Human-environment dynamics in the Sonoran Desert and *Ae. aegypti*, the vector of dengue, Zika and chikungunya

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WRRC Brown Bag, 4/8/2020
Potential for transmission

Reproductive number for mosquito-borne diseases
(modification of the vectorial capacity equation)

\[ R_0 = \frac{ma^2bc \ p^n}{(-\ln (p))r} \]

- m: ratio of mosquitoes to humans
- a: mosquito biting rate (on humans)
- b and c: pathogen transmission efficiencies (human to mosquito and mosquito to human)
- p: daily survival rate of mosquitoes
- r: the recovery rate in humans (i.e., the reciprocal of the infective period of the human host)
- n: the duration of the extrinsic incubation period (EIP).
**Aedes aegypti** aka “The Yellow Fever Mosquito”

- Highly adaptable
- Human commensal
- Day-biter (bednets less useful)
- Transmits
  - Yellow fever virus
  - Dengue viruses
  - Chikungunya virus
  - Zika virus
  - Mayora virus
Mosquito life-cycle

Diagram showing the life cycle of a mosquito, including blood-fed female laying eggs, adult emerging, eggs, pupa, and larva.
Oviposition sites

Precipitation Driven

Anthropogenic water sources
1. Shifting climate patterns may influence disease dynamics

Morin, C.W., Comrie A.C., Ernst, K.C., EHP, 2013
Aedes aegypti infest urban areas throughout the Arizona-Sonoran Desert region.
Transmission disparities in dengue

Reported yearly incidence of dengue per 100,000

<table>
<thead>
<tr>
<th>Year</th>
<th>Hermosillo</th>
<th>Nogales</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006</td>
<td>22.6</td>
<td>1.4</td>
</tr>
<tr>
<td>2007</td>
<td>15.4</td>
<td>0.5</td>
</tr>
<tr>
<td>2008</td>
<td>92.0</td>
<td>No cases</td>
</tr>
<tr>
<td>2009</td>
<td>22.2</td>
<td>1.9</td>
</tr>
<tr>
<td>2010</td>
<td>504.0</td>
<td>1.9</td>
</tr>
<tr>
<td>2011</td>
<td>26.3</td>
<td>1.0</td>
</tr>
<tr>
<td>2012</td>
<td>12.3</td>
<td>0.0</td>
</tr>
<tr>
<td>2013</td>
<td>33.1</td>
<td>1.9</td>
</tr>
<tr>
<td>2014</td>
<td>155.0</td>
<td>6.6</td>
</tr>
<tr>
<td>2015</td>
<td>88.1</td>
<td>1.9</td>
</tr>
</tbody>
</table>

Source: Reyes-Castro, P., et. al. 2015
Age structure differences

Avg. percent of *Ae. aegypti* >14 days old identified in traps

Ernst and Walker et. al., JME, 2017

![Graph showing age structure differences in *Ae. aegypti* between 2013 and 2014, with data for Nogales and Hermosillo for each month.]
Weather conditions in Nogales

Rainfall

Rainfall (cm)

Climate Average

2014

2013

Jul Aug Sep
Humidity-temperature interact to influence longevity

- At upper and lower thermal limits humidity plays a significant role in longevity.

- Example: at 35°C, est. survival per day is roughly 80% at 90% RH to 60% at 10% RH.

Comparison of survival rates from the original adult mortality algorithm based on temperature only (black line), and the new algorithm based on both temperature and humidity (colored lines for different values of relative humidity). In this example both algorithms assume a base field mortality of 14% (i.e., a survival rate of 0.86).

Schmidt et. al. Parasites and Vectors 2018
Morin et. al. under revision
Extrinsic incubation period is dependent on temperature

Field collections identify longer EIP and shorter longevity in Nogales may, at least partially, explain variability

<table>
<thead>
<tr>
<th>Year</th>
<th>City</th>
<th>Proportion Parous</th>
<th>Mean Age, days</th>
<th>Median EIP +2 days</th>
<th>% Exceeds EIP</th>
<th>Mosquito Density (females/ trap/ day)</th>
<th>No. Potential Vectors/ trap/day</th>
<th>RR (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>Nogales</td>
<td>0.68</td>
<td>6</td>
<td>16.9</td>
<td>0.12</td>
<td>1.95</td>
<td>0.16</td>
<td>ref</td>
</tr>
<tr>
<td></td>
<td>Hermosillo</td>
<td>0.69</td>
<td>7.5</td>
<td>6.3</td>
<td>0.43</td>
<td>2.92</td>
<td>1.14</td>
<td>6.0 (3.5, 10.5)</td>
</tr>
<tr>
<td>2014</td>
<td>Nogales</td>
<td>0.66</td>
<td>7.9</td>
<td>19.1</td>
<td>0.14</td>
<td>3.26</td>
<td>0.3</td>
<td>ref</td>
</tr>
<tr>
<td></td>
<td>Hermosillo</td>
<td>0.66</td>
<td>7.7</td>
<td>9</td>
<td>0.43</td>
<td>1.94</td>
<td>0.55</td>
<td>1.9 (1.2, 3.1)</td>
</tr>
<tr>
<td>2015</td>
<td>Nogales</td>
<td>0.67</td>
<td>6.9</td>
<td>15.1</td>
<td>0.14</td>
<td>2.32</td>
<td>0.21</td>
<td>ref</td>
</tr>
<tr>
<td></td>
<td>Hermosillo</td>
<td>0.66</td>
<td>6.5</td>
<td>7</td>
<td>0.46</td>
<td>2.44</td>
<td>0.74</td>
<td>3.5 (2.1, 5.9)</td>
</tr>
</tbody>
</table>

- Source: Ernst et al. in preparation, Joy et al.
2. Extreme weather events

Recent systematic review – Extreme precipitation events and mosquito-borne diseases.

Coalson et. al. in prep
3. Landuse/landcover

Satellite image: Google Maps, accessed Oct 8, 2018

In prep D. Richard and J. Coalson et. al.
Methods

• Mosquito counts: Maricopa County Vector Control Division
  • Weekly counts from 700-800 geolocated, CO₂–baited EVS traps
  • Adult female *Ae. aegypti* counts from 2014 – 2017

• Climate data: PRISM Climate Group
  • Monthly avg. temperature
  • Monthly total rainfall

• Potential predictors assessed w/in 50 m of each trap:
  • Sociodemographics: U.S. Census Bureau
  • Land cover/land use: National Agricultural Imagery Program (1 meter resolution)
    • Categories: Pool, Lake, Pavement, Structure, Bare earth, Cactus/shrub, Shadow, *Grass*, *Trees*

• Data analysis: SAS version 9.4
  • Zero-inflated negative binomial regression of *Ae. aegypti* female counts
  • Multilevel model with random effect for repeat measurements at each trap
Average counts of *Ae. aegypti* females during monsoon season months are higher in southeastern communities and city center

<table>
<thead>
<tr>
<th></th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of traps</td>
<td>666</td>
<td>785</td>
<td>794</td>
<td>881</td>
</tr>
<tr>
<td>Number of trap-nights</td>
<td>28,131</td>
<td>34,447</td>
<td>38,177</td>
<td>38,972</td>
</tr>
<tr>
<td><em>Ae. aegypti</em> total count</td>
<td>27,208</td>
<td>24,155</td>
<td>28,986</td>
<td>28,934</td>
</tr>
<tr>
<td>Trap-nights positive for <em>Ae. aegypti</em></td>
<td>13.6%</td>
<td>16.3%</td>
<td>16.7%</td>
<td>18.3%</td>
</tr>
<tr>
<td>Number of females when positive, median (range)</td>
<td>3 (1 – 215)</td>
<td>2 (1 – 375)</td>
<td>2 (1 – 300)</td>
<td>2 (1 – 325)</td>
</tr>
</tbody>
</table>
Rainfall and Temperature associations with Ae. aegypti presence

Rainfall (total mm previous month)

Temperature (avg. in Celsius for previous month)
Higher quartiles of tree cover had higher mean counts of *Ae. aegypti*
4. Interplay between social and environmental

- Municipality level
  - State of Sonora, MX
- NLDAS – climate data
- Census data
- ZINB models

Factors Associated with municipality-level dengue transmission

Reyes-Castro, 2015
5. Human dimensions in Tucson – flower pots
Co-benefits and inadvertant consequences-water management

- Drought – water storage – dengue fever
- The case of Australia, Honduras, Brazil

Factors associated with *Ae. aegypti* presence

<table>
<thead>
<tr>
<th></th>
<th>DF</th>
<th>Chi-2</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>House factors</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neighborhood</td>
<td>19</td>
<td>33.49</td>
<td>0.03</td>
</tr>
<tr>
<td>Percent yard vegetated</td>
<td>3</td>
<td>6.48</td>
<td>0.09</td>
</tr>
<tr>
<td><strong>Human and behavioral factors</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of people in house</td>
<td>1</td>
<td>4.29</td>
<td>0.04</td>
</tr>
<tr>
<td>Number of children in house</td>
<td>1</td>
<td>1.42</td>
<td>0.23</td>
</tr>
<tr>
<td>Household Income</td>
<td>4</td>
<td>8.91</td>
<td>0.06</td>
</tr>
<tr>
<td>Frequency of removing water</td>
<td>5</td>
<td>15.36</td>
<td>0.009</td>
</tr>
</tbody>
</table>

Household level factors

- Household survey
- Tucson
- 387 households – paired with larval survey
Long term predictions to early warning and early detection

Use in public health response and planning

Long-term prediction
Driven by:
- climate change scenarios
- Population projections

Early warning systems
Driven by:
- seasonal forecasts
- current census information

Early detection
Sources:
- syndromic
- data mining
- HC-based
- CBP

Traditional surveillance

Ernst, NAS Workshop, 2018
<table>
<thead>
<tr>
<th>Public Health Activity</th>
<th>Federal</th>
<th>Tribal</th>
<th>State/Territorial</th>
<th>City/County</th>
<th>University / Academia</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Developing policies and plans such as municipal heat-wave preparedness plans that support individual and community health efforts.</td>
<td>75%</td>
<td>26%</td>
<td>35%</td>
<td>62%</td>
<td>20%</td>
<td>38%</td>
</tr>
<tr>
<td>Linking people to needed health services and ensuring the provision of health care following disasters.</td>
<td>25%</td>
<td>42%</td>
<td>48%</td>
<td>57%</td>
<td>15%</td>
<td>31%</td>
</tr>
<tr>
<td>Forming public health partnerships with industry, other professional groups, faith communities or others, to craft and implement solutions.</td>
<td>0%</td>
<td>37%</td>
<td>35%</td>
<td>62%</td>
<td>40%</td>
<td>62%</td>
</tr>
<tr>
<td>Conducting program assessments of preparedness efforts such as heat-wave plans.</td>
<td>25%</td>
<td>26%</td>
<td>30%</td>
<td>53%</td>
<td>20%</td>
<td>15%</td>
</tr>
<tr>
<td>Training health care providers on health impacts of climate change.</td>
<td>0%</td>
<td>5%</td>
<td>22%</td>
<td>21%</td>
<td>35%</td>
<td>15%</td>
</tr>
<tr>
<td>Informing the public about the health impacts of climate change.</td>
<td>75%</td>
<td>53%</td>
<td>65%</td>
<td>47%</td>
<td>55%</td>
<td>62%</td>
</tr>
<tr>
<td>Informing policymakers about the health impacts of climate change.</td>
<td>50%</td>
<td>53%</td>
<td>48%</td>
<td>36%</td>
<td>50%</td>
<td>62%</td>
</tr>
<tr>
<td>Investigating the relationships among weather and water, food, or vector-borne outbreaks.</td>
<td>25%</td>
<td>26%</td>
<td>35%</td>
<td>40%</td>
<td>35%</td>
<td>15%</td>
</tr>
<tr>
<td>Tracking of diseases and trends related to long-term climatic changes.</td>
<td>25%</td>
<td>5%</td>
<td>52%</td>
<td>49%</td>
<td>40%</td>
<td>0%</td>
</tr>
<tr>
<td>Working with partners to develop or use early warning systems for climate sensitive diseases.</td>
<td>50%</td>
<td>11%</td>
<td>4%</td>
<td>34%</td>
<td>10%</td>
<td>15%</td>
</tr>
<tr>
<td>Researching health effects of climate change, including innovative techniques such as modeling, and research on optimal adaptation strategies.</td>
<td>75%</td>
<td>32%</td>
<td>57%</td>
<td>28%</td>
<td>55%</td>
<td>0%</td>
</tr>
<tr>
<td>None of the above.</td>
<td>0%</td>
<td>5%</td>
<td>4%</td>
<td>4%</td>
<td>10%</td>
<td>8%</td>
</tr>
</tbody>
</table>

- **Most frequently reported**
- **Least frequently reported**

*Climate Change Activities*  
Arora, M. 2019
Zika Risk in CONUS

- Climate-driven mosquito models with
  - travel,
  - socioeconomic conditions
  - virus history
- Rapid analysis
- Designed for widespread dissemination to stakeholders and the public.
- One time assessment

Monaghan AJ, Morin CW, Ernst K. PLOS Currents (March 2016)
Adaptation strategies: Early Warning and Public Engagement

Monaghan et. al. 2019
Theoretical framework of Kidenga surveillance functionality

Community more informed about risk during high risk time periods
Early detection of people with symptoms. Public health can take early action.
Reduce vector contact and transmission.
Kidenga 2.0: Iterate with alerts and cues to action

“some kind of notification that there was activity”

“relating it to the weather”

“a good prompt for me in my environment”

“check-ins”
Discussion points

• Enormously complex systems determine infectious potential
• Developing methodologies to predict and prepare for complex interactions
• Capitalize on benefits of anthropocene
  • Global networks
  • Rapid information sharing
  • Technological breakthroughs
  • Capacity building
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