

COVID-19 Model for Dynamic Analysis of Combination Interventions for Disease Elimination - Using Reinforcement Learning

"Work-In-Progress" Disease Prediction and Prevention Modeling Lab Contact: Chaitra Gopalappa

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Collaborators









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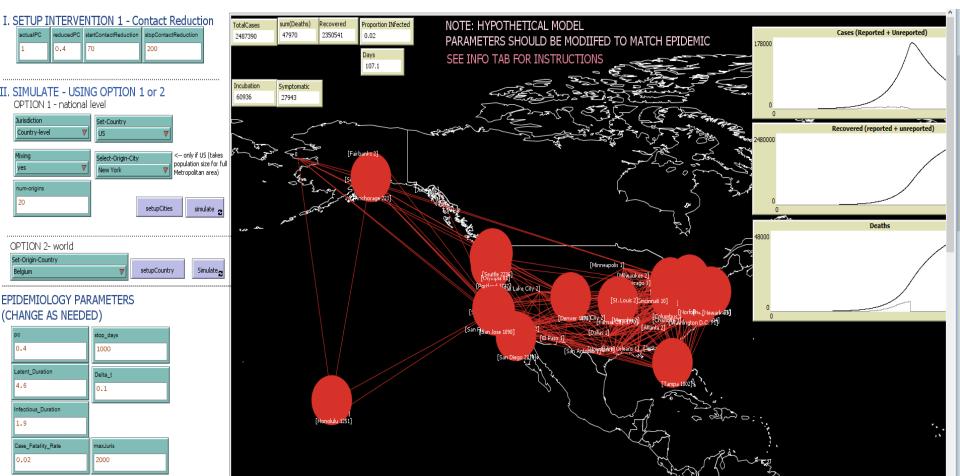
Sonza Singh Hanisha Tatapudi



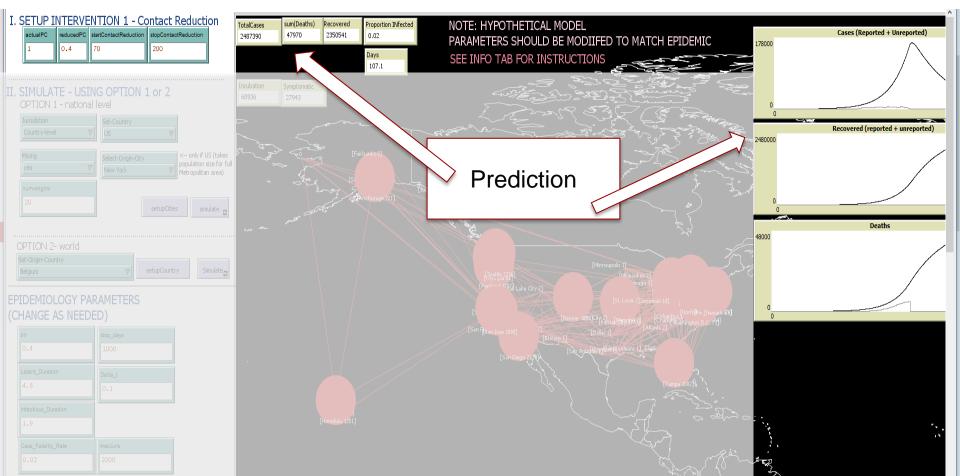
Xinmeng Zhao

Disease Prediction and Prevention Modeling Lab

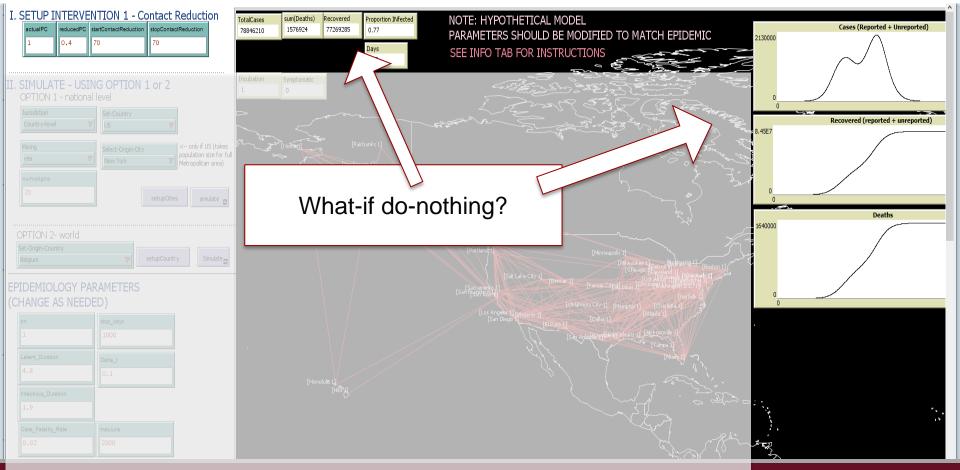
Current Simulation Modeling Overview

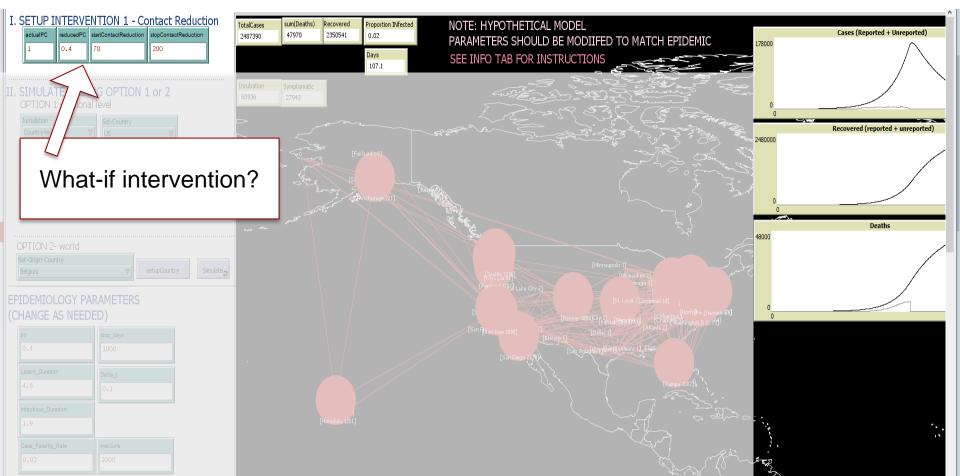


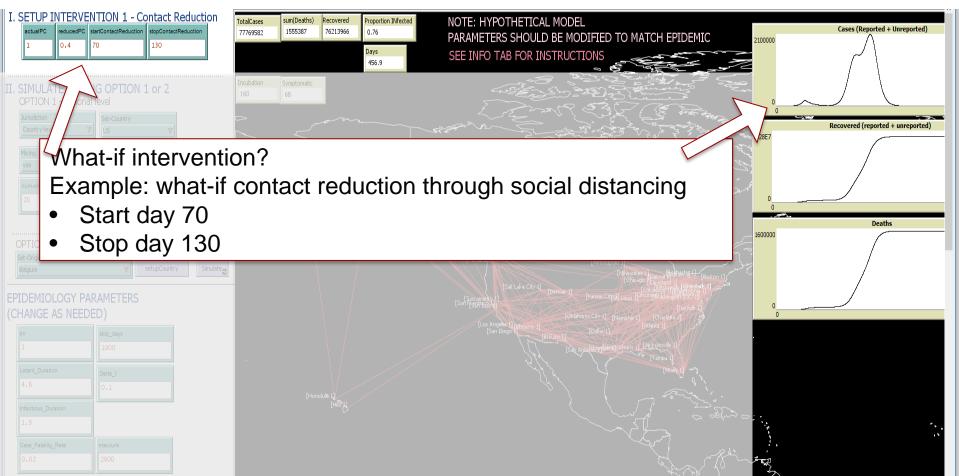
Current Simulation Modeling- Prediction

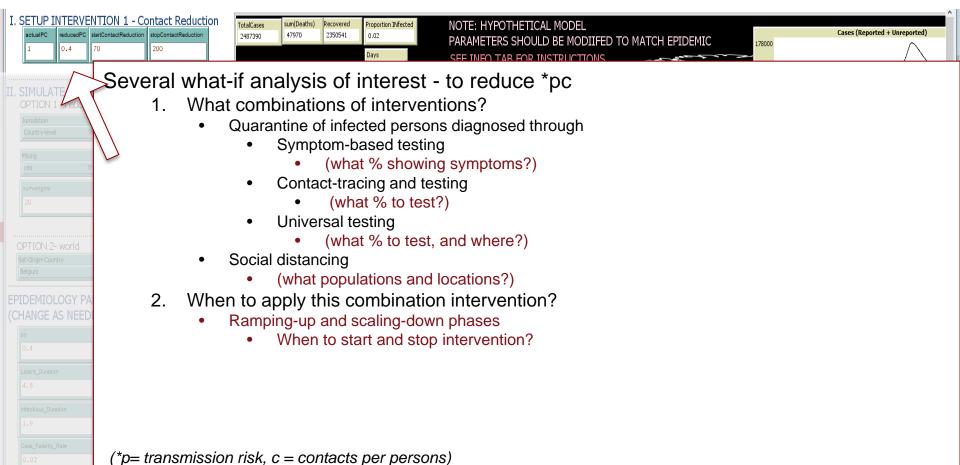


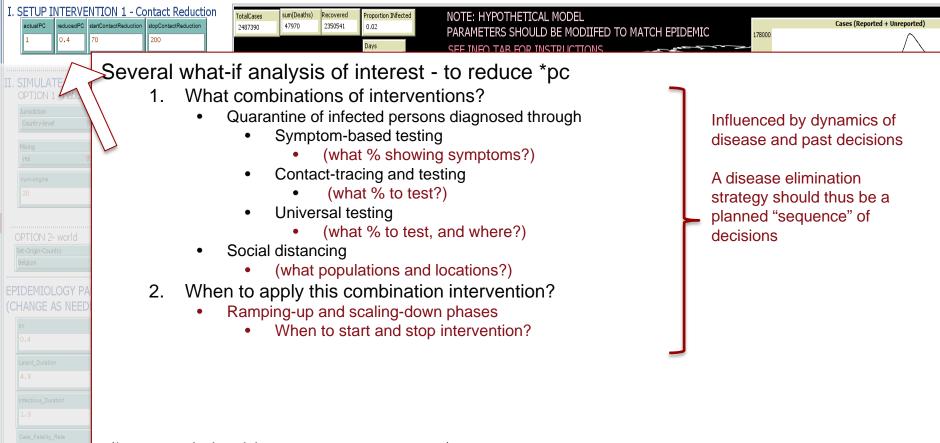
Current Simulation Modeling- What-if analysis

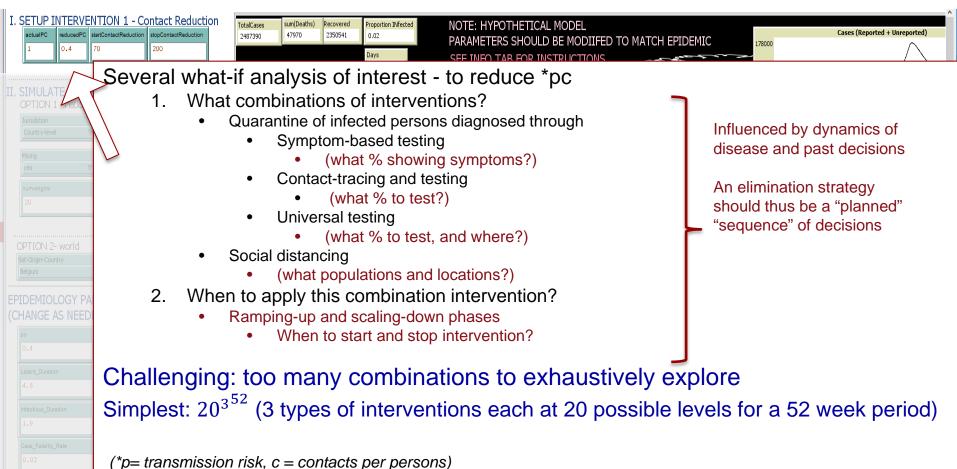












Research Focus

- Develop a model to identify best disease elimination strategies
 - combination of interventions
 - sequence /phases

Formulation of Decision Question

- At time t
- Given "observable" system state = $[Q_I, Q_E, H, R, D]_t$ *
 - $Q_I = \%$ infectious (symptomatic and diagnosed)
 - $Q_E = \%$ exposed (asymptomatic and diagnosed)
 - H = % hospitalized
 - R = % recovered
 - D = % dead
- What is optimal policy sequence = { $[s, u, c]_t$, $[s, u, c]_{t+1}$, $[s, u, c]_{t+2}$,} *
 - s = % social distancing
 - u = % universal testing
 - c = % testing reached through contact tracing
- to "optimally" lead to zero infections or disease elimination?

Formulation of Optimality (objective function)

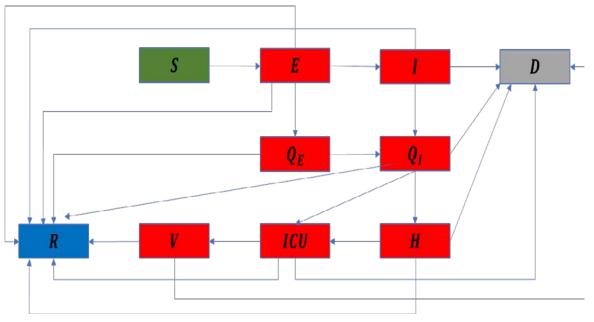
- Maximize QALYs (qualityadjusted life-years lived)
 - Value per person per year
 - 1 healthy
 - (0,1] sick
 - 0 death
- Maximize productivity
 - Economic value per person per year
 - 0 Unemployed
 - (0,1] partial
 - 1 Employed

- Minimize cost
 - Unit costs
 - Contact tracing and testing
 - Universal testing
 - Hospitalization
- Subject to: Constraints (supply constraints)
 - Strict v what-if
 - Hospital capacity (number who can receive care)
 - Testing (=number with test outcome)₁₂

Methods

- Prediction model
- Decision analytic model

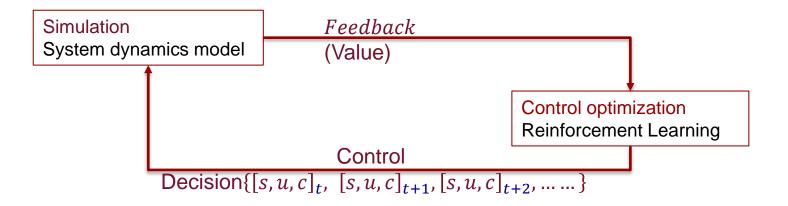
Prediction Model System dynamics modeling (differential equations modeling)



- *S* = the number of **susceptible** persons,
- *E* = the number of **exposed (asymptomatic or presymptomatic)** persons,
- *I* = the number of **infected** (symptomatic) persons,
- Q_I = the number of **tested and diagnosed** who are infected and symptomatic,
- Q_E = the number of **tested and diagnosed** who are infected and asymptomatic,
- *H* = the number of **hospitalized** persons,
- *ICU* = the number of persons in **ICU**,
- *V* = the number of persons on **ventilation**,
- *R* = the number of persons **recovered**,
- *D* = the number of **deaths**,

Decision Analytic Method

- Reinforcement Learning (simulation based control optimization)

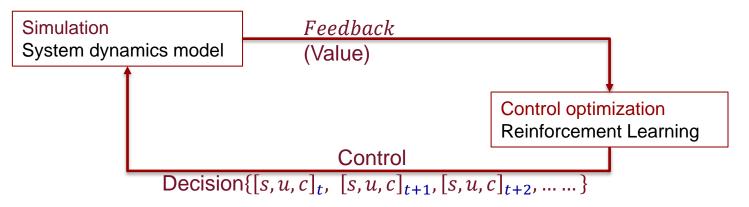


Identify optimal policy-

A sequence of decisions that optimally leads to disease elimination

Decision Analytic Method

- Reinforcement Learning (simulation based control optimization)



Identify optimal policy-

A **sequence** of **(combination controls**) decisions that optimally lead to disease elimination (**completion of task**)

Analogous to autonomous helicopter control

-Identify **sequence** of **combination controls** (main-rotor's blade tilt, tail rotor pitch, rotor plane/ cyclic pitch) for successful **completion of task**

Expected output

 $\underline{\text{Model output: } Optimal policy} = a \ sequence \ of \ decisions = \\ \{[s, u, c]_t, [s, u, c]_{t+1}, [s, u, c]_{t+2}, \dots, [s, u, c]_{t+N}\} \mid [Q_I, Q_E, H, R, D]_t$

- Helps in planning response strategies and resource allocation decisions
- Helps eliminate bad decisions

 $[Q_I, Q_E, H, R, D]_t$ = observed state of system at time t (reported cases of disease)

 Q_I = the number of **tested and diagnosed** who are infected and symptomatic,

 Q_E = the number of **tested and diagnosed** who are infected and asymptomatic,

H = the number of **hospitalized** persons,

ICU = the number of persons in **ICU**,

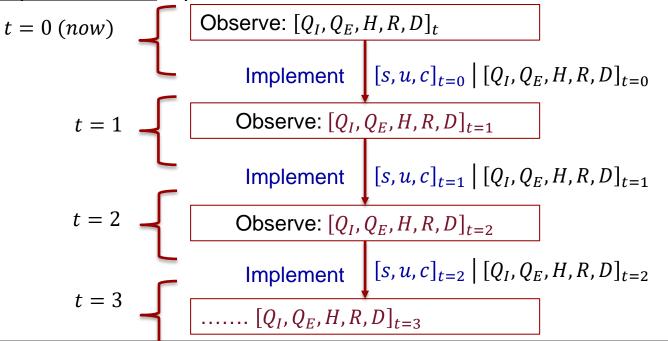
V = the number of persons on **ventilation**,

- *R* = the number of persons **recovered**,
- *D* = the number of **deaths**,

Expected output

 $\underline{\text{Model output: } Optimal policy = a sequence of decisions = } \\ \{ [s, u, c]_{t=0}, [s, u, c]_{t=1}, [s, u, c]_{t=2}, \dots, [s, u, c]_{t=N} \} | [Q_I, Q_E, H, R, D]_{t=0}$

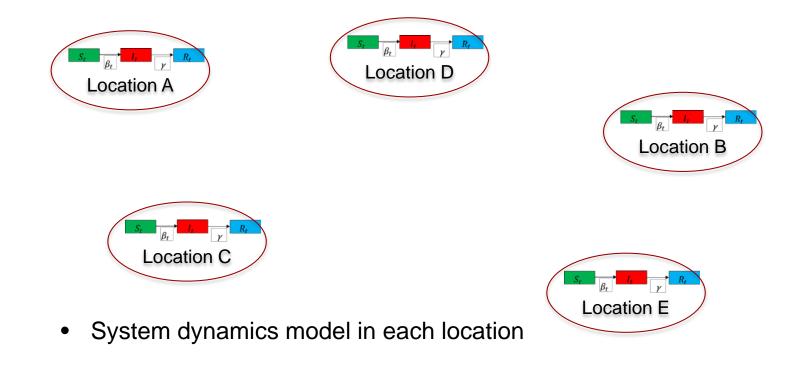
Implementation: update based on observation





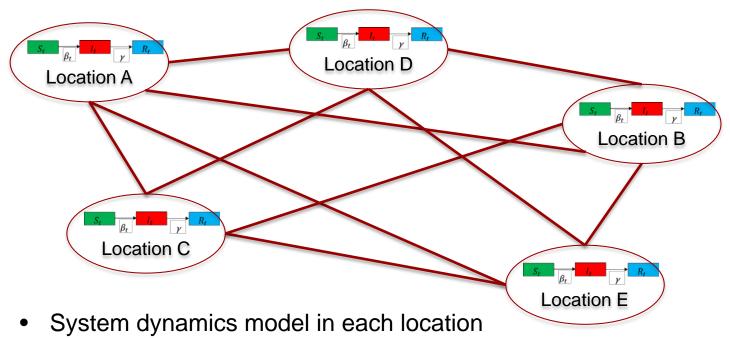
Phase I

• Independent jurisdiction models



Phase II

• Interactions between jurisdictions



• Locations connected through network

Persons Interested in Collaborating Contact

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Research lab **Disease Modeling Lab**

Objective: Develop new mathematical and computational methods necessary to analyze complex decisions related to public policy

of Health

Collaborators

- CDC U.S. Centers for Disease Control and Prevention
- WHO- World Health Organization
- IARC- International Agency for Research on Cancer
- PAHO- Pan-American Health Organization
- UNAIDS Joint United Nations Agencies Programmed on HIV/AIDS
- UNICEF United Nations International Children's Emergency Fund

Funded By

- National Institutes of Health
- National Science Foundation
- World Health Organization



Graduate and undergraduate students





















