


## Developing a Modeling Approach for Real-time Tracking of Heat-related Morbidity Counts in Maricopa County

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## Presenter Disclosure

- No relationships to disclose

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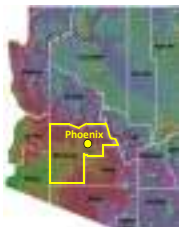
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## Maricopa County, Arizona

One of the largest urban centers to experience the nation's most extreme heat



Typical year:	
Environmental temperatures $\geq 100^{\circ}\text{F}$	Start: mid-May End: 1 <sup>st</sup> week October
Days where max. temp $\geq 110^{\circ}\text{F}$ (119 $^{\circ}\text{F}$ )	26 days (average)
Days where min. temp $\geq 90^{\circ}\text{F}$ (95 $^{\circ}\text{F}$ )	13 days (average)

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### Surveillance for Heat-Related Morbidity and Mortality (HRM/M)

- MCDPH has been tracking HRM/M since 2006
  - Death certificates
  - Medical examiner data
  - Hospital discharge data (HDD)
  - Syndromic Surveillance (under development)
    - Biosense 2.0
    - AZ-PIERS (prehospital data)

Heat-related	Total	Average per year
<b>Deaths</b>	694 (2006 – 2014)	77
<b>Injuries</b>	9,419 (2008 – 2013)	1,569

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### Heat Surveillance Goals

- To obtain real-time data and timely detection of any aberrations
  - Situational awareness
  - Disseminate more timely information to stakeholders (heat relief network)
  - Activate more timely responses
  - Decrease the burden of heat-related morbidity / mortality
  - Examine long term trends, risk factors




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### Study objective

To identify the baseline levels & epidemic thresholds for heat-related morbidity (HRM) in Maricopa County using Hospital Discharge Data (HDD)

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## Methods: Data source

- Hospital Discharge Data (HDD)
  - Date range: January 2006 – December 2012
  - Emergency department & inpatient visits in Maricopa County, Arizona
  - Extracted ICD-9 codes associated with HRM from:
    - Primary diagnosis
    - Secondary diagnosis

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## Methods: Statistical Analysis

- The total number of hospital visits (regardless of reason for visit) from January 2006 to December 2012 was used as the denominator to calculate proportion of heat morbidity
- Heat morbidity rate (per 100,000 visits) along a 95% binomial confidence interval were calculated for year and month in the study period
- Extracted data were organized in a time-series format for the analysis

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## Methods: R package

- In R, the *surveillance package* was used to build and run the model for aberration detection <sup>1, 2</sup>
- The model:
  - Based on a statistical process control methods known as “prospective cumulative sum” (CUSUM)
  - Makes use of the generalized additive models for location, scale, and shape (GAMLSS); a flexible method for various model distributions <sup>3</sup>

(1) Michael Hahn, Sebastian Meyer and Michaela Paul (2015). Surveillance: Temporal and Spatio-Temporal Modeling and Monitoring of Epidemic Phenomena  
 (2) R: A Language and Environment for Statistical Computing (2015). R Core Team, Vienna, Austria.  
 (3) Rigby RA, Stasinopoulos DM. Generalized additive models for location, scale and shape. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*. 2005;54(1):507-54.

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## Methods: Baseline & Threshold



- The model used known reference values to make predictions
  - A baseline representing the overall expected mean number of heat related visits (years 2006 – 2007)
  - An epidemic threshold representing the expected mean number of visits corresponding to two-fold increase in the odds of heat morbidity
- The model can accommodate seasonal variations

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## Study Results



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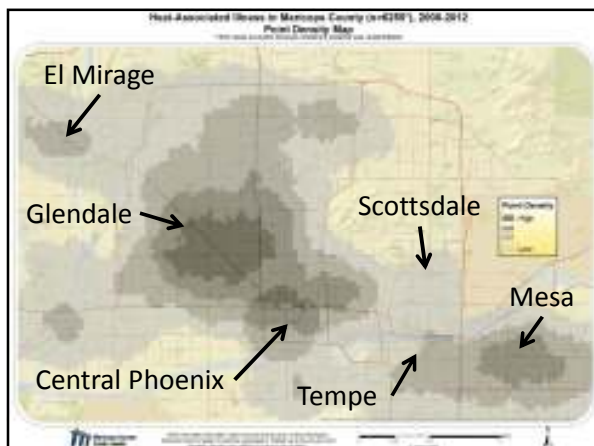
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### Heat Morbidity Rates by Year

Year	Total hospital visits	Rates (95% CI) *
2006	1,490,708	83.65 (79.01-88.29)
2007	1,574,666	84.02 (79.49-88.54)
2008	1,630,952	73.82 (69.65-77.99)
2009	1,692,626	72.90 (68.84-76.97)
2010	1,696,305	82.12 (77.81-86.43)
2011	1,790,260	95.96 (91.43-100.50)
2012	1,822,682	94.53 (90.07-98.99)

\*per 100,000 hospital visits

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### Heat Morbidity Rates by Month

Month	Total Visits	Rates (95% CI) *
January	1,021,104	5.68 (4.22-7.14)
February	979,397	5.82 (4.31-7.33)
March	1,036,538	19.39 (16.71-22.07)
April	980,012	34.59 (30.91-38.27)
May	985,802	81.66 (76.02-87.3)
June	912,737	205.1 (195.82-214.38)
July	931,847	300.4 (289.26-311.48)
August	971,069	249.5 (239.6-259.44)
September	965,131	96.98 (90.77-103.19)
October	983,024	21.67 (18.76-24.58)
November	958,665	9.7 (7.73-11.67)
December	972,873	4.73 (3.36-6.09)

\*per 100,000 hospital visits

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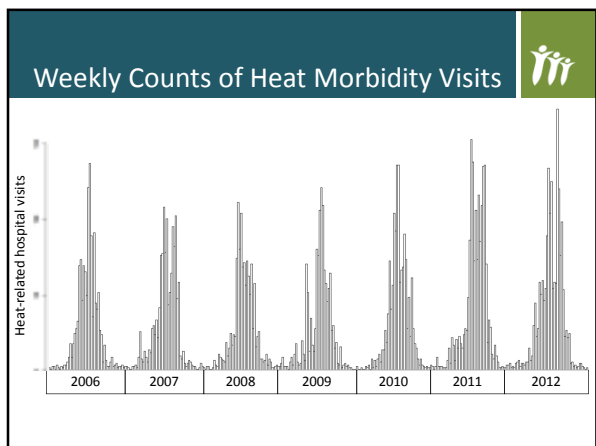
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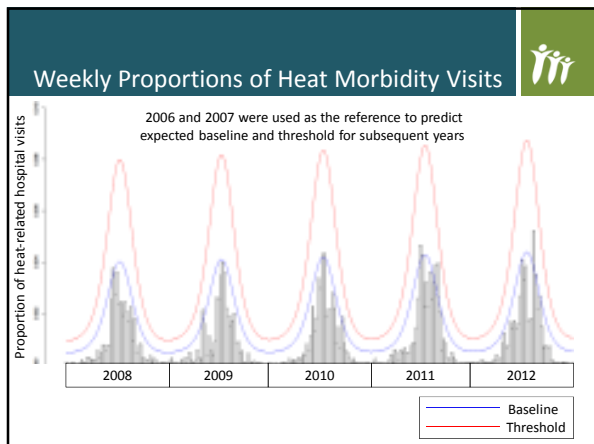
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### Conclusions

- We used surveillance tools designed in R to predict the expected proportions and thresholds for heat-related morbidity among hospital visits
- The prediction model requires:
  - Reference data for estimating expected values
  - A threshold for determining the accepted deviation from the expected values

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### Many Applications

- The advantage of this model is flexibility
  - Can fit a wide range of distributions
  - Allows inclusion of covariates
  - Can accommodate seasonality
- This methodology can be applied to other data sources that are more real-time
  - Would need to consider which aberrations warrant further investigation or taking action
- This model can be modified for other morbidities or health-related issues to aid in trend evaluation and decision making

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## Next Steps



- Validate model against real-time data
  - Improve model sensitivity
- Make the necessary adjustments to improve the model's predictions

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- MCDPH Office of Epidemiology Staff
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- Maricopa County Office of Vital Registration (OVR)
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- Arizona State University (ASU)
- National Weather Service (NWS)
- Local hospitals (infection preventionists, emergency departments, social worker staff)

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## Questions?



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