Cognitive Simulations for COVID-19 Analysis, Exploration, and Scenario Planning

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Modeling and Simulating COVID-19 Outbreaks: Challenges and Opportunities

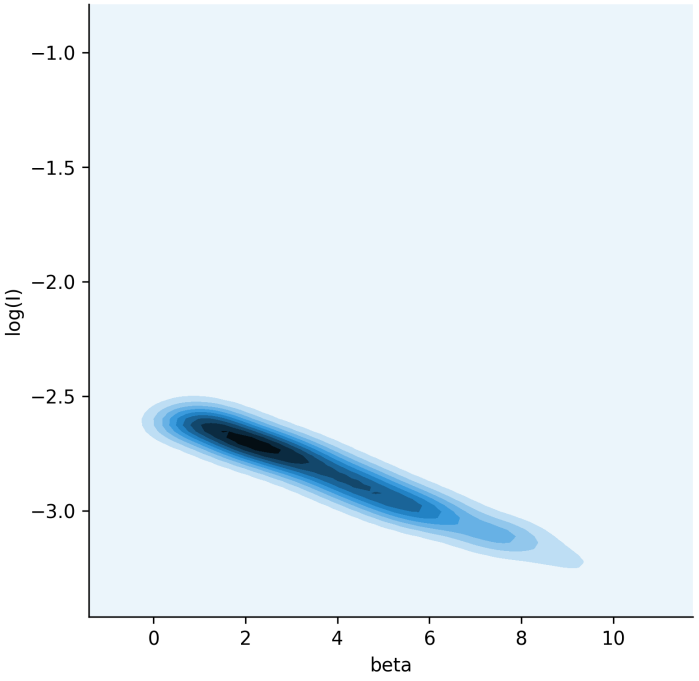
- Modeling and subsequently simulating disease spread at various levels of precision is crucial to support the three major component of developing a response
  - Understand the current state of the pandemic through intuitive parameter fits, i.e. R_0
  - Provide short to medium term predictions and the ability to explore “what if” scenarios
  - Support the development of “optimal” policy recommendations
- Case data does not sufficiently constrain even simple models leading to significant uncertainties in both parameter estimations and predictions
- Common phenological models are not detailed enough for scenario exploration
- Agent-based models are challenging to calibrate and more computationally expensive

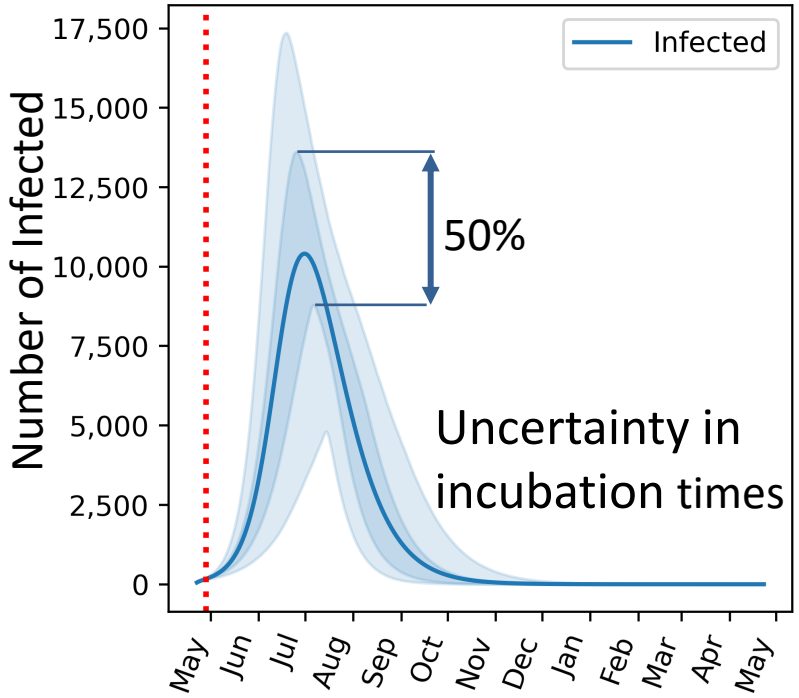
The NVBL and CAA Teams are Jointly Addressing Common Challenges, Developing new Models, and Providing new Capabilities

- Account for uncertainties in calibration and prediction to enable more informed decisions
- Extent SEIR models to explore different testing protocols for the Army
- Provided new calibration techniques to make agent-based models (EpiCast) self-consistent
- Developed constraint optimization technique to explore optimal policy schedules
- Within less than 6 months the team has provided
  - New capabilities in uncertainty aware modeling and scenario exploration for CDC, CAA, DHS, etc.
  - Provided actionable insight to the CAA, changing the test protocol for unit deployment
  - Advanced the state of the art in machine learning for epidemiological modes (two AAAI submissions)
- These capabilities will provide new emergency response models and better planning tools

We Account for Underconstrained Parameters Through Uncertainties Which are Propagated Forward to Enable More Informed Decisions

- Case data does not fully constrain SEIR parameters leading to large uncertainties
- Using LLNL UQ workflow we explicitly model and propagate the uncertainties resulting in more informative analysis and more reliable decisions





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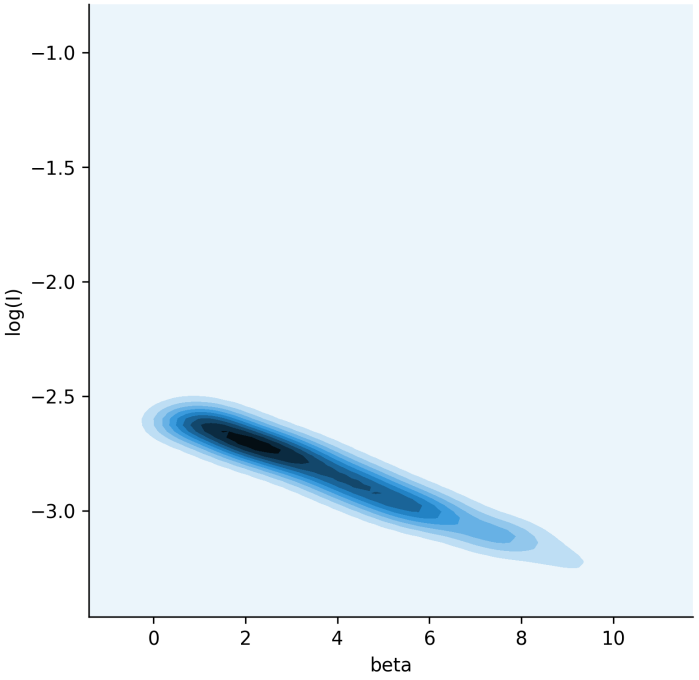
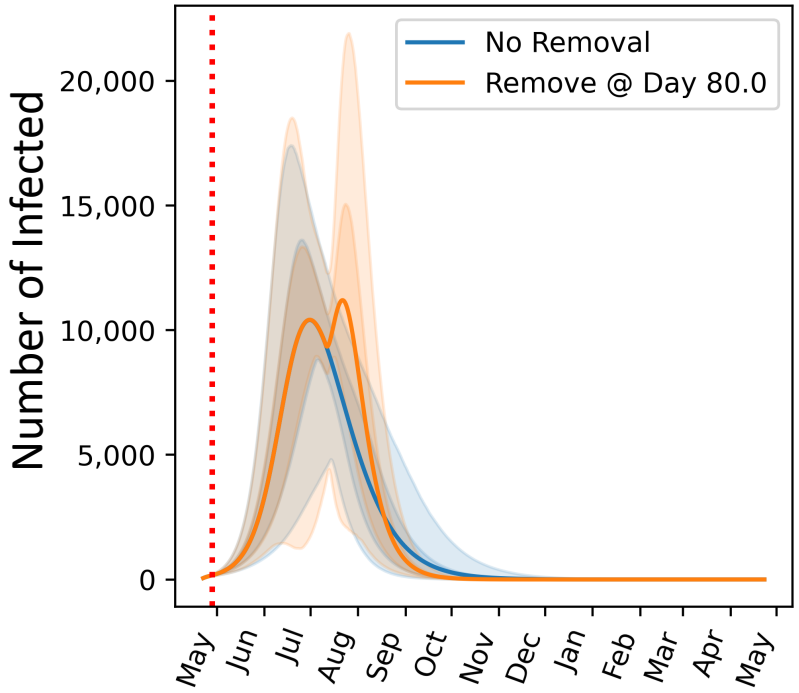
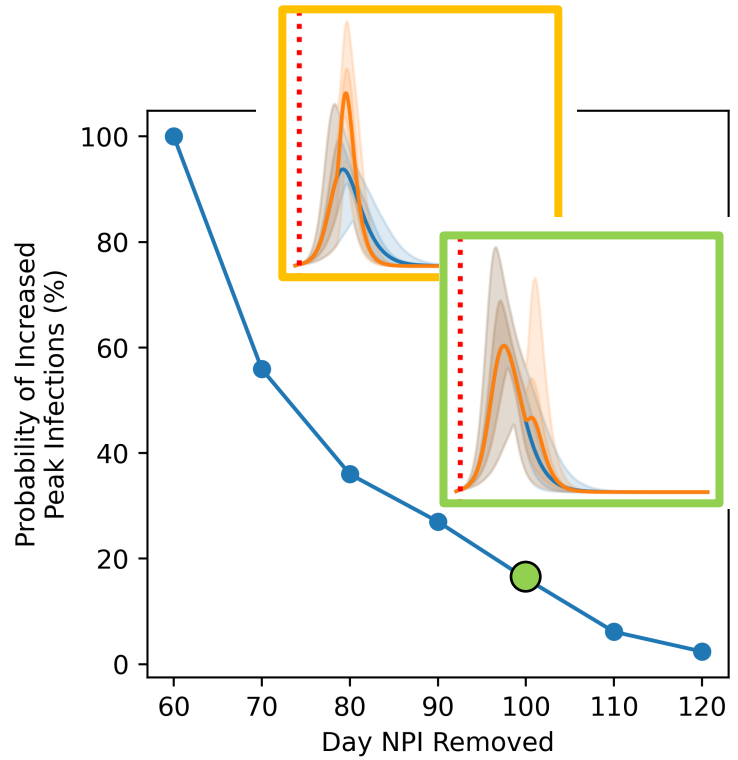
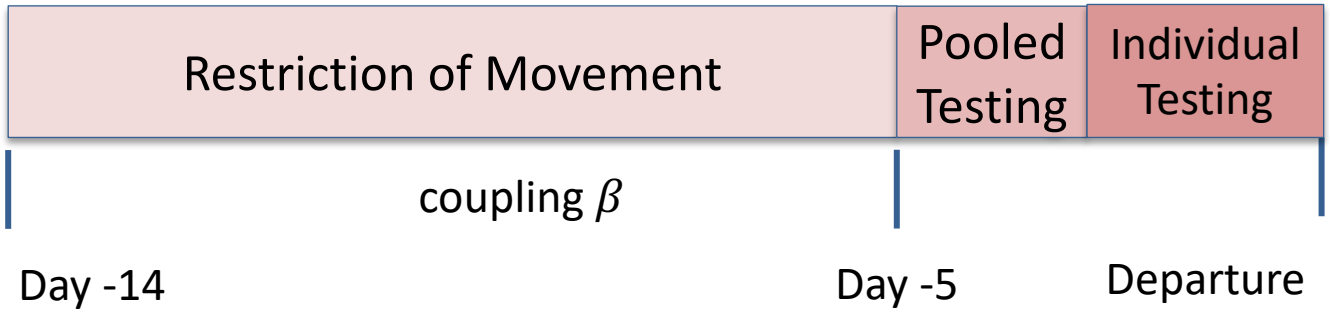


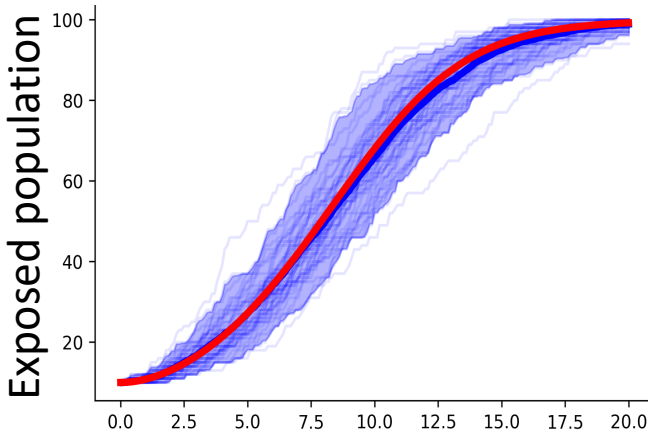


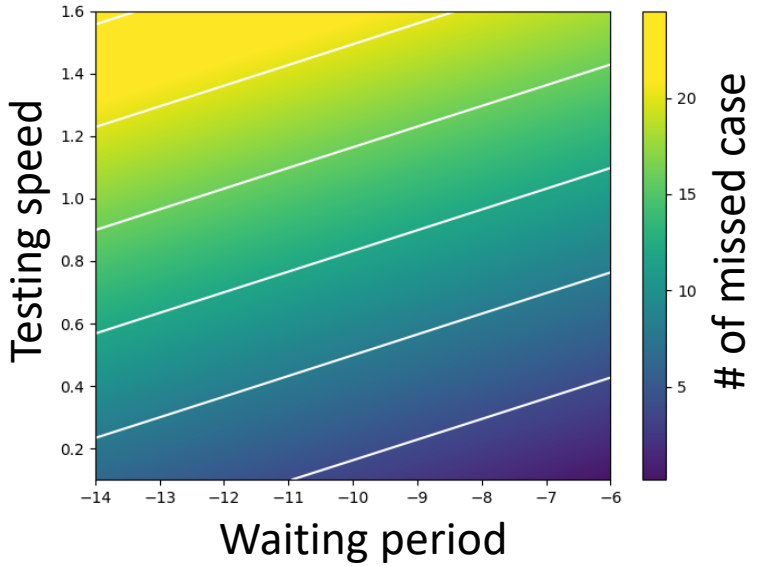


Together with CAA We have Extended SEIR Models to Investigate Testing Protocols Which has Led to New Guidance for the Army

- Proposed protocol suggested 2 week waiting period with pooled testing
- Small cohorts make SEIR predictions unreliable
- Discrete MC based variants reestablish uncertainty bounds
- Key insight: Waiting period increases the likelihood of missed cases

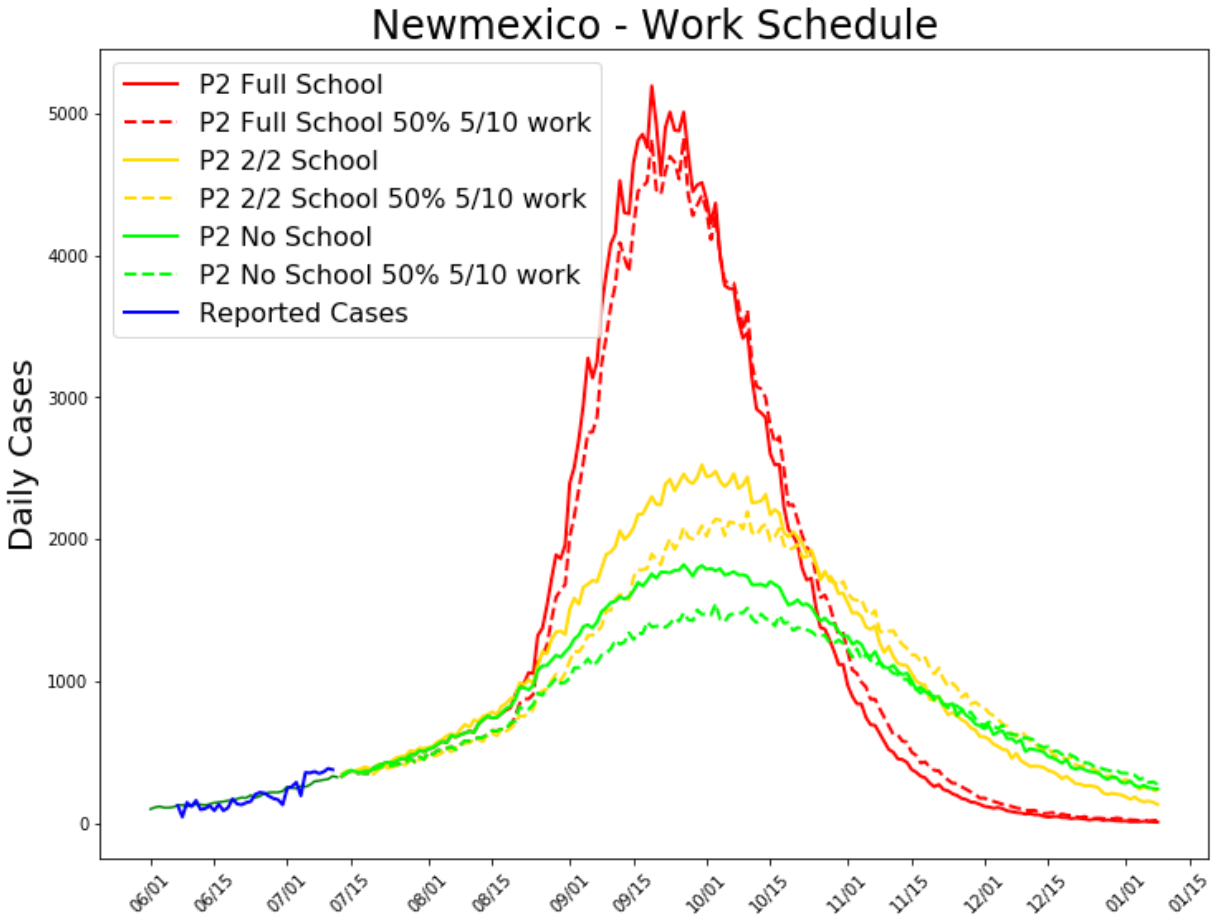


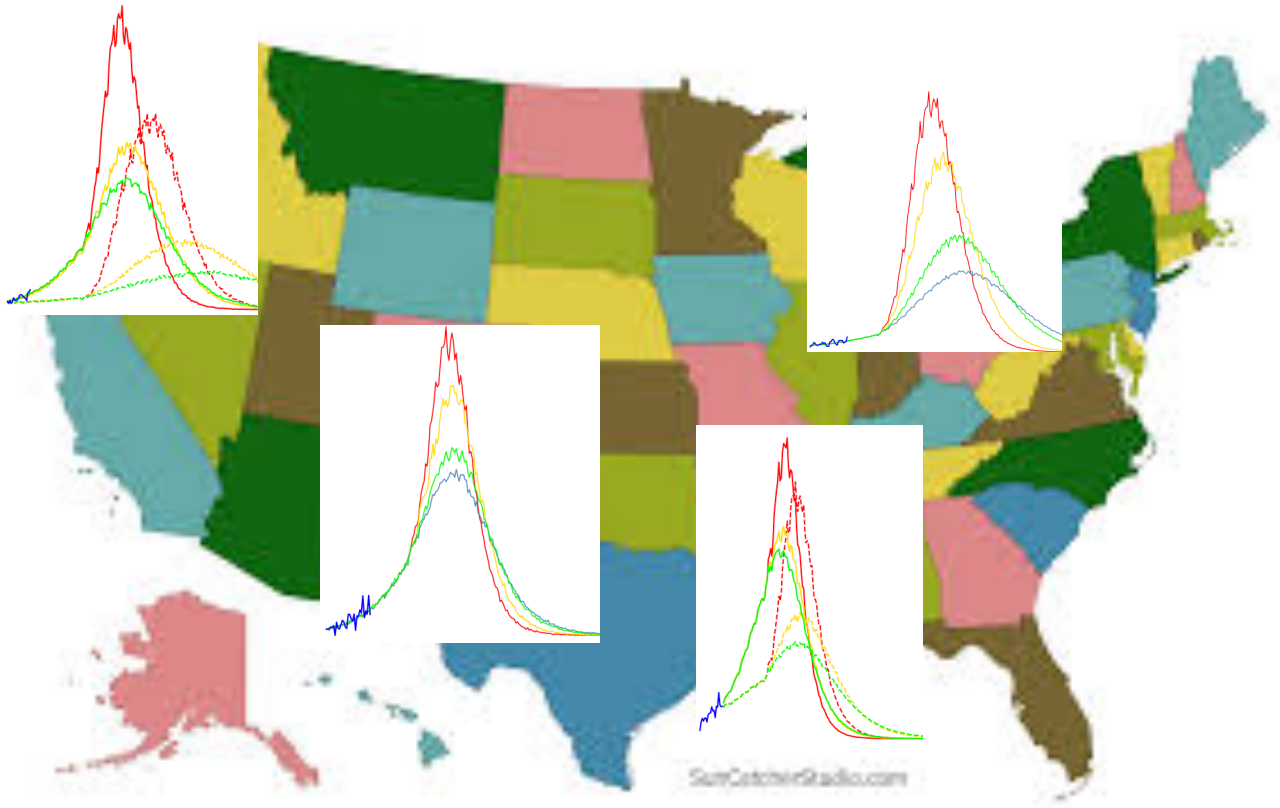




Agent-Based Models Enable More Detailed Scenario Exploration but also Pose Additional Challenges in Fitting Parameters

- EpiCast provides more flexibility but also requires more parameters to be estimated

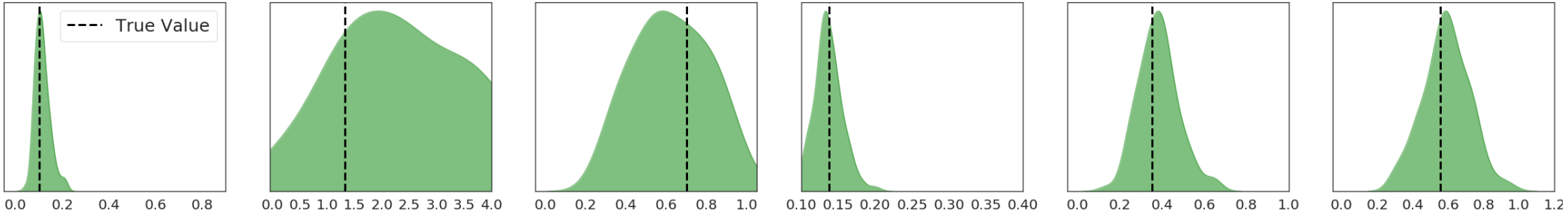




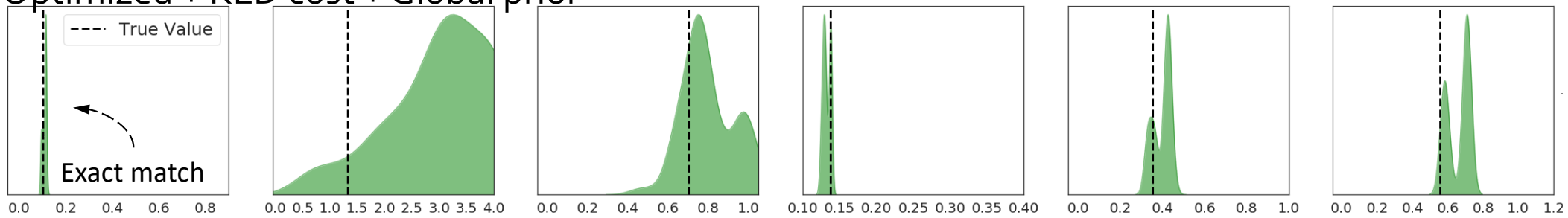
Using Deep Learning Surrogates and New Mixed Local and Global Parameter Estimation Provides Accurate and General Models

- Deep learning surrogate for 15 of the largest MSAs provides generalizable solution
- New joint parameter estimation approach provides tight posteriors (submitted to AAAI)

Naïve Posterior (top-100 of 200K samples)



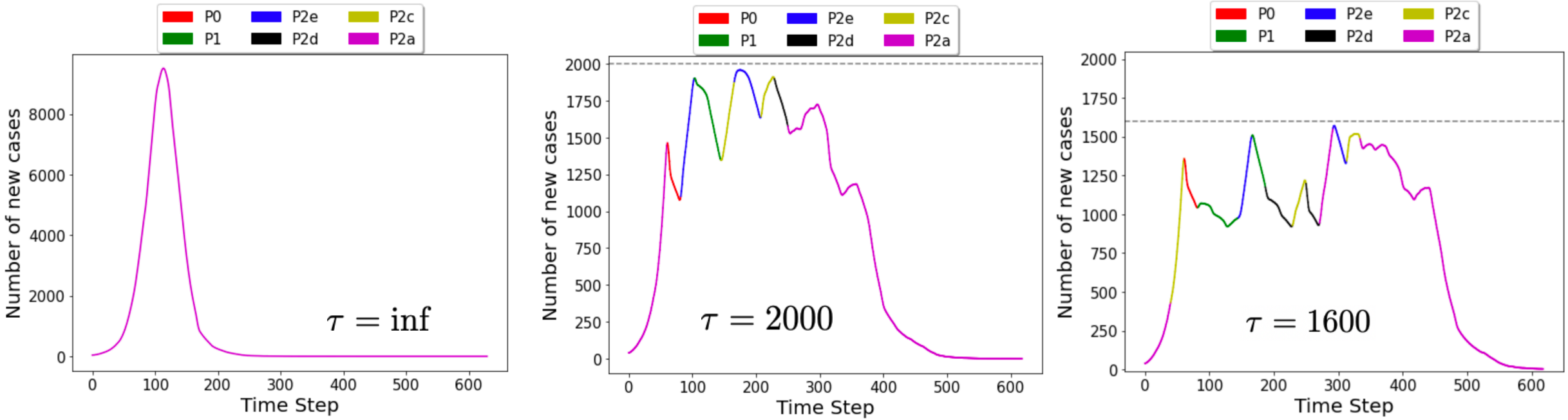
Optimized + KLD cost + Global prior



#1 INFECTED **#2 REMOVED** **#3 COMPLIANCE** **#4 TRANSPROP** **#5 PROP-ASYM** **#6 REL-INF**

Short-Term Deep Learning Surrogates Enable Modeling of Time Dependent Parameters and Policy Optimization

- Even perfectly calibrated predictions typically assume steady state conditions
- We build short term (2-4 weeks) flexible surrogates that allow us to
  - Change parameters of time
  - Optimize over (discrete) sets of parameter choices (submitted to AAAI)



Existing Capabilities Coupled with Diverse Expertise Provided Rapid Response and the Seed for Standing Emergency Resources

- DoE, LLNL, and LANL have provided two crucial resources
  - Existing tools for modeling complex systems, under uncertainties, with incomplete knowledge
  - Diverse expertise in tightly coupled teams able to rapidly prototype advanced solution
- Within months of the outbreak and limited resources the team made significant progress
  - Delivered new capabilities and decision-making tools to partner organizations
  - Advanced the state-of-the-art in epidemiological modeling and simulations
- Currently evaluating
  - How to transition this emergency response into standing capabilities for future outbreaks
  - What longer term research and capability developed will be needed

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CASC

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