Heat waves

Current and Future Risks to Human Health

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Biography

Training:

- B.S., Chemical Engineering, N.C. State
- B.A., French Language and Literature, N.C. State
- Ph.D., Environmental Engineering, Yale University
- Postdoc, Dept. of Biostatistics, Johns Hopkins School of Public Health

Biography

Research interests:

- Health impacts of climate-related disasters (heat waves, hurricanes)
- Effects of air pollution on human health in China
- R open source software for "open" science

Service:

- Editorial Board, *Epidemiology*
- Board of Associate Editors, *Environmental Health Perspectives*

Teaching:

- R Programming

Current heat risks: Heat and respiratory hospitalizations

Heat and respiratory hospitalizations

Primary study question

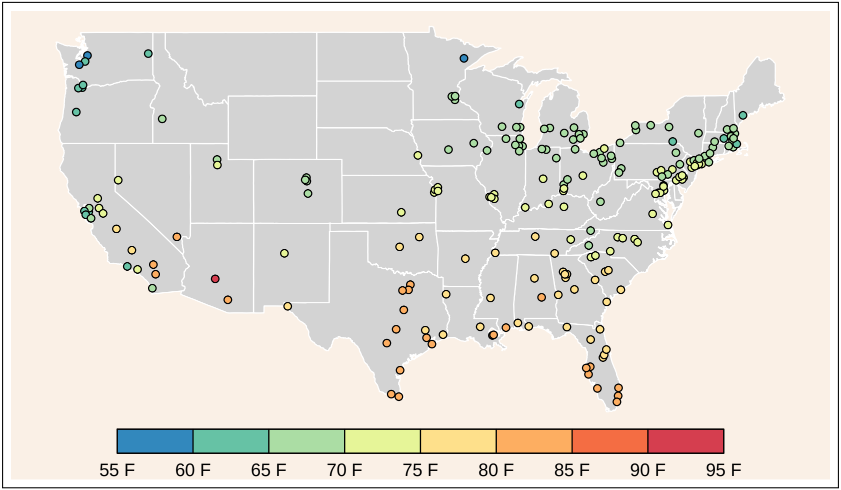
Are daily Medicare hospitalizations for respiratory diseases associated with increased summertime temperature?

Additional study questions

- Do effects differ by gender, age, or specific hospitalization cause?
- Do observed effects change when the model includes air pollution?
- What are the costs associated with heat-related hospitalizations?

Study data

213 US counties included in study.



Color of circle shows the county's daily mean temperature, averaged May–September, 1999–2008.

Study model

Statistical model

$$log(\mu_t^c) =$$

$$\text{Daily hospitalizations} = \text{function of} \left\{ \right.$$

Study model

Statistical model

$$log(\mu_t^c) = \alpha_0^c + \beta^c T_t^c +$$

$$\text{Daily hospitalizations} = \text{function of} \begin{cases} \text{temperature} \\ \\ \\ \end{cases}$$

Study model

Statistical model

$$log(\mu_t^c) = \alpha_0^c + \beta^c T_t^c + \delta^c D_t +$$

$$\text{Daily hospitalizations } = \text{function of } \begin{cases} \text{temperature} \\ \text{day of week} \\ \\ \\ \\ \end{cases}$$

Study model

Statistical model

$$log(\mu_t^c) = \alpha_0^c + \beta^c T_t^c + \delta^c D_t + f(H_t^c) +$$

$$\text{Daily hospitalizations } = \text{function of} \begin{cases} \text{temperature} \\ \text{day of week} \\ \text{dewpoint} \\ \\ \\ \end{cases}$$

Study model

Statistical model

$$log(\mu_t^c) = \alpha_0^c + \beta^c T_t^c + \delta^c D_t + f(H_t^c) + f(L_t^c)$$

$$\text{Daily hospitalizations} = \text{function of} \begin{cases} \text{temperature} \\ \text{day of week} \\ \text{dewpoint} \\ \text{long-term trends} \end{cases}$$

Study model

Statistical model

$$log(\mu_t^c) = \alpha_0^c + \beta^c T_t^c + \delta^c D_t + f(H_t^c) + f(L_t^c) + B_t^c$$

$$\text{Daily hospitalizations} = \text{function of} \begin{cases} \text{temperature} \\ \text{day of week} \\ \text{dewpoint} \\ \text{long-term trends} \\ \text{offset} \end{cases}$$

Combining county-level estimates for national estimate

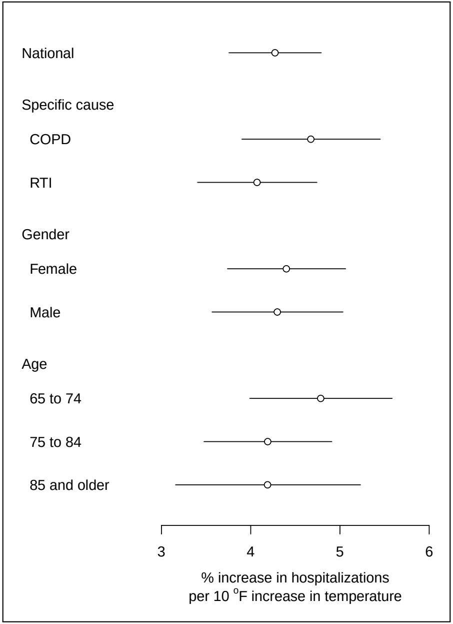
Two-level normal independent sampling estimation

$$\hat{\beta}^c | \beta^c, \hat{\nu}^c \sim \mathcal{N}(\beta^c, \hat{\nu}^c), c = 1, ..., 213$$
$$\beta^c | \phi, \tau^2 \sim \mathcal{N}(\phi, \tau^2)$$

where:

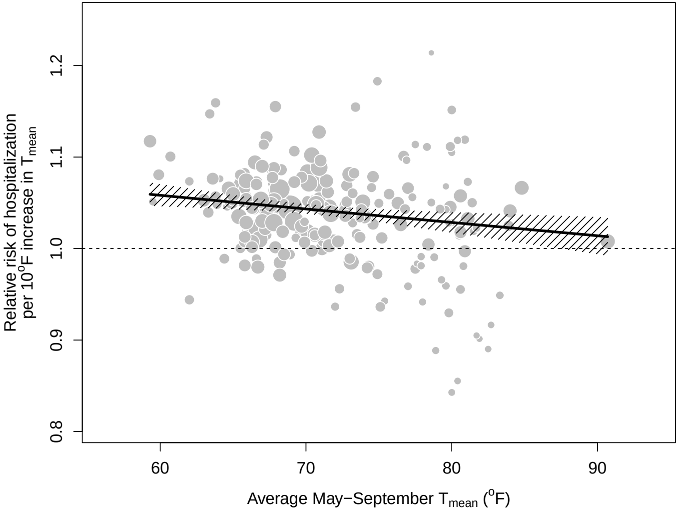
- $\hat{\beta}^c$ Estimated temperature effect for county c
- β^c True temperature effect for county c
- $\hat{\nu}^c$ Estimated variance of temperature effect for county c
- ϕ True national temperature effect
- τ^2 Between-county variance in true temperature effects

Temperature effects on Medicare respiratory hospitalizations.



Effect modification by county climate

County-level heat effects by average county temperature, May–September.



Study conclusions

- Same-day respiratory hospitalizations increase significantly with hotter temperatures
- These effects are similar for different respiratory causes, age groups, and genders
- Effects are lower for cities with cooler climates
- Effect estimates were stable to including ozone and particulate matter in the model
- Based on results, each 10^oF increase in temperature is associated with 30 excess respiratory Medicare hospitalizations across the 213 study communities

Other research on present risks of heat

First / senior author

- Heat and risk of cardiorespiratory mortality in 107 U.S. communities
- Modification of heat wave risks on mortality by heat wave characteristic in 43 US communities
- County-level preparedness and response to 2011's extreme heat in the US
- Impact of the 2003 power outage on human mortality in New York, NY

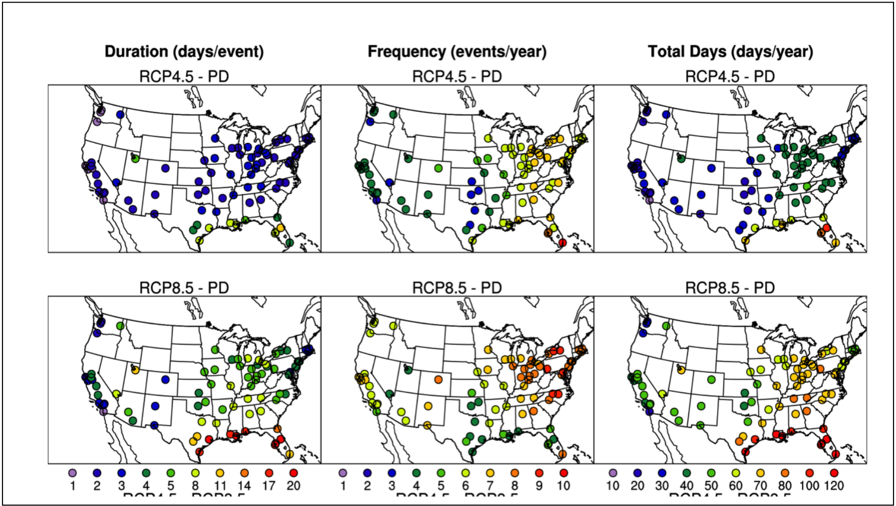
Contributing author

- Occupational heat-related mortality in the United States
- Heat waves and mortality risk in Korea

`futureheatwaves` package: Identifying, Characterizing, and Exploring Heat Waves in Climate Projections

Patterns in heat waves with climate change

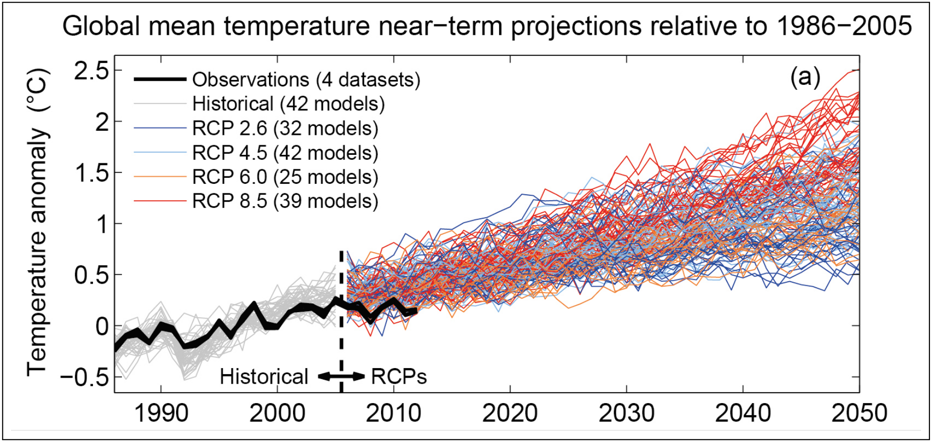
Patterns in heat wave length, frequency, and total days, 2061–2080



Source: Oleson et al. 2015

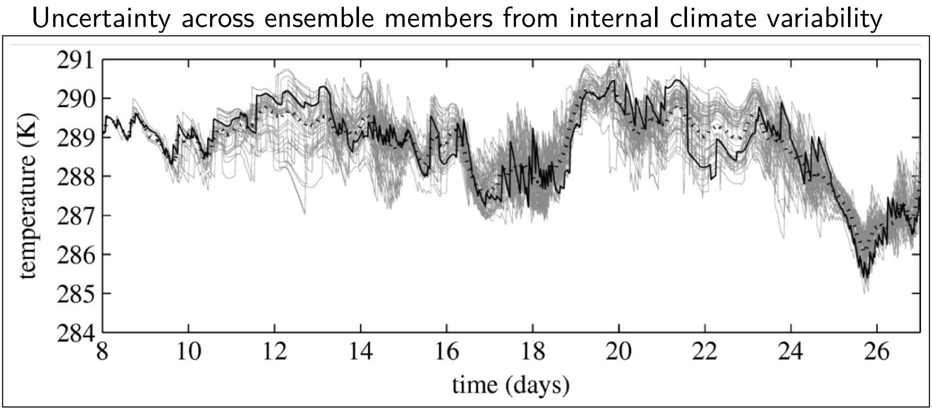
Multiple climate models

Uncertainty across climate models



Source: IPCC Fifth Assessment, Working Group I, Figure 11-25

Large-ensemble climate models



Source: Ball and Plant, 2008

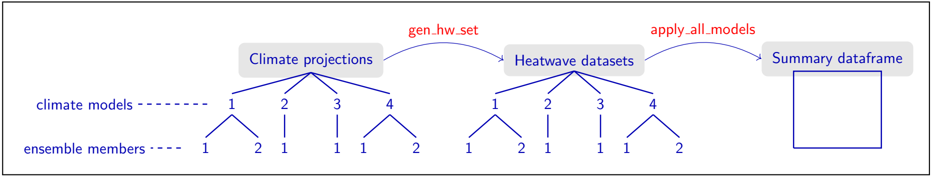
futureheatwaves package

Design goals:

- Ease processing of large sets of climate projections often needed for research on health impacts of heat waves under climate change
- Not only identify, but also characterize, all heat waves, to allow use of more complex epidemiological models
- Increase processing speed with C++
- Allow easy exploration across all resulting heat wave datasets

futureheatwaves package

Overview of ‘futureheatwaves‘ package.



Heat wave definitions

Examples of heat wave definitions used for health or climate studies.

Table 1. Summary of data on HIs, PTB (n = 60,466), and NAD (n = 301,126) in 640 Alabama ZIP codes during 1990–2010.

HI	Definition	Reference	HI days/year/ZIP [n (%)][a]	PTB [n (%)]	NAD [n (%)]
HI01	Mean daily temperature > 95th percentile for ≥ 2 consecutive days	Anderson and Bell 2011	1.34 (0.9)	652 (1.1)	2,678 (0.9)
HI02	Mean daily temperature > 90th percentile for ≥ 2 consecutive days	Anderson and Bell 2011	5.41 (3.5)	2,373 (3.9)	10,463 (3.5)
HI03	Mean daily temperature > 98th percentile for ≥ 2 consecutive days	Anderson and Bell 2011	0.18 (0.2)	111 (0.2)	444 (0.2)
HI04	Mean daily temperature > 99th percentile for ≥ 2 consecutive days	Anderson and Bell 2011	0.01 (0.0)	1 (0.0)	11 (0.0)
HI05	Minimum daily temperature > 95th percentile for ≥ 2 consecutive days	Anderson and Bell 2011	0.08 (0.1)	44 (0.1)	104 (0.0)
HI06	Maximum daily temperature > 95th percentile for ≥ 2 consecutive days	Anderson and Bell 2011	3.54 (2.3)	1,610 (2.7)	7,385 (2.5)
HI07	Maximum daily temperature ≥ 81st percentile every day, ≥ 97.5th percentile for ≥ 3 nonconsecutive days, and consecutive day average ≥ 97.5th percentile	Peng et al. 2011	1.77 (1.2)	839 (1.4)	4,106 (1.4)
HI08	Maximum daily apparent temperature[b] > 85th percentile for ≥ 1 day	Hattis et al. 2012; Steadman 1984	19.33 (12.6)	8,333 (13.8)	37,169 (12.3)
HI09	Maximum daily apparent temperature[b] > 90th percentile for ≥ 1 day	Hattis et al. 2012; Steadman 1984	10.91 (7.1)	4,681 (7.7)	21,018 (7.0)
HI10	Maximum daily apparent temperature[b] > 95th percentile for ≥ 1 day	Hattis et al. 2012; Steadman 1984	3.51 (2.3)	1,568 (2.6)	6,826 (2.3)
HI11	Maximum daily temperature > 35°C (95°F) for ≥ 1 day	Tan et al. 2007	1.43 (0.9)	497 (0.8)	2,276 (0.8)
HI12	Minimum daily temperature > 26.7°C (80.1°F) or maximum daily temperature > 40.6°C (105.1°F) for ≥ 2 consecutive days	Robinson 2001	2.90 (1.9)	1,203 (2.0)	5,701 (1.9)
HI13	Maximum daily heat index[c] > 80°F for ≥ 1 day	Rothfusz 1990; Steadman 1979	125.47 (82.1)	50,176 (83.0)	245,833 (81.6)
HI14	Maximum daily heat index[c] > 90°F for ≥ 1 day	Rothfusz 1990; Steadman 1979	78.26 (51.2)	31,495 (52.1)	151,189 (50.2)
HI15	Maximum daily heat index[c] > 105°F for ≥ 1 day	Rothfusz 1990; Steadman 1979	3.35 (2.2)	1,368 (2.3)	5,581 (1.9)
HI16	Maximum daily heat index[c] > 130°F for ≥ 1 day	Rothfusz 1990; Steadman 1979	NA	NA	NA

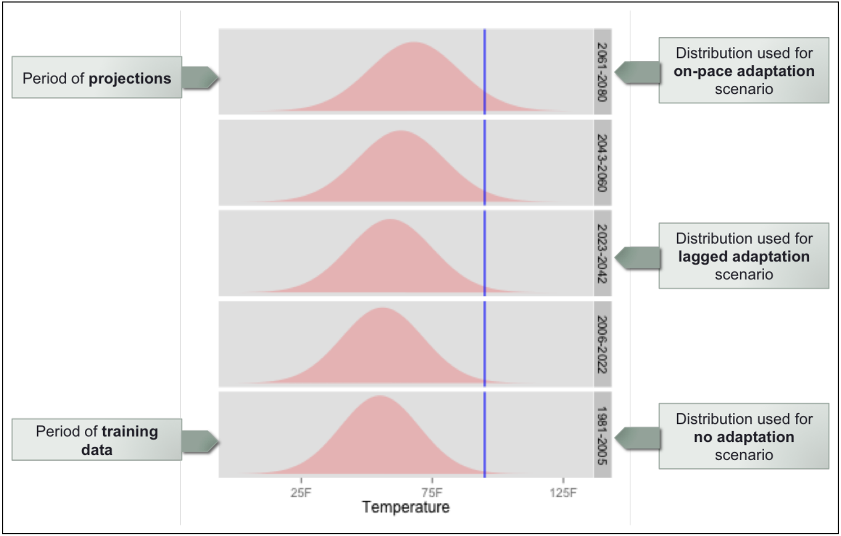
Source: Kent et al., 2014

Heat wave definitions

```
gen_hw_set(out = "example_results",
           dataFolder = projection_dir_location ,
           dataDirectories = list("hist" = c(1990, 1999),
                                  "rcp85" = c(2060, 2079)),
           citycsv = city_file_location,
           coordinateFilenames = "latlong.csv",
           tasFilenames = "projections.csv",
           timeFilenames = "timepoints.csv",
           IDheatwavesFunction = "new_function")
```

Adaptation assumptions

Relationship between "reference temperatures" and adaptation scenarios.



Adaptation assumptions

```r
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           dataFolder = projection_dir_location ,
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                                  "rcp85" = c(2060, 2079)),
           citycsv = city_file_location,
           coordinateFilenames = "latlong.csv",
           tasFilenames = "projections.csv",
           timeFilenames = "timepoints.csv",
           referenceBoundaries = c(1990, 1999))
```

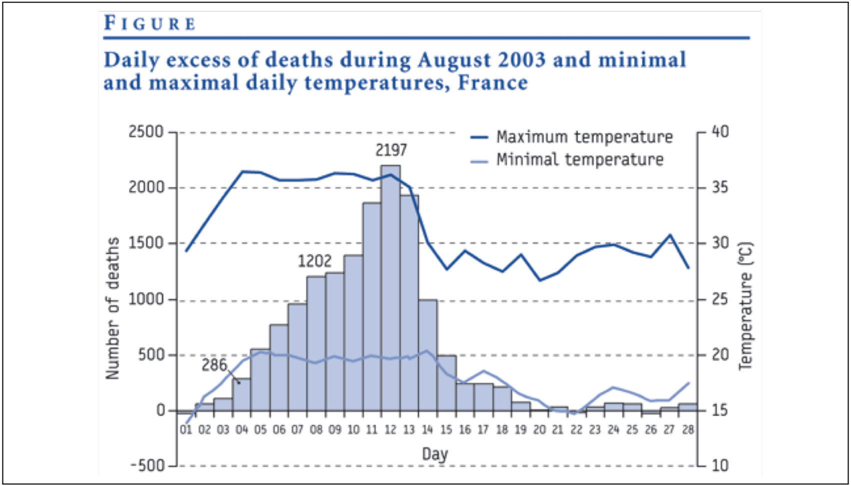
Work on other packages

- `weathermetrics`: Convert between common weather metrics (including calculating heat index based on the National Weather Service's algorithm)
- `hurricaneexposure`: Create time series of tropical storm exposure based on rain, wind, and distance criteria
- `stormwindmodel`: Model tropical storm winds based on historical hurricane tracking data
- `countyweather`: Coordinate with `rnoaa` to pull observed weather data for county-level health studies

Predicting high-mortality heat waves

High-mortality heat waves

Mortality during the 2003 French heat wave



Source: Pirard et al., 2005

High-mortality heat waves

High-mortality heat wave in Russia, 2010

Source: pbs.org, 2010

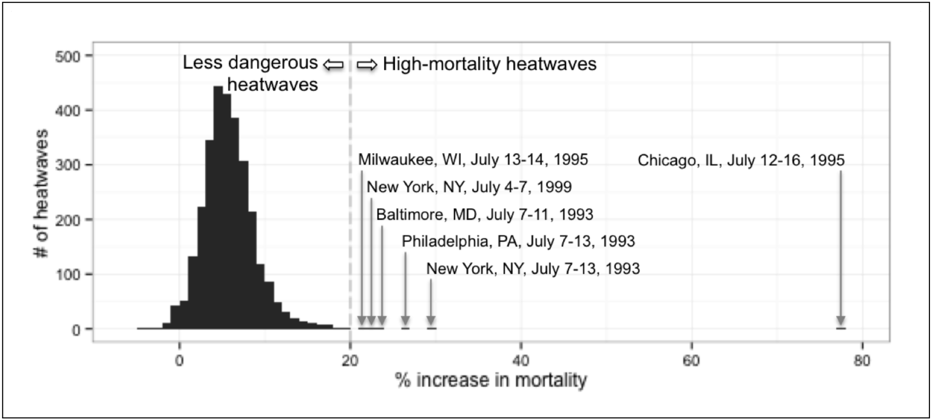
Predictive model of high-mortality heat waves

Applications:

- (Short-term) Will next week have a high-mortality heat wave?
- (Mid-term) Which communities need to prioritize heat response plans?
- (Long-term) What are the health impacts and costs of severe heat waves under climate change scenarios?

High-mortality heat waves

Mortality risks during all heat waves in 82 US communities, 1987–2005



Predicting high-mortality heat waves

Category	Variable
Absolute intensity	Average T_{mean}
.	Highest daily T_{mean}
.	Lowest daily T_{mean}
Relative intensity	Quantile of average T_{mean}
.	Quantile of highest T_{mean}
.	Quantile of lowest T_{mean}
Timing	Day of year heat wave started
.	Month heat wave started
.	Whether heat wave was first in year

Predicting high-mortality heat waves

Category	Variable
Length	Number of days
.	Days with $T_{mean} > 80^o F$
.	Days with $T_{mean} > 85^o F$
.	Days with $T_{mean} > 90^o F$
.	Days with $T_{mean} > 95^o F$
.	Days with $T_{mean} > 99^{th}$ perc.
.	Days with $T_{mean} > 99.5^{th}$ perc.
Community	Population
.	Population density
.	Long-term average T_{mean}
.	Long-term warm-season T_{mean}

Predicting high-mortality heat waves

Model types

- Classification tree
- Conditional tree
- Bagging
- Random forest
- Boosting

Accounting for class imbalance

- No adjustment
- Oversampling from rare class
- Over / under sampling
- Randomly Over-Sampling Examples (ROSE)

Model performance

Model performance based on Monte Carlo cross-validation (all models use ROSE to account for class imbalance).

Model	Recall	Precision (IQR)
Classification tree	94.0%	2.6% (0.7%)
Conditional tree	87.5%	7.2% (4.5%)
Bagging	94.0%	2.6% (0.6%)
Random forest	94.0%	4.1% (2.0%)
Boosting	94.0%	2.3% (0.5%)

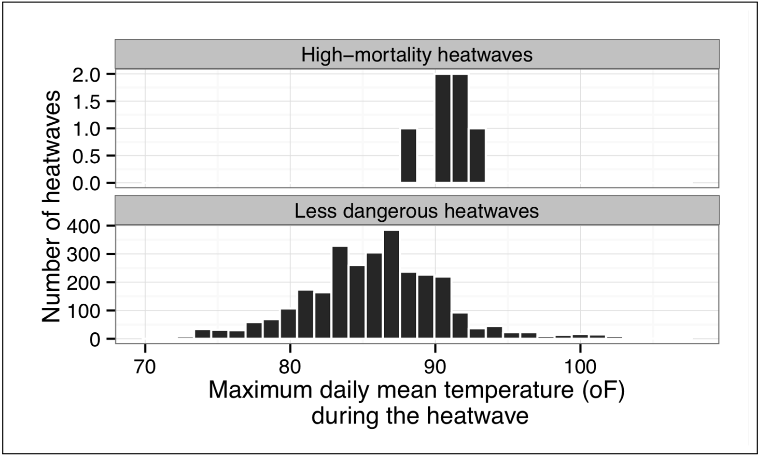
Variable importance

Most important variables across models (scaled to sum to 100% across each model).

Variable	Class. tree	Bagging	Boosting
Quantile of highest daily T_{mean}	x	64.44	64.60
Month heat wave started	x	34.51	35.26
Average community warm T_{mean}		0.33	0.00
Average community T_{mean}		0.29	0.01
Number of days with $T_{mean} > 95^oF$		0.27	0.12

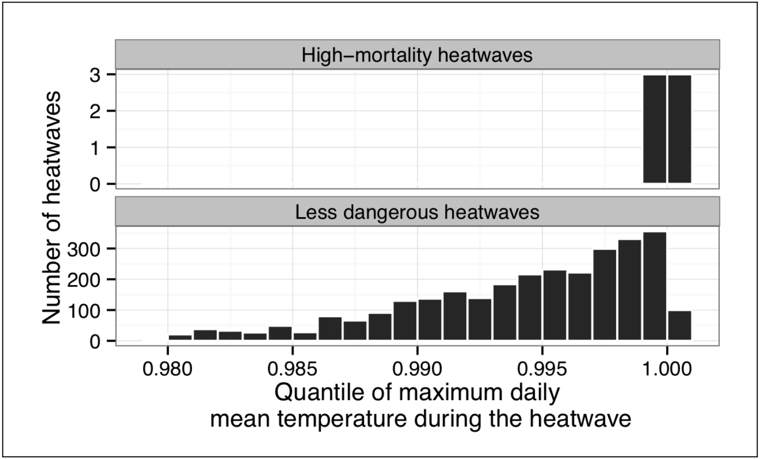
Heat wave characteristics

Absolute intensity for high-mortality and less-dangerous heat waves

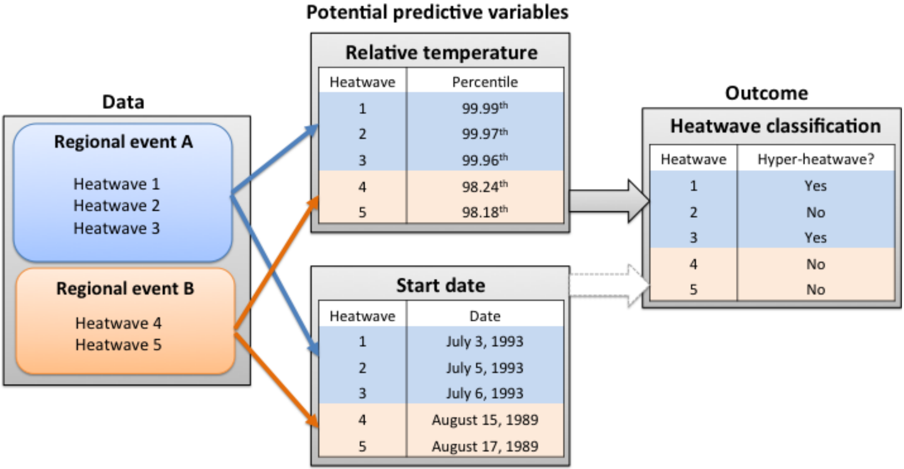


Heat wave characteristics

Relative intensity for high-mortality and less-dangerous heat waves



Multi-level structure



“Out of sample” heat waves

Year	Location	Estimated mortality increase	Start date	Noteworthy relative intensity?	Reference
Within United States					
1872	New York, NY	104%	June 30	Yes	Ellis et al. 1975
1896	New York, NY	124%	August 9	Yes	Ellis et al. 1975
1939	Los Angeles, CA	109%	late September	Yes	Oechsli and Buechley 1970
1955	Los Angeles, CA	122%	early September	Yes	Oechsli and Buechley 1970
1966	St. Louis, MO	91%	July	Yes	Bridger et al. 1976
1972	New York, NY	54%	July 14	No	Ellis et al. 1975
1980	St. Louis, MO	57%	July	Yes	Jones et al. 1982
1980	Kansas City, MO	64%	July	Yes	Jones et al. 1982
Outside of United States					
2003	Paris, France	142%	August 1	Yes	Vandentorren et al. 2004
2003	Dijon, France	93%	August 1	Yes	Vandentorren et al. 2004
2003	Le Mans, France	82%	August 1	Yes	Vandentorren et al. 2004
2003	Lyon, France	80%	August 1	Yes	Vandentorren et al. 2004
2003	Poitiers, France	79%	August 1	Yes	Vandentorren et al. 2004
2003	Nice, France	53%	August 1	Yes	Vandentorren et al. 2004
2003	Strasbourg, France	51%	August 1	Yes	Vandentorren et al. 2004
2010	Moscow, Russia	90%	July 6	Yes	Shaposhnikov et al. 2014

Improving the model?

- “Whole-pipeline” analysis
- Adding other variables:
  - Power outages
  - Atmospheric patterns
  - Concurrent exposures (air pollution, humidity)

Climate projection applications

- Avoided high-mortality heat waves under RCP8.5 versus RCP4.5
  - Collaboration with NCAR group
  - Used NCAR's large-ensemble model
- Uncertainty in projections of frequency of and exposure to high-mortality heat waves
  - Uncertainty related to climate model (CMIP5 models)
  - Uncertainty related to assumptions about adaptation