Spatial Resource Allocation for Emerging Outbreaks:

Application to the 2014 Ebola Epidemic

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Punchline

Geospatial epidemic model + Dynamic behavior change + Optimization = Better allocation
Challenges to an effective Ebola response

**Epidemic forecasting**

- Rapidly evolving epidemic substantially differs from initial projections
- **Heterogeneous** epidemic intensity and growth among affected regions
- Available models aggregate country-level forecasts

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The New York Times

Ebola Cases Could Reach 1.4 Million Within Four Months, C.D.C. Estimates

By DENISE GRADY  Sept. 22, 2014

A Red Cross team removed the body of a woman believed to have died of Ebola in Monrovia, Liberia, last week. Officials urged caution in handling victims’ bodies. David Birdfield for The New York Times
Challenges to an effective Ebola response (cont’d)

**Mitigation**

- Limited resource availability
  - Decisions about **which interventions** and **where to focus**
  - Trained health care workers, Ebola treatment units (ETUs), transport, safe burials, etc.

- Decentralized response efforts
  - Multiple regional, international, and NGOs deploying **resources** to the crisis regions
  - No model-based **decision support tool** available

- Public fear, skepticism, misinformation, stigma

**Our approach**

**Stage 1**: Develop inter-region epidemic model calibrated to past data

**Stage 2**: Optimize resource allocation based on epidemic forecasts
Hospital beds are key to Ebola containment efforts

**Ebola intervention measures**

- Community education for improving awareness
- Contact-tracing
- Safe burial teams
- Personal protection equipment
- Medical transport services
- Health care worker education
- Ebola Treatment Unit (ETU) bed capacity

**Why optimize ETU resources?**

- Hospitalization rate is a key factor in containing the epidemic (Legrand et al, 2007; Meltzer et al, 2014)
- Future impact of hospitalization can be directly reflected in the epidemic model
Stage 1: SIR epidemic model

**Notation**

- $t$: Time since epidemic start
- $N_i$: Size of population $i$
- $S_i$: Susceptible individuals in $i$
- $I_i$: Infected individuals in $i$
- $R_i$: Removed individuals in $i$
- $K$: Number of regions
- $\beta_j$: Transmission coefficient in $j$
- $\psi_j$: Dampening coefficient in $j$
- $m_{i,j}$: Proximity coefficient between population $i$ and $j$
Two extensions to basic SIR model

**Population connectivity**

- Infected individuals can move between geographic regions and infect others → need dependency between populations
- $c_0 = \text{share of contacts within home region}$
- $1 - c_0 = \text{remaining contacts inversely proportional to distance } d_{i,j}$ between capitals

**Behavioral dampening**

- Initial overestimation of case counts did not account for behavioral change (e.g. reduced social contact, safe burials, etc)
- Dampening coefficient $\psi_j$ follows logistic function, representing 3 phases of behavior change:

$$\psi_{j,t} = 1 - \frac{\bar{\psi}_j}{1 + e^{-\alpha_j t}}$$

- Awareness remains low at epidemic start
- Behavior dampening converges to $1 - \bar{\psi}$

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Elisa Long | UCLA
Epidemic model calibration to case count data

- Data source: Humanitarian Data Exchange [https://data.humdata.org/](https://data.humdata.org/)
- Included **21 regions** in Guinea, Liberia, Sierra Leone (excluded regions with <50 cases or <5 data points)
- Up to **20 weeks as training data** (start Sep 2014) → next **4 weeks for projection**
- Estimated model parameters with Markov Chain Monte Carlo (MCMC) approach
- Goal: minimize error between model projections and observed data
Complete model calibration
(20 weeks of training data)
Stage 2: Optimal resource allocation

**Static Policies**
- **Benchmark Heuristic**: Proportional to cumulative Ebola cases in each region.
- **Greedy $R_0$**: Prioritize only regions where $R_0 > 1$.

**Dynamic Policies**
- **Myopic LP**: Estimate parameters and optimize allocation across all regions; repeat next period.
- **ADP Algorithm**: Minimize future cases across all regions using epidemic model approximation.

*Easy to understand*
Where to allocate beds?

(16 weeks of training data, 120 beds)

**Greedy** $R_0$ concentrates resources in regions where $R_0 > 1$

**Myopic LP** generally allocates beds to centrally located regions (Moyamba) over distant regions with more cases (Conakry)

**Benchmark Heuristic** mitigates epidemic at current “hot-spots” (Conakry) but under-invests in areas that surge later (Kerouane)

**ADP Algorithm** more evenly distributes bed, allocating 2-6 beds per region per week
Conclusions

- A compartmental model with **distance-based transmission** and **behavior dampening** closely matches historical data on Ebola case counts.
- Model performance still good during **early stages of outbreak** (first 4 weeks).
- **Myopic LP** performs best over range of data & resource availability and is computationally fast:
  - With 100 beds/week, 50% of future cases are averted; best “shadow price” of all policies.
- Other policies are more complicated to implement (ADP) or sub-optimal (Greedy $R_0$).

**Some important caveats**

- Data quality is critical for accurate epidemic projections and optimized resource allocation.
- Optimal allocation requires coordination among decision-makers and health organizations.

**Future extensions**

- Consider multiple intervention types or stochastically arriving resources.
- Apply to other infectious diseases, especially Zika virus.

*Thank you!*