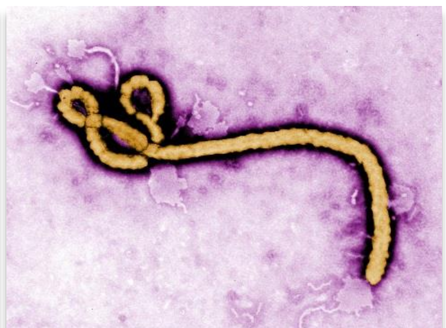
Spatial Resource Allocation for Emerging Outbreaks:

Application to the 2014 Ebola Epidemic



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Punchline

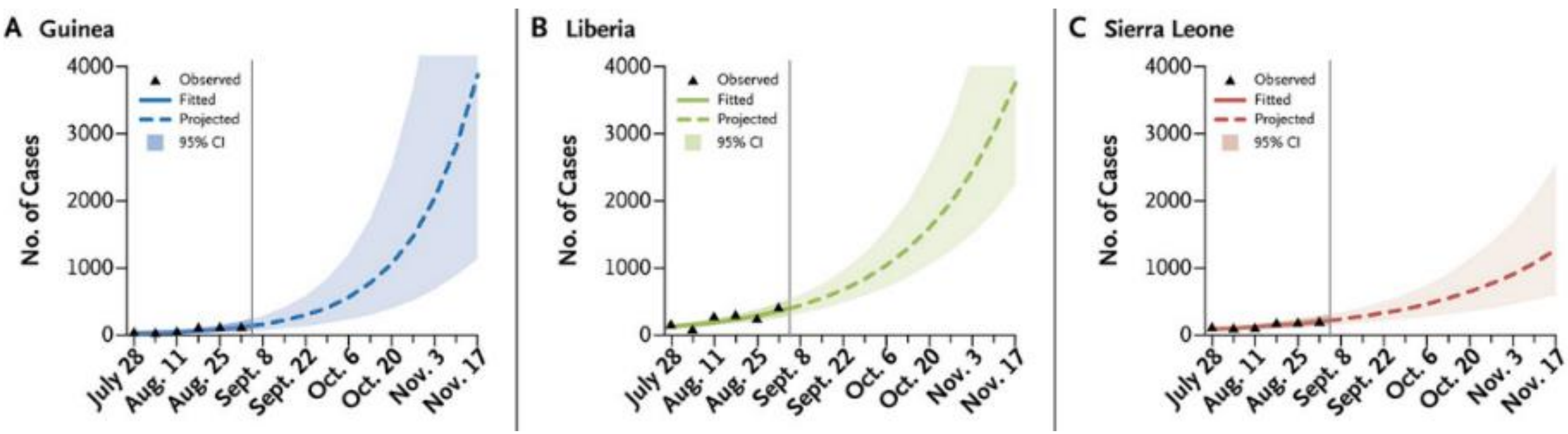
Geospatial epidemic model* + *Dynamic behavior change* + *Optimization* = *Better allocation

Challenges to an effective Ebola response


The New York Times
HEALTH
Ebola Cases Could Reach 1.4 Million Within Four Months, C.D.C. Estimates
By DENISE GRADY SEPT. 23, 2014
246
A Red Cross team removed the body of a woman believed to have died of Ebola in Monrovia, Liberia, last week. Officials urge caution in handling victims' bodies. Daniel Berehulak for The New York Times

Epidemic forecasting

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



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

www.msf.org.uk

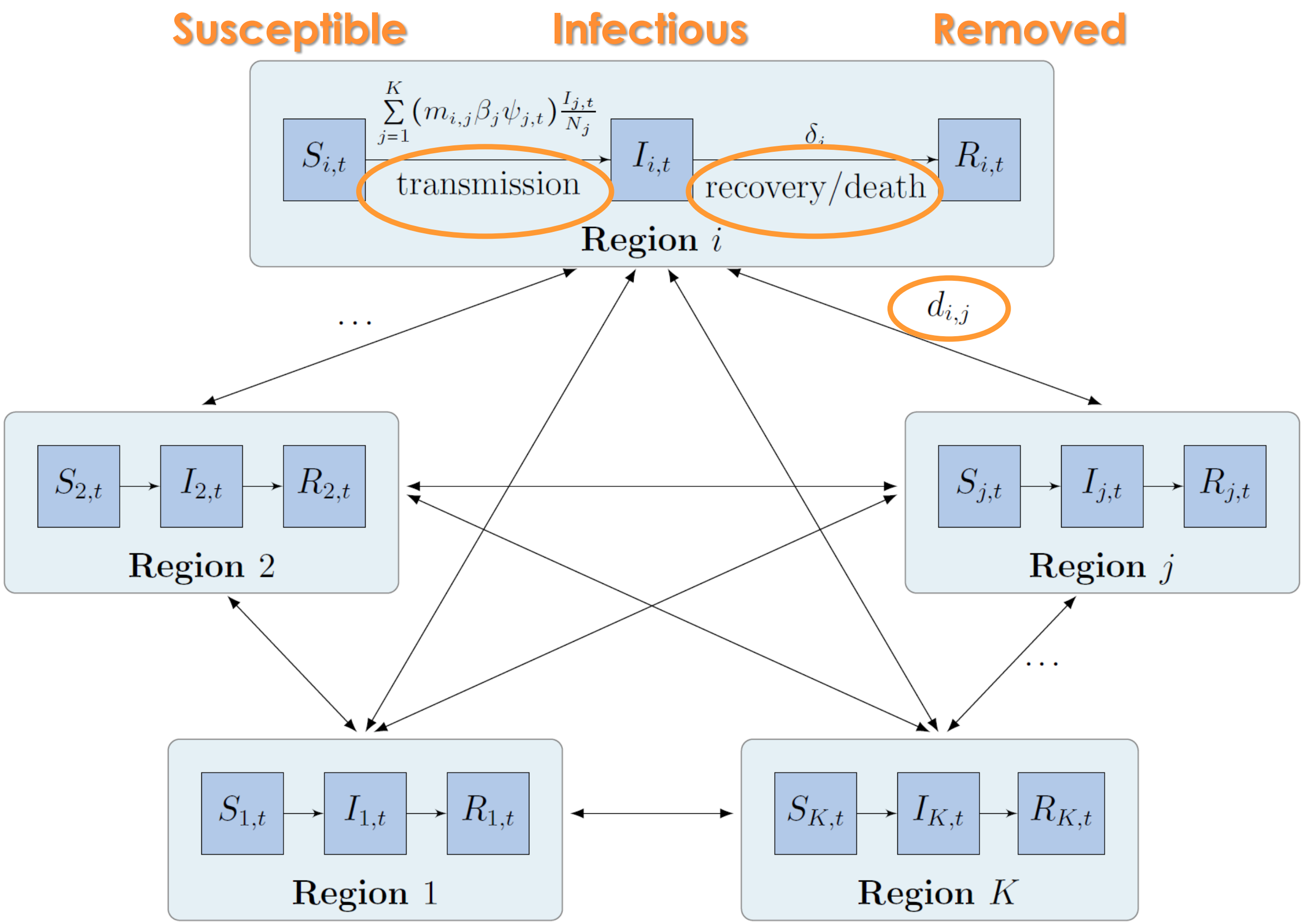
Ebola intervention measures

- 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
β_j	Transmission coefficient in j
ψ_j	Dampening coefficient in j
$m_{i,j}$	Proximity coefficient between population i and j

Two extensions to basic SIR model

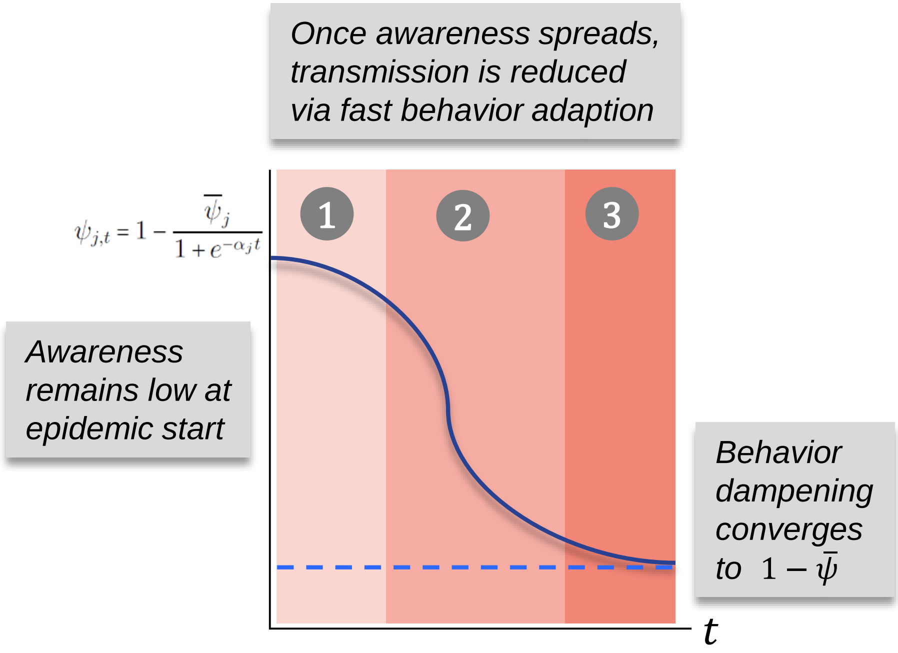
Population connectivity

- Infected individuals can move between geographic regions and infect others

  → need dependency between populations
- c_0 = share of contacts within **home region**
- $1 - c_0$ = 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** ψ_j follows logistic function, representing 3 phases of behavior change:



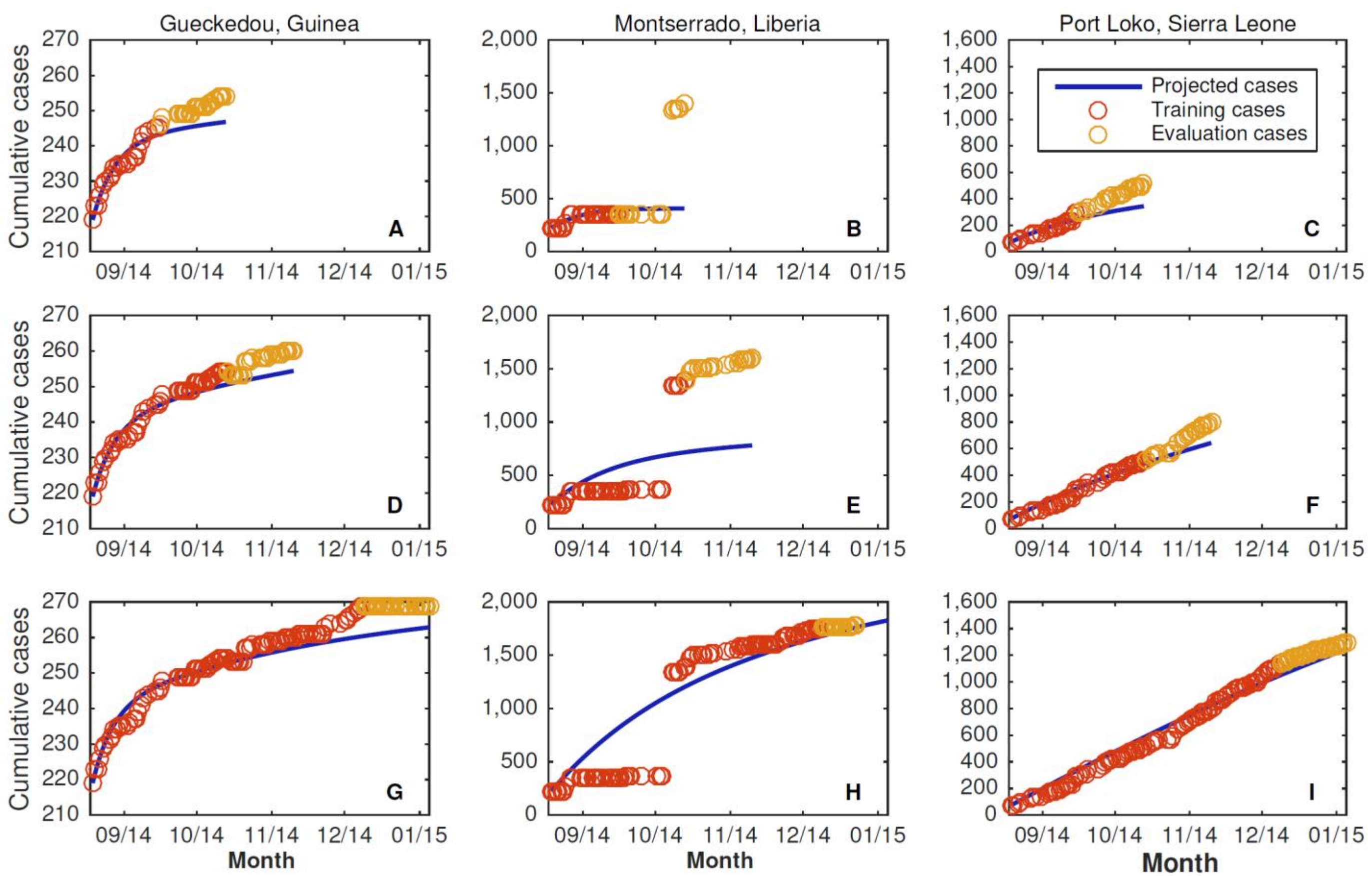
Epidemic model calibration to case count data

- Data source: Humanitarian Data Exchange 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**

4 weeks

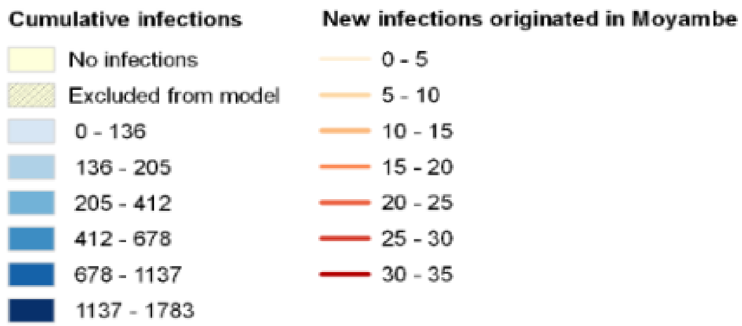
8 weeks

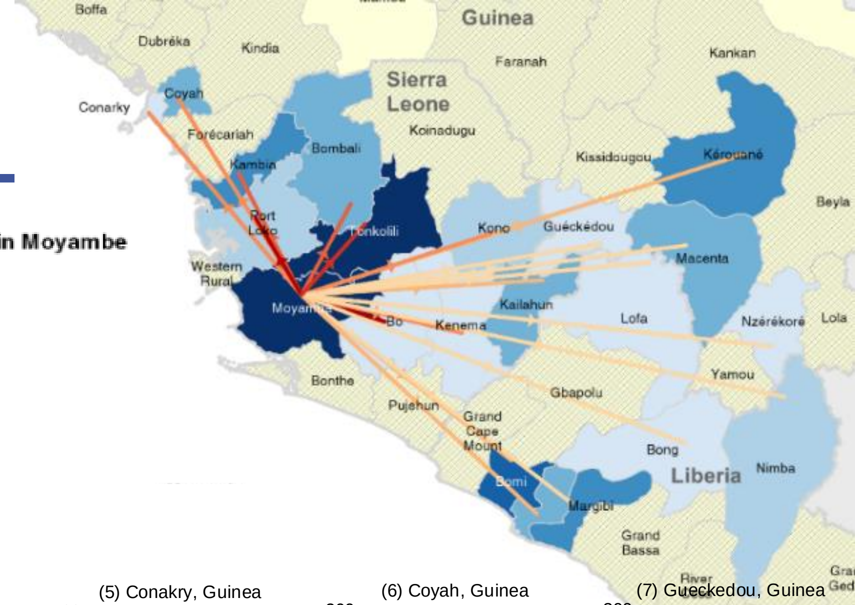
16 weeks

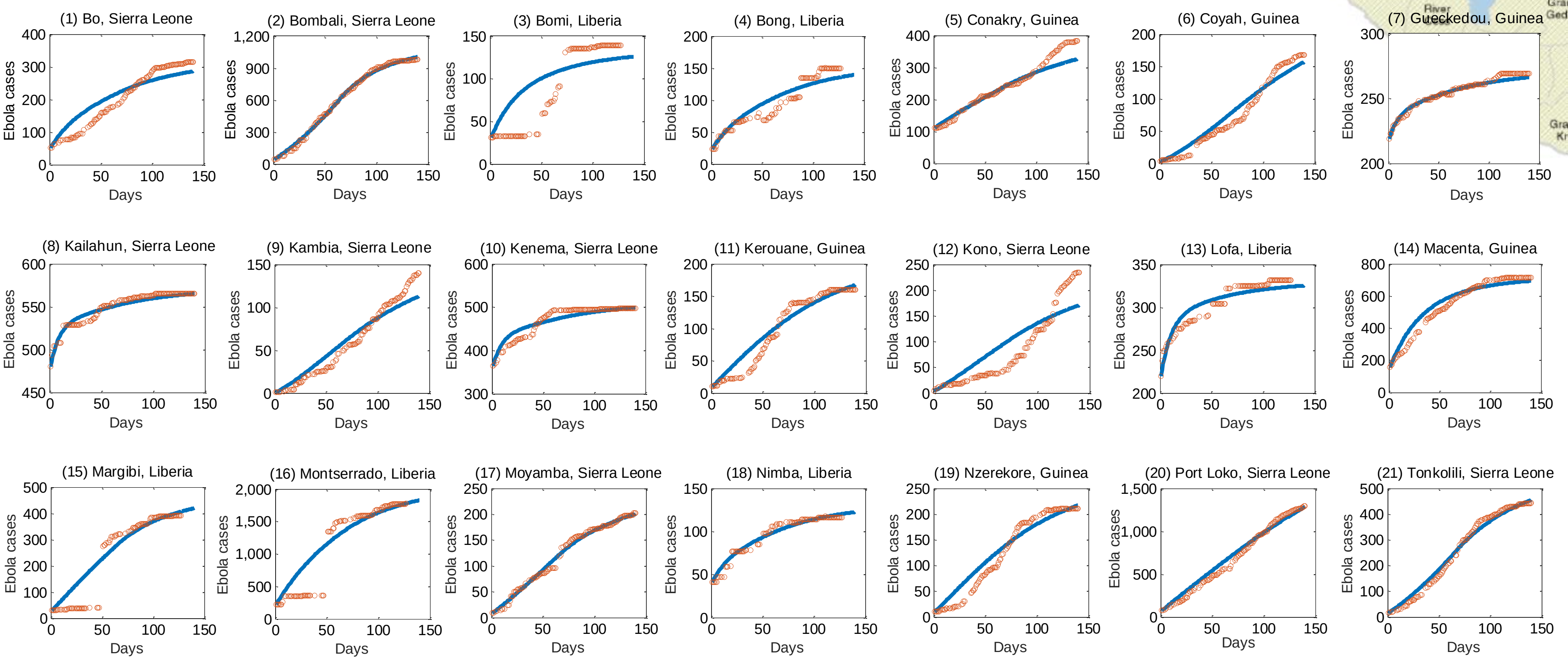


Complete model calibration

(20 weeks of training data)







Stage 2: Optimal resource allocation

Static Policies

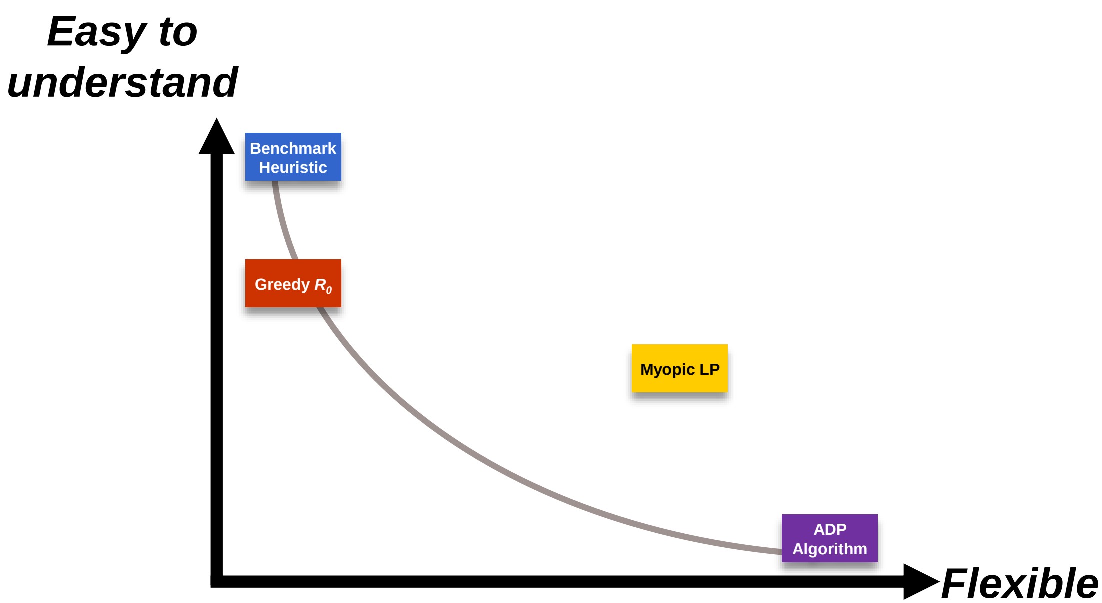
Benchmark Heuristic — Proportional to cumulative Ebola cases in each region

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

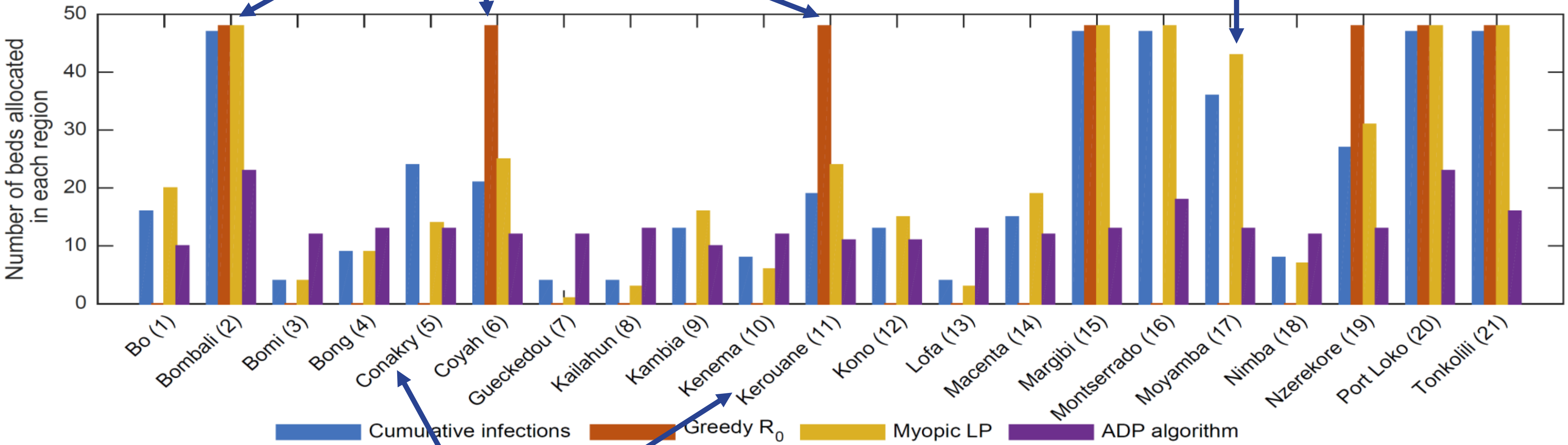
ADP Algorithm — Minimize future cases across all regions using epidemic model approximation



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

Geospatial epidemic model **+** ***Dynamic behavior change*** **+** ***Optimization*** **=** ***Better allocation***

- 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!