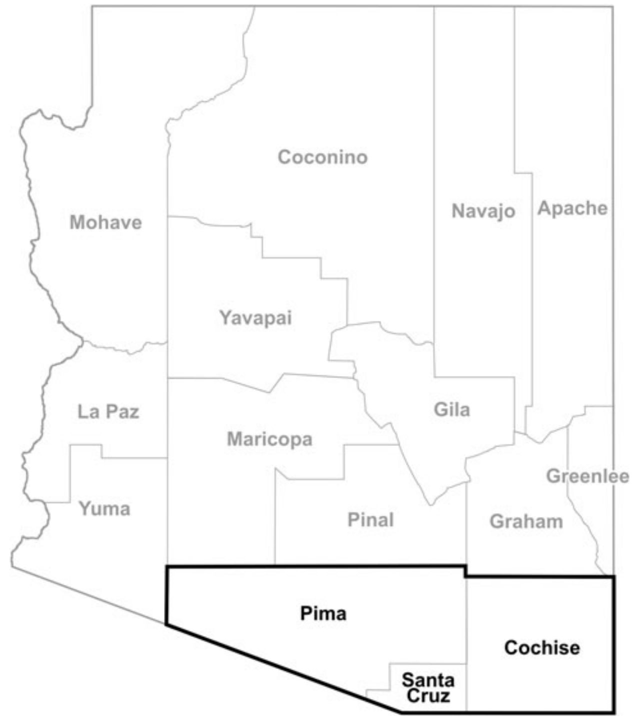

Fig. 1 Map of Arizona with Pima, Santa Cruz, and Cochise counties[2]

Inclusion/Exclusion Criteria

We included all cases with a cause of death attributed as heat related (hyperthermia, probable hyperthermia, exposure, or probable exposure) and that were suspected undocumented border crossers (nationality other than U.S. or unknown nationality). We excluded all cases from our analysis that did not have a reported date of death. The unit of analysis was each 24 h day during the study period and the outcome variable was the presence or absence of a heat-related death of a suspected UBC.

Statistical Analysis

Descriptive statistics are presented as proportions for categorical data, means and standard deviations for normally distributed data, and median and interquartile range for skewed data. We used the Kruskal–Wallis equality-of-populations rank test to test the hypothesis that median DHT and number of heat deaths did not differ by year or months.

We used logistic regression to model $\pi(x)$, the probability of one or more heat-related deaths in the geographical region on a given day, using daily high temperature (DHT) in degrees Celsius (°C) as the independent variable. We used fractional polynomials to find the optimal transformation of DHT as a continuous variable in the logit scale [27]. In order to prevent over-fitting our predictive model to our entire data set, and thus limiting its external applicability/validity, we divided our data into two sets: (1) a model development set that spanned January 1, 2002–August 31, 2008 (2,435 consecutive days) and (2) a model validation set that spanned September 1, 2008–August 31, 2009 (365 consecutive days). After developing our initial logistic regression predictive model (development model) using the development data set, we calculated model fit (Hosmer–Lemeshow goodness-of-fit test) and discrimination [area under the receiver operator characteristics curve (AUC)] as well as classification metrics (sensitivity, specificity, positive predictive value, negative predictive value) to insure good fit and discrimination. We then used the logistic regression coefficients from the development model to predict $\pi(x)$ for our validation data set and compared model fit and discrimination for the predictions from the validation data set to those from the development data set. Finally, we combined the two data sets (final data set) and constructed a final logistic regression model (final model), again calculating model fit and discrimination. We then used the final model and the final data set to predict $\pi(x)$ for each observed DHT. We used the regression equation for the final model to determine the DHT at which the probability of death was 50 % or greater. We then calculated the odds ratio for at least one death in the region on a given day when the DHT was equal to or greater than the DHT corresponding to $\pi(x) \geq 0.5$, compared to days when the DHT corresponded to $\pi(x) < 0.5$.

Model diagnostics were assessed according to Hosmer and Lemeshow [27] by plotting residuals and leverage values versus the probability of a heat death to identify covariate patterns that had disproportionate influence on the final logistic regression model (e.g., a cold day with a heat death) [27]. Covariate patterns with excessively large residual and leverage values were removed one at a time to assess their impact on the final model and were excluded from the final model if their removal resulted in a significant change in the logistic regression coefficients.

We also conducted a sensitivity analysis to determine if using the daily high heat index (DHHI) as the independent variable (as opposed to DHT) is superior to using DHT in the predictive logistic regression model. The DHHI was calculated according to Steadman (1979) [28]. DHHI was only calculated for days when the DHT was 27 °C or above and thus for days with a DHT below 27 °C, DHHI = DHT [28]. We again used fractional polynomials to determine the optimal transformation for DHHI as a continuous variable for best fit in the logit scale. We calculated goodness-of-fit and AUC for the LR model using DHHI as the independent variable and compared AUC to that for the final LR model using DHT.

All analyses were done using Stata v12.0 (StataCorp, College Station, TX, USA). The Institutional Review Board of the University of Arizona exempted this study from review.

Results

During our study period, there were a total of 1,457 deaths for suspected UBCs, 801 (55.0 %) attributed to heat-related causes, 275 (18.9 %) attributed to other causes (e.g., trauma from motor vehicle collision, trauma from a gun-shot wound, hypothermia, drowning), and 381 (26.1 %) not attributed to any cause (cause of death unknown). Of the 801 heat-related deaths, 661 (82.5 %) had a date of death assigned by the coroner, and thus were included in our analyses. Table 1

Table 1 Demographic characteristics of heat death cases of suspected undocumented border crossers in Pima, Santa Cruz, and Cochise Counties, Arizona 2002–2009

Year (number of days sampled)	Number of days with 1 or more heat deaths					Total heat-deaths N	Males n (%)	Age Available n (%)	Age mean (SD)
	1 death n (%)	2 deaths n (%)	3 deaths n (%)	4+ deaths n (%)	Total n (%)				
2002 (365)	35 (9.6)	9 (2.5)	2 (0.6)	1 (0.3)	47 (12.9)	63	44 (70)	46 (73)	34 (16)
2003 (365)	37 (10.1)	9 (2.5)	1 (0.3)	4 (1.1)	51(13.4)	75	56 (74)	64(85)	34 (14)
2004 (366)	38 (10.4)	7 (1.9)	0 (0)	0 (0)	45 (12.3)	52	37 (71)	51 (99)	33 (15)
2005 (365)	41 (11.2)	19 (5.2)	7 (1.9)	9 (2.5)	76 (20.8)	146	110 (75)	139 (95)	32 (12)
2006 (365)	39 (10.7)	8 (2.2)	3 (0.8)	2 (0.6)	52 (14.3)	72	60 (74)	64 (89)	30 (12)
2007 (365)	55 (15.1)	18 (4.9)	7 (1.9)	1 (0.3)	81 (22.2)	116	82 (69)	93 (79)	33 (11)
2008 (366)	34 (9.3)	9 (2.5)	3 (0.8)	1 (0.3)	47 (12.8)	65	47 (75)	47 (72)	31 (12)
2009* (243)	29 (11.9)	9 (3.7)	7 (2.9)	1 (0.4)	46 (18.9)	72	54 (76)	41 (57)	35 (12)
Total	308 (11.0)	88 (3.1)	30 (1.1)	19 (0.7)	445 (15.9)	661	490 (74)	586 (81)	33 (14)

* Only includes January 1–August 31

shows the number of days with heat deaths and basic demographics for UBCs with a heat related death by year. Out of 2,800 days in our study, 15.9 % of days had one or more deaths, 11.0 % had one death, 3.1 % had two deaths, 1.1 % had 3 deaths and 0.7 % had 4 or more deaths. Five days (0.2 %) had 5 deaths each, 1 day (0.04 %) had 6 deaths, and 1 day (0.04 %) had 8 deaths, the highest number on any day. Demographic data on this cohort of heat deaths is similar to prior studies (Table 1) [4, 5]. The majority of UBCs who die of heat related causes are male (73 % overall) and relatively young (mean age = 33 years, standard deviation = 14). Figure 2a shows the distribution of DHTs within each month and across months as a box plot. Observed DHTs ranged from a low of 7 °C (December, January) to a high of 44 °C (June, July). A total of 31.5 % of all days in our study had a DHT of 35 °C or higher and 7.9 % had a DHT of 40 °C or higher. Year to year variation was much lower than month to month variation in DHT and median DHT did not differ across years ($p = 0.70$) while median DHT differed significantly across months ($p < 0.001$). Figure 2b shows the distribution of heat-deaths within each month and across months as a box plot. Like DHT, the median number of heat deaths differed significantly across months ($p < 0.001$) while they did not differ significantly across years ($p = 0.94$).

The goodness-of-fit test for untransformed DHT resulted in poor fit of the model ($p = 0.003$). Using fractional polynomials, we found that a squared transformation of DHT was the simplest transformation that significantly improved model fit and more complicated transformations did not significantly improve model fit. Thus we transformed DHT to $(\mathrm{DHT}/10)^2$, significantly improving model fit (goodness-of-fit test, $p = 0.18$) and used the transformed variable in all subsequent logistic regression modeling. Table 2 shows the various measures of model fit and discrimination for the prediction of probability of death for a given day [$\pi(\mathrm{x})$] for the development, validation, and final data sets. The equation to calculate $\pi(\mathrm{x})$ using DHT from our final predictive model is as follows:

$$\pi(\mathrm{x}) = \frac{e^{\mathrm{b}_0+\mathrm{b}_1\mathrm{x}}}{1 + e^{\mathrm{b}_0+\mathrm{b}_1\mathrm{x}}}$$

where $\mathrm{b}_0 = -5.5946$, and $\mathrm{b}_1 = 0.3450$, and $\mathrm{X} = (\mathrm{DHT}/10)^2$.

The goodness-of-fit of the development model was adequate ($p = 0.39$) for the development data set as well as the validation data set ($p = 0.60$). The AUC using the development model to predict $\pi(\mathrm{x})$ was not statistically different ($p = 0.38$) between the development data set (0.844, 95 % CI: 0.824, 0.864) and the validation data set (0.815, 95 % CI: 0.754, 0.877). The fit of the final logistic regression model using the final combined data set was adequate ($p = 0.18$), and the AUC was 0.840 (95 % CI: 0.822, 0.859).

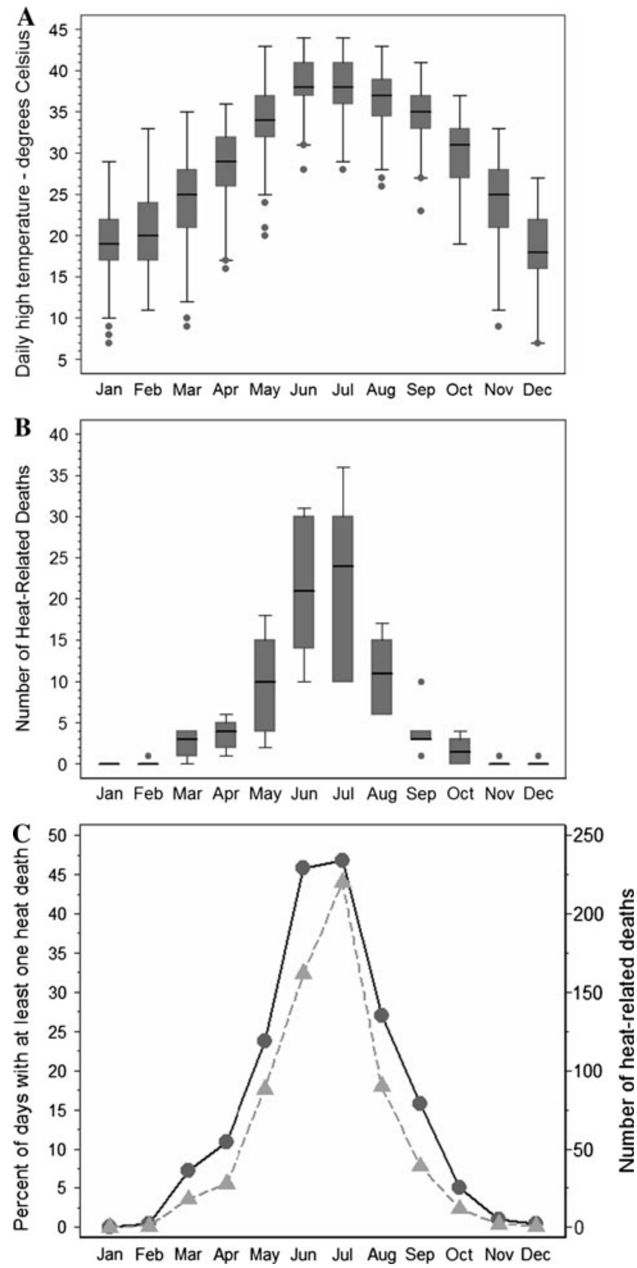

Fig. 2 Monthly temperature and death data from January 1, 2002 through August 31, 2008. **a** *Box* plot of monthly daily high temperatures (*black line* equals the median, *solid gray boxes* bound the 75th and 25th percentile, *whiskers* bound the 95th and 5th percentiles; *dots* represent values outside the 95th and 5th percentiles). **b** *Box* plot of monthly number of heat-related deaths (*black line* equals the median, *solid gray boxes* bound the 75th and 25th percentile, *whiskers* bound the 95th and 5th percentiles; *dots* represent values outside the 95th and 5th percentiles). Percent of days per month that had at least one heat death (*circle*) and total number of monthly deaths (*triangle*) during the 8 year study period. **c** shows the percent of days per month that had a least one heat death as well as the total number of heat deaths per month. The 2 months with the highest median DHT (38 °C, June and July) also had the highest median deaths (21 and 24, respectively), highest proportion of days with at least one death (46 and 47 %, respectively), and the highest total number of deaths (162 and 220, respectively) for the entire study period

Table 2 Comparison of fit and discrimination for logistic regression predictive models

	Development data set	Validation data set	Final data set
Days with ≥1 death/total days	394/2,435 (16.2 %)	51/365 (14.0 %)	445/2,800 (15.9 %)
Regression coefficients (95 % CI)*	−5.604 (−6.094, −5.114)		−5.598 (−6.058, −5.137)
b_0	0.354 (0.317, 0.391)		0.350 (0.315, 0.385)
b_1			
Model likelihood ratio χ^2 (p value)	558.8 ($p < 0.0001$)		618.4 ($p < 0.001$)
Goodness-of-fit p value	0.39	0.29	0.17
AUC (95 % CI)	0.844 (0.824, 0.864)	0.815 (0.754, 0.877)	0.840 (0.824, 0.864)
Classification statistics (95 % CI)			
Sensitivity	30.5 % (26.0, 35.3)	29.4 % (17.4, 43.8)	30.4 % (26.2, 34.9)
Specificity	96.4 % (95.5, 97.2)	96.2 % (93.4, 98.0)	96.4 % (95.6, 97.1)
Positive predictive value	62.2 % (54.9, 69.0)	55.6 % (35.3, 74.5)	61.4 % (54.6, 67.8)
Negative predictive value	87.8 % (86.4, 89.1)	89.4 % (85.6, 92.4)	88.0 % (86.7, 89.2)
Percent correctly classified	85.8 % (84.3, 87.1)	86.9 % (83.0, 90.1)	85.9 % (84.6, 87.2)

* Regression equation: $\hat{g}(x) = b_0 + b_1X$, where $X = (DHT/10)^2$, b_0 = constant, and b_1 = log odds ratio for one unit increase in X

AUC area under the receiver operator characteristics curve, *CI* confidence interval, *DHT* daily high temperature in °C

Figure 3 shows the probability of one or more deaths on a given day versus the DHT in °C from the final logistic regression model. At 40 °C, the probability of one or more deaths is 50 %, with the probability of death greater than 50 % when the DHT exceeded 40 °C. The proportion of days with one or more deaths when the DHT was below 40 °C was 310/2580 (12.0 %; 95 % CI: 10.8, 13.3 %) compared with 135/220 (61.4 %; 54.9, 67.8 %) when the DHT was ≥40 °C ($p < 0.001$). The associated odds ratio for at least one death on a given day when the temperature was 40 °C or higher compared to less than 40 °C is 11.6 (95 % CI: 8.6, 15.6).

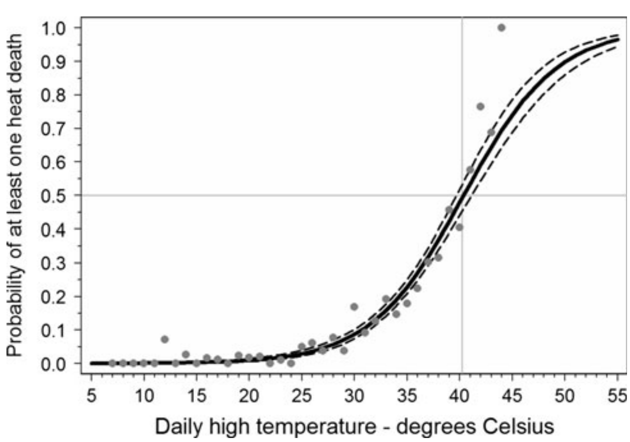

Fig. 3 Predicted probability of one or more heat related deaths for undocumented border crossers in the Arizona–Mexico border region versus daily high temperature based on logistic regression modeling. (*black line*) predicted probability of at least one death, (*dashed line*) 95 % confidence bands, (*circle*) observed proportion of days with at least one death

Model diagnostics revealed several covariate patterns with large leverage and residual values. Two of these represented days with a DHT of 14 and 16 °C along with a reported heat death, and thus represented potential non-heat related deaths miscoded as heat deaths. We were unable to confirm that these deaths were miscoded after review of the coroner's reports. Eliminating these two cases from analysis did not significantly change final model coefficients (change in coefficients = +2.0 %), model fit ($p = 0.2$), or model discrimination (AUC = 0.844) and thus, were left in the final model.

For our sensitivity analysis using DHHI as the independent variable for the LR predictive model, we used the same squared transformation as for DHT following goodness-of-fit testing and fractional polynomial regression. The DHHI model showed adequate fit using the final data set ($p = 0.31$) and the AUC was 0.839 (95 % CI: 0.820–0.858). The AUCs for the LR models using DHHI did not differ significantly from the AUC from the final LR predictive model using DHT ($p = 0.53$). A total of 1,753/2,800 days had a DHT of 27 °C or greater and had a DHHI calculated. Of these, the calculated DHHI was greater than the DHT for 68 days (3.9 %), was equal to the DHT for 137 days (7.8 %), and was lower than the DHT for 1,548 days (88.3 %). The proportion of days with a heat death did not differ significantly across these three categories ($p = 0.71$). However, for the monsoon months in Arizona (June–August) when relative humidity is highest, the proportion of days with at least one death when the calculated DHHI was greater than the DHT (15/63, 23.8 %) was significantly ($p = 0.007$) lower than when the DHHI was equal to or lower than the DHT (278/673, 41.3 %).

Discussion

Our results support our hypothesis that a strong and predictable association exists between the daily high temperature and the risk of heat death in undocumented border crossers along the Arizona–Mexico border. This study should not be interpreted as predicting the risk of death for an individual attempting to cross the border. Due to the lack of information on individual UBCs, the observed association is between the DHT and the daily UBC population within the region. The covert nature of UBCs in the process of crossing makes it unlikely that detailed information on individual UBCs behaviors and characteristics will become available. Consequently, this study takes the limited available data and focuses on the effect of the DHT on the risk of death in the geographic region studied. In so doing, the focus was on what is knowable and predictable to create a pragmatic and potentially useful model. The available demographic data on UBCs that suffered heat death in this study is similar to prior studies [4, 5].

The predictive model tested and validated by this study confirms prior preliminary work that temperatures exceeding 40 °C are associated with high and accelerating risk of UBC heat death in this region. The initial models in previous work have been expanded and validated in the current data set, confirming the robustness of using the DHT in the Southern Arizona US–Mexico border region to predict the risk of heat-related deaths in the population of UBCs [4, 5]. Prior studies have shown that although UBC volume estimates dramatically decrease during the summer months, heat deaths, as well as USBP search and rescue events, greatly increase [6]. When the temperature is above 36 °C (97.5°F), there is a greater than 25 % probability of at least one heat-related death in the study region. The risk of a death occurring began to increase dramatically when the daily high temperature was above 32 °C (90°F). Above the critical DHT threshold of 40 °C, the probability that there will be at least one regional UBC heat death crosses the 50 % level and accelerates rapidly.

Our sensitivity analysis showed that using the highest daily temperature recorded at a single weather station (DHT) was as good a predictor for heat death among UBCs along the Arizona–Mexico border for a given day as heat index, which takes into account the relative humidity. Heat index might be expected to be a better predictor, especially during the summer days with high daily temperatures and humidity during the monsoon season. However, the discrimination of the predictive model using heat index was lower—although not significantly—than the predictive model using only temperature. Additional confounding variables regarding which individuals choose to cross at times of both high humidity and high temperatures may impact the risk of death, but such individual level data is not available for analysis. In addition, the proportion of days during the summer monsoon months (June–August) with one or more heat deaths was actually lower when the DHHI was higher than the DHT compared to days when the DHHI was lower than the DHT. These results along with the fact that DHT is easier to obtain suggest that DHT might be preferable for predicting a heat death among UBCs along the Arizona Sector of the U.S.–Mexico border on any given day.

Using the predictions of our final logistic regression model, the odds of a death occurring is 11.6 times higher on a day when the temperature is 40 °C or higher compared to days with a lower DHT. As can be seen in Fig. 2a, this temperature threshold is crossed frequently from May through September (nearly 1 in 5 days). This strong association creates a clear message for potential first responders and hospitals in Southern Arizona—when the high temperature for a day exceeds 40 °C the chance is high that a heat-death will occur. From a public health standpoint, our predictive model is useful to prepare and direct resource deployment and allocation [6]. Emergency Medical Services (EMS) in the border region can expect heat fatalities and patients with severe heat illness once the temperature crosses 40 °C. An even more important opportunity could be the utility of the models in prevention. While multiple factors influence risk perception and risk-taking behavior on the part of border crossers, efforts to communicate the extreme risk of crossing during one of the frequent days with temperatures in excess of 40 °C in Southern Arizona to increase awareness of the danger posed by high temperature have the potential to decrease mortality in the border region. One such example already in place is an online risk prediction based on this model (Fig. 4) [29].

Our study is limited by several factors. First and foremost is the limited information that is available on the living UBCs at risk for heat death. Conducting any study on UBCs is difficult due to desire of the individuals involved to avoid contact with anyone in a position of authority. Traditionally, the volume of the UBC population has been estimated by the surrogate marker of USBP apprehensions in the region. The accuracy and precision of this surrogate is unknown and immeasurable. It is also likely that many UBCs suffer heat death and their bodies are never discovered due to the remote nature of the wilderness areas that are used for many crossings. Furthermore, our model is based on cause and date of death determinations performed by the local medical examiner and then entered into our database. Potential for miscoding error exists at any step in the process, and complete data is not available for all deaths. Given the conservative practices of the board certified pathologists in the medical examiner's office, however, our model likely underestimates the number of heat-related deaths and the impact of

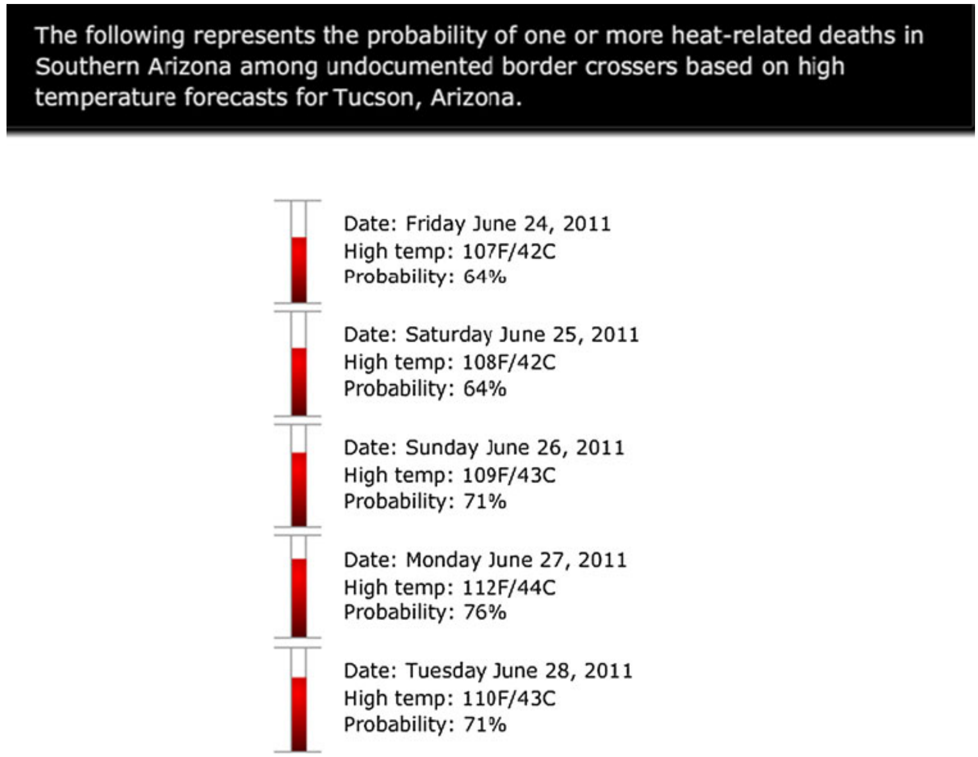

Fig. 4 Online risk prediction tool

the DHT. Nearly 13 % of heat-related deaths could not be assigned a date of death (and thus a DHT), and 26 % of all deaths could not be assigned a cause of death. Given the many cases with unknown cause of death, as well as heat-deaths with missing age or gender, our estimates for the proportion of deaths due to heat related causes and demographics of the heat-deaths may be prone to bias if cases with missing data are not representative of the cases with complete data. However, since we included deaths with an unknown cause in our denominator, our estimate of the proportion of deaths due to a heat-related cause are likely to be conservative because it is likely that some of the unknown cases were in fact heat-related. In addition, our results are not meant to be generalizable to other geographic regions, but instead are limited to only the geographic area studied. Finally, it is possible there are confounding factors related to increasing ambient temperatures that we have not considered.

Heat deaths account for over half of all deaths in the population of UBC deaths recorded in our study. The likelihood of a heat related death along the Arizona portion of the US–Mexico border for UBCs on a given day is driven strongly by the DHT. We have constructed several heat death prediction models from a cohort of 661 heat death victims spanning eight consecutive years along the Arizona–Mexico border. Our final predictive model demonstrates that the DHT strongly drives the risk of death for UBCs and that the probability for one or more deaths in the region is 50 % or greater when the DHT is 40 °C or higher. This information could be used in public health and first responder interventions attempting to reduce these deaths.

Human Participant Protection

The Institutional Review Board of the University of Arizona exempted this study from review.

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