Spatial heterogeneity and infectious disease dynamics: two case studies on cholera and malaria

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Two stories: one on cholera, the other on malaria

Climate variability
(Sea Surface Temperature; rainfall)

Spatial heterogeneity
(human susceptibility)
Outline:

• Urban cholera in Dhaka (Bangladesh): effect of ENSO and flooding

• Desert *P. falciparum* malaria in India: rainfall variability and land-use change
London, 1854

Bangladesh, 2000

Cholera cases

Time

courtesy ICDDR, B
Rank correlation at 90% confidence

Cholera cases in September

Warming in January

Cash, Rodo and Kinter (J. Climate 2008); Pascual, Chaves, Rodo, Cash, Yunus (Climate Research 2008); SST data from HadSST1: Rayner et al. 2003
Link between cholera and ENSO

- Observed precipitation enhanced following El Niño
- Coupled atmosphere-ocean climate model

Cash, Rodo and Kinter, J. Climate 2008
Highly localized sensitivity to climate forcing drives endemic cholera in a megacity

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Motivation:

- Spatial effects have not been considered before in the response of cholera to climate variability. We may expect global climate drivers such as ENSO to operate at regional scales.

- We still have a poor understanding of proximal mechanisms that mediate the effect of global climate drivers in urban environments.

- Statistical models in the literature cannot be used effectively for prediction because of their short lead times (ranging from 0 to 1 months).
Data Transformation

The histogram represents the distribution of log-transformed data for a given set of cases. The counts are shown along the vertical axis, and the log-transformed cases +1 are shown along the horizontal axis.

Key observations:
- Approximately 45.86% of the cases are denoted as "0".
- Approximately 27.07% of the cases are denoted as "1".
- Approximately 27.07% of the cases are denoted as "2".

The log-transformed cases +1 range from 0 to 4, with the majority of cases clustering around the values 0.5 and 1.
- The topology of the data is maintained by the transformation. In other words, whichever months were in the top $x$ percent in the raw data are still in the top $x$ percent in the transformed data (mostly).

- However, the transformation clearly removes the heavy tail from the distribution of cases.
Model Description

### Markov Chain Model

- We start with a simple Markov Chain model to describe the data.

- This model assumes the only difference between any two observations is what the value of the thanas were the month before.

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
<th>2</th>
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<tbody>
<tr>
<td>0</td>
<td>( p(0, 0) )</td>
<td>( p(0, 1) )</td>
<td>( p(0, 2) )</td>
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<tr>
<td>1</td>
<td>( p(1, 0) )</td>
<td>( p(1, 1) )</td>
<td>( p(1, 2) )</td>
</tr>
<tr>
<td>2</td>
<td>( p(2, 0) )</td>
<td>( p(2, 1) )</td>
<td>( p(2, 2) )</td>
</tr>
</tbody>
</table>
Model Description

Multi-Dimensional Markov Chain Model

- To account for local spatial effects, we expand the model to allow for a different transition matrix depending on the maximum state of the nearest neighbors of that thana.

- All thanas must now be simultaneously tracked, hence we now have a multi-dimensional model (21 dimensions, one for each thana).
Model Description

MDIMC model

\[ P\left( X_{k,t} = j | X_{k,t-1} = i, \max_{l \in N(k)} X_{l,t-1} = v, ENSO = s \right) = \]
\[ = P_{i,j,D(k)} \times \text{Neigh}(i, j, v, D(k)) \times \text{Seas}(i, j, t, D(k)) \times \text{Nino}(j, s, D(k)) \]

- For example, the Nino function, for a given standardized ENSO value \( s \), is

\[ 1 + A \frac{\tan \left( \frac{h \cdot s}{2M} \right)}{\tan \left( \frac{h}{2} \right)} \]
Probabilistic model (discrete state Markov chain model): probabilities a function of group, season, neighbors’ states, and climate covariates.
Spatial heterogeneity: the dynamics between groups are significantly different (p-value=0.0001)

Local effect: the state of neighboring districts matters (p-value =0.01)

Interaction between spatial structure and climate forcing: the parameters governing the effect of ENSO are significantly different between the groups (p-value= 0.03); and similarly for flooding (p-value= 0.015)

> ENSO is a significant covariate (p=value < 0.0001); lag of 11 months for the spring months and 9 months for the fall ones.

> Flooding is also significant (p-value < 0.0001)

> Flooding still significant when tested in the presence of ENSO (p-value = 0.008) and vice-versa (p-value < 0.0001)

Reiner et al. (PNAS 2012)
Prediction
Lead time 11 months
Socio-economic conditions
Cholera outbreaks in Dhaka (and Bangladesh) are strongly driven by climate variability (ENSO and flooding). The effect of El Niño is partly through precipitation and associated flooding.

Population susceptibility shows pronounced geographic variation within Dhaka, with a part of the city acting as a susceptible core, in a way that highlights the key role of sanitary, and associated, socio-economic conditions.

John Snow (London 1864) ‘revisited’, but in the context of climate forcing and a megacity of the developing world.
 Bayesian approach to classify districts based on a dynamical model and time series data:

Baskerville et al. 2011. Spatial Guilds in the Serengeti Food Web Revealed by a Bayesian Group Model. PloS Computational Biology 7(12)
Epidemic malaria and rainfall variability in arid India under land-use change
Epidemic malaria in Kutch

P. falciparum
22 Talukas (sub-districts) from the state of Gujarat

- Confirmed monthly cases of *Plasmodium falciparum* and *P. vivax* [1997-2011]
- IRS (Indoor Residual Spray) application (population covered) [2000-2010]
questions

1) What are the main patterns of irrigation and the changes in irrigation? Based on remote sensing data (NDVI, Normalized Difference Vegetation Index) as a surrogate for irrigation.

2) Are there groups of talukas with similar temporal dynamics? How do these groups map into the above regional patterns of irrigation?

3) How do these regions map into levels of control (IRS)

→ Transition regime between the two main states of high and low risk
Irrigation patterns

Irrigated land 2009

Narmada Irrigation project
Irrigation profile

- Agricultural seasons: Kharif (Sep-Dec) and Rabi (Dec-March)

NDVI seasonality

Irrigated
Non irrigated
Temporal change in vegetation (NDVI) outside monsoon season (i.e. irrigated agriculture)

2001

2009
Spatial groups based on temporal dynamics
Best two groups

Irrigation gradient

A

Best 2 groups

B

Epidemics of the year 2003

C

Log Prevalence

Proportion of irrigated land
patterns of control by IRS

LR-LC: Low Risk-Low Control
HR-LC: High Risk-Low Control
HR-HC: High Risk-High Control

Control (% population covered)

10000*Cases/Population

LR-LC
HR-HC
HR-LC

Map showing different regions with color coding representing control levels.
Change in control and risk

Change in relative risk

A

2000-2005

2006-2010
In summary,

- In areas that have been irrigated for a long time, the risk has declined to a level in which control is no longer needed.

- In areas with low irrigation, regular epidemics are possible because of low levels of control.

- In areas with pronounced land-use change over the last decade, higher disease levels continue despite intensive IRS intervention.
High risk "sustainable" low risk

Long lasting transition regime

"sustainable" low risk
Climate change vs. Development / Control

Water as a key limiting resource

Change in climate variability extreme events (in rainfall, more frequent and less predictable)

“Despite the high costs and depleting water tables, irrigated areas have increased steadily, making livelihoods even more precariously dependent upon sustainable groundwater management” (Kumar et al., Economic and Political Weekly 2004).
Gracias

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Ben Cash: COLA Center for Ocean Land Atmosphere Studies
Malaria epidemics highlight influence of the Tropical South Atlantic on the Indian monsoons.
Lobitz et al., 2000, PNAS

cholera and remote sensing (Sea Surface Temperature in the Bay of Bengal and Chlorophyll as a measure of phytoplankton blooms)
“Water mingles with every kind of natural phenomenon; and more than one might imagine, it has also mingled with the particular destiny of mankind”

--- Fernand Braudel
(from Water, The Epic Struggle for Wealth, Power and Civilization, S. Solomon)
\[ p_{i,0,k,t} = P_{i,0,D(k)} \times \text{Neigh}(i, 0, V(k, t - 1), D(k)) \times \text{Seas}(i, 0, t - 1, D(k)) \]

\[ p_{i,2,k,t} = P_{i,2,D(k)} \times \text{Neigh}(i, 2, V(k, t - 1), D(k)) \times \text{Seas}(i, 2, t - 1, D(k)) \]

\[ p_{i,1,k,t} = 1 - p_{i,0,k,t} - p_{i,2,k,t} \]

The neighborhood function is multiplicative in its effect and has the following form:

\[ \text{Neigh}(i, j, V, D(k)) = (1 + \alpha_{i,j,D(k)})^V, \ j = 0, 2. \quad [S4] \]

The 12 coefficients \( \alpha_{i,j,d} \) are parameters to be estimated. The seasonality function also enters multiplicatively. It takes the form

\[ \text{Seas}(i, j, t, D(k)) = \left(1 + \beta_{i,j,D(k)}\right)^{Se(t,D(k))}, \ j = 0, 2, \quad [S5] \]

where \( Se(t, d) \) is periodic in \( t \) with a period of 12 mo.
\[ p'_{i,2,k,t} = f \left( p_{i,2,k,t} \times \text{Nino}(t-1, D(k)) \right), \]

where the El Niño function has the sigmoidal form

\[ \text{Nino}(t, d) = 1 + A_d \frac{\tan \left( \frac{h_d}{2} \cdot \frac{\text{ENSO}(t-10)}{M_d} \right)}{\tan \left( \frac{h_d}{2} \right)} \]

\[ p'_{i,0,k,t} = \left( 1 - p'_{i,2,k,t} \right) \frac{p_{i,0,k,t}}{p_{i,0,k,t} + p_{i,1,k,t}} \]

\[ p'_{i,1,k,t} = \left( 1 - p'_{i,2,k,t} \right) \frac{p_{i,1,k,t}}{p_{i,0,k,t} + p_{i,1,k,t}}. \]
Two stories: one on cholera, the other on malaria
Data Description

- Dhaka, the capital of Bangladesh, contains more than 14 million people (almost tripled in last 25 years, projected to double in next 25).

- The data we analyze is the number of cases of cholera of the O1 El Tor biotype over 14 years (1995-2008), broken down by thana (i.e. administrative region).