Benton County COVID 19 Modeling

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Background

In an effort to produce local projections of the COVID-19 epidemic, epidemiologists at the Benton County Health Department in Corvallis, Oregon, developed an implementation of an SEIR model in R using the SimInf package. This presentation reviews the model, the package, and results from some different scenarios.

R package: SimInf

A flexible and efficient framework for data-driven stochastic disease spread simulations.

Developed by Widgren, Bauer, Eriksson, and Engblom

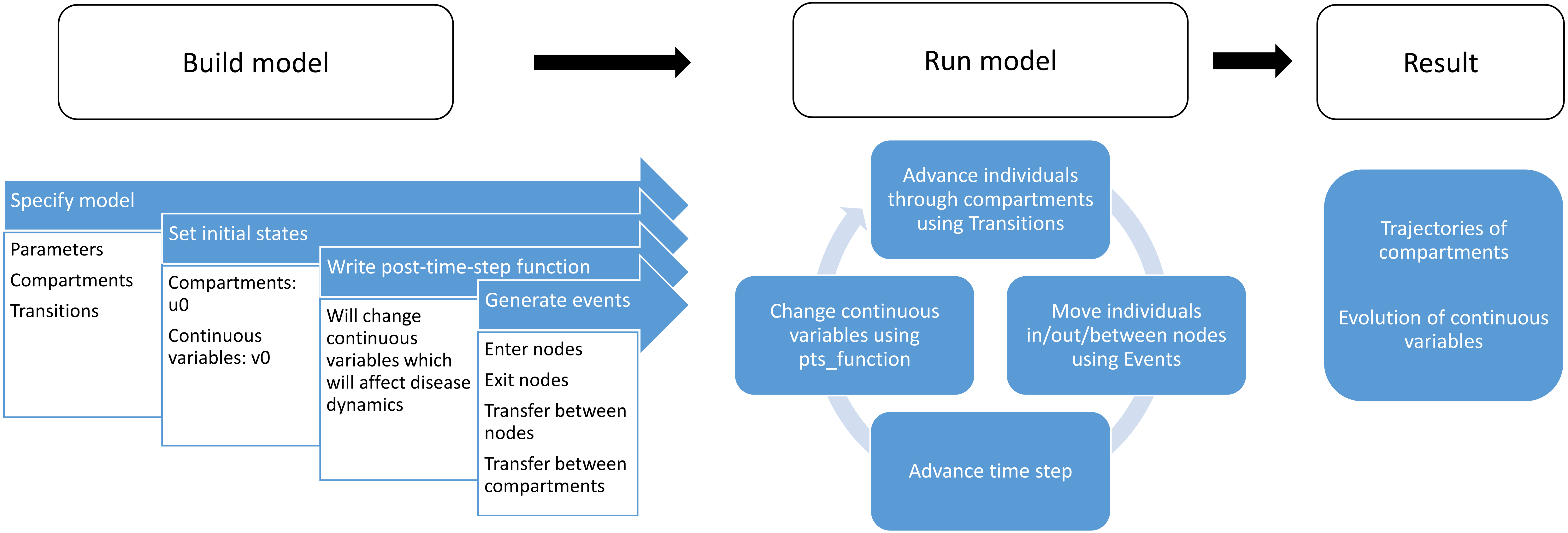
Widgren S, Bauer P, Eriksson R, Engblom S (2019). “SimInf: An R Package for Data-Driven Stochastic Disease Spread Simulations.” Journal of Statistical Software, 91(12), 1–42. doi: 10.18637/jss.v091.i12.

https://cran.r-project.org/web/packages/SimInf/vignettes/SimInf.pdf
https://cran.r-project.org/web/packages/SimInf/SimInf.pdf
https://github.com/stewid/SimInf

Components of SimInf

- Nodes – self-contained sub-populations within which the disease can spread.
- Compartments – the various disease compartments (e.g. SIR)
- Transitions – the disease dynamics model
- gdata = global parameters common to all nodes and trials
- ldata = local parameters that can vary by node/trial
- u0 = the initial state for the different compartments
- v0 = the initial state for continuous variables used in the transitions
- Events = a set of timed events for moving individuals into, out of, and between different nodes and compartments.
- pts_function = Post-time-step function. A function written in C that can alter any of the continuous variables, which in turn can alter the disease dynamics.

SimInf conceptual flow



The Benton County COVID-19 model

Susceptible/Exposed/Infected/Recovered with some isolation of infectious individuals, some hospitalizations, imperfect post-infection immunity, and mortality confined to the hospitalized population: SEIR *(S,Is,Im,H,M)*.

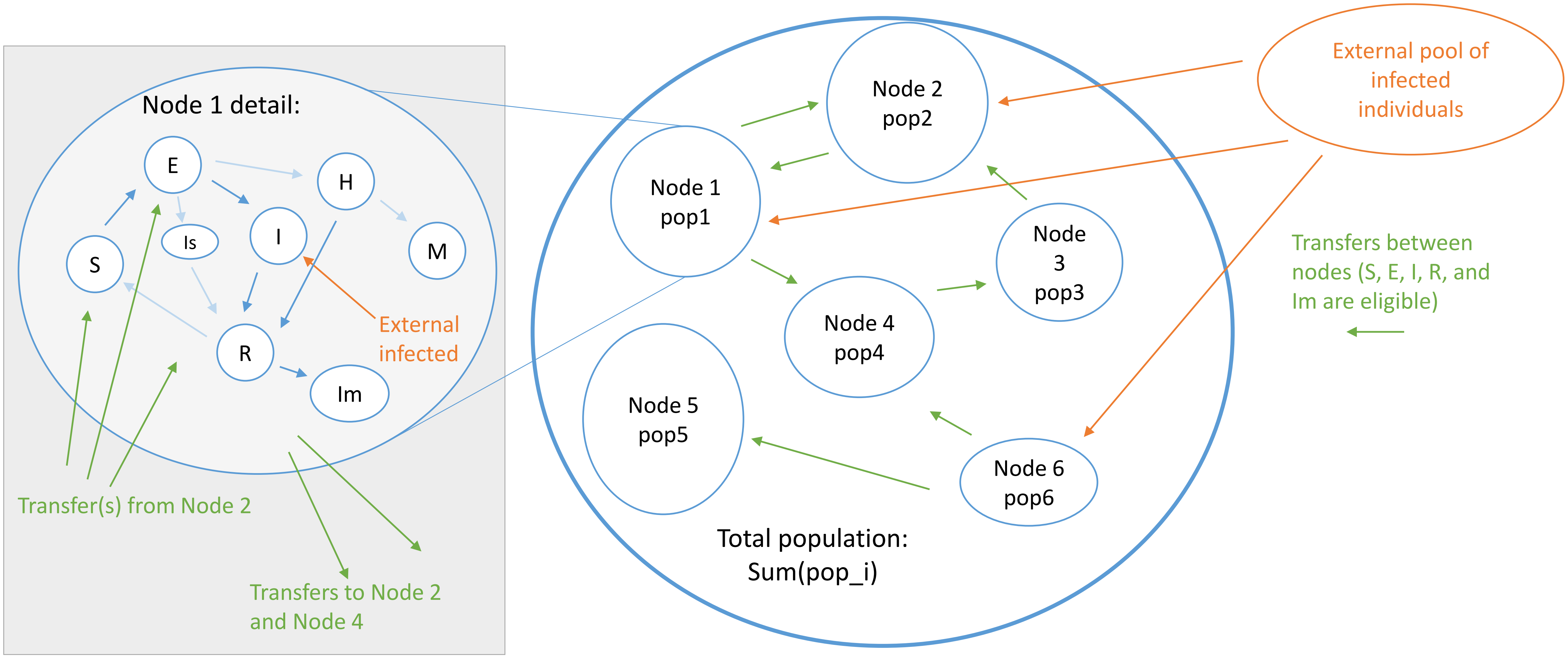
Characteristics of the Benton County COVID-19 model

- Multiple nodes within the total population to model segmented population
- Random movement of individuals between nodes to model mixing
- Parachuting infectious individuals to seed epidemic
- Unequal distribution of initial infectious across nodes, representing epidemic clustering
- Ability to change 73 different parameters to model different scenarios
- Multiple simultaneous trials to generate confidence intervals
- Policy responses to rising cases can decrease effective R0
- Seasonality of the coronavirus changes effective R0
- Enhanced contract tracing can reduce number of infectious
- Physical distancing reduces effective R0, with gradual decay toward no physical distancing
- Plots of compartments as well as cumulative and daily infections
- Ability to switch off policy responses for counterfactual scenarios
- Option to add a large number of individuals at discrete times, e.g. university students or super spreader event
- Discrete events that step down the current stay-at-home orders in 3 phases
- Options for natural birth rate and non-COVID-19 death rate

COVID-19 model transitions

Compartment	Transition (→ represents the greater fraction; -> represents the smaller fraction)
S = Susceptible	S → E according to density of infectious and susceptible, modulated by seasonality, physical distancing, and policy responses
E = Exposed	E → I according to natural transition to infectious; E -> Is according to effectiveness of contact tracing
I = Infectious	I → R according to natural recovery; I -> M according to case fatality rate
R = Recovered	R → Im according to development of natural immunity; R -> S according to loss of immunity
Is = Isolated	Is → R according to natural recovery
Im = Immune	Im remains in Im permanently
M = Deceased (mortality)	M remains in M permanently

COVID-19 model visual at a random time step



Events specific to Oregon and Benton County

- Current high level of stay-at-home/physical distancing in place. Stay-at-home will be lifted in three phases, physical distancing will remain.
- Stay-at-home will be re-instituted if COVID-19 prevalence crosses a certain threshold.
  - Two levels of increased stay-at-home orders available (minor and major).
- Population of Benton County will increase sharply when OSU students return in late September.
  - Assumes that most students will be susceptible, but that some will be exposed, infected, recovered, or immune.
  - Students are randomly distributed across a subset of the existing nodes.

Model specification

All of the following parameter categories can be changed to simulate different scenarios.

- Simulation parameters
- Population parameters
- Disease dynamic parameters
- Physical distancing parameters
- Event parameters
- Plotting parameters

Simulation parameters

- numTrials = Number of trials. Used to produce confidence intervals. Minimum number of trials = 1, maximum allowed = 100
- tSpan = Time span. How long the simulation lasts in days. No minimum or maximum.
- startofSimDay = Day that the simulation starts.

Population parameters

- N = Number of nodes – used to partition the population into different segments to represent partial mixing.
- trialPop = Total population of the trial.
  - Population per node is approximately (trialPop/N) with some randomization
- S0Pop … Im0Pop = Initial number of individuals in different compartments.
- maxINodeProp = Proportion of nodes with one or more infectious individuals – models the fact that disease distribution is not uniform across nodes.

Disease dynamics parameters

- R0 = Basic reproduction number. Used to calculate beta = R0*gamma
- RIsolated = Basic reproduction number of isolated individuals
- exposedPeriod = reciprocal of exposed period (how long after infection before individual becomes contagious)
- infectiousPeriod = reciprocal of infectious period (aka recovery rate)
- isoRate = proportion of exposed individuals identified through contact tracing
- isoPeriod = reciprocal of length of isolation period, which accounts for the infectious period of isolated individuals
- nonHospDeathRate = Fatality rate among non-hospitalized; generally assumed = 0
- hospDeathRate = Fatality rate among those hospitalized – generally assumed that all deaths occur in hospitals
- reSuscepRate = proportion of recovered who lose immunity and become susceptible again
- tempImmPeriod = reciprocal of recovered period; how long an individual has temporary immunity before either becoming permanently immune or susceptible again.
- Phi = Proportionate reduction in beta due to physical distancing. Beta is multiplied by 1/phi. Phi is changed in the post-time-step function
- Season = factor that represents seasonality of effective reproduction number. Calculated using cosine function with peak in February and trough in August.
- cosAmp = Amplitude of season factor. Large cosAmp = more seasonal variation.
- R0Spread = randomizer to create more variation in R0 between different trials.

Physical distancing parameters

- maxPrev1 = first prevalence threshold for instituting minor physical distancing. When prevalence > maxPrev, phi starts to increase.
    - maxPrev1 can be a number (e.g. 40 infected individuals) or a proportion (e.g. 1% of the population)
- maxPrev2 = second prevalence threshold for instituting major physical distancing. When prevalence > maxPrev1, phi starts to increase even more. maxPrev2 can also be a number or a proportion.
- phiFactor1 = Target for increased phi under minor physical distancing.
- phiFactor2 = Target for increased phi under major physical distancing.
- upDelay = how many days after maxPrev1 (maxPrev2) is exceeded before phi begins to change toward phiFactor1 (phiFactor2). Represents how long COVID-19 prevalence increases before we notice.
- downDelay = how many days after prevalence drops below maxPrev2 (maxPrev1) before phi begins to change toward phiFactor1 (toward baseline = 1). Represents how long we wait before relaxing physical distancing.
- phiMoveUp = how quickly phi converges up to phiFactor1 or phiFactor2. Larger phiMovement means phi converges more quickly. Represents how quickly people respond to changes in physical distancing policies.
- phiMoveDown = how quickly phi converges down to phiFactor or baseline. Larger phiMovement means phi converges more quickly. Represents how quickly people respond to changes in physical distancing policies.
- RPhysicalDistancing = ongoing baseline R0 representing people using physical distancing
- RNoAction = ongoing baseline R0 representing no policies and no physical distancing. RPhysicalDistancing decays to RNoAction as people return to their pre-pandemic social interactions.
- pdDecay = how quickly RPhysicalDistancing decays to RNoAction in number of days
- kbSwitch = Indicator if current major physical distancing is still in place. kbSwitch = 0 means current (March 23rd) physical distancing requirements are in effect. kbSwitch = 1 through 3 represents the three phases of lifting the physical distancing policies.
- switchOffPolices = Indicator if physical distancing policies will no longer be used after a certain day. switchOffPolicies = 0 means that phi will change according to the prevalence of COVID-19, representing physical distancing. switchOffPolicies = 1 means that phi will always equal 1, representing no more physical distancing policies. Used mostly to explore counterfactuals “what if we stopped responding to COVID-19 with physical distancing?”

Event parameters - Event types

There are six event types in the simulation:

- Parachuting events – one infected individual enters a random node in the otherwise closed population at random times.
- Transfer events – a random number of individuals from S, E, I, R, and Im compartments transfer from a random subset of nodes to another random subset at a random time.
- Super spreader event – a random subset of nodes transfers individuals from S to E in response to a super spreader.
- Student event – OSU students return in September
- Three events representing the phased lifting of current stay-at-home policies
- A “switch off policies event”, used for counterfactuals

Event parameters – Parachuting events

- parachuteRate = the reciprocal of the expected number of days between a parachute event. E.g. if parachuteRate = 1/30, then every month or so a parachute events occurs.
- parachuteNum = the number of infected individuals in each parachute event.
- parachuteDist = the distribution of parachute events. Allows the simulation to have more parachute events at certain times than others.
- paraChi_df = parameter to shape the distribution of parachute events. Default is to assume events start low due to travel restrictions, increase once restrictions ease, then decrease once global prevalence decreases.

Event parameters – transfer events

- transferRate = expected number of days between transfer events. E.g. if transferRate = 1/7, then people move between nodes approximately every week.
- transferNodeNum = the average number/proportion of nodes that transfer in every transfer event.
- transferMinProp = minimum proportion of node population that can transfer.
- transferMaxProp = maximum proportion of node population that can transfer.

- Transfers are constrained to nodes within the same trial. Transfers can happen at any time step during the simulation.

Event parameters – super spreader events

- There can be one or more super spreader events with different parameters
- superInfections = Number of infections caused by super spreader
- superNodes = number of nodes that the super spreader contacts
- superDate = the date the super spreader lands
- superSpread = symmetric spread in days of super spreader infections

Event parameters – student event

- StudentReturnDate = expected date students return to Benton County.
- StudentReturnSpread = parameter that spreads student return out across the selected number of days
- StudentPop = Number of students. How many students return to Benton County for Fall Term.
- maxStudentNodes = number of nodes into which students are added. Models the fact that students don't distribute uniformly across the whole county when they arrive.
- sSProp through sMProp: Student proportions of SEIRIm – used to specify the mix of students when they are added. Must sum to 1; sMProp = 0.

Event parameters – Lift stay-at-home and switch off policies events

- These events are controlled within pts_function.
- kbDay1 through kbDay3 = dates that all current (i.e. March 23rd) stay-at-home policies are phased out.
- switchOffPolicies = Indicator if stay-at-home policies will no longer be used after a certain day. switchOffPolicies = 0 means that phi will change according to the prevalence of COVID-19, representing stay-at-home. switchOffPolicies = 1 means that R0 will always equal RBaseline, representing no more stay-at-home policies. Used mostly to explore counterfactuals "what if we stopped responding to COVID-19 with stay-at-home orders?"
- switchOffDay = date that stay-at-home policies will no longer be used.

Plotting parameters

- Each trial produces its own trajectory for the compartments, as well as for prevalence and other continuous variables. The plotting function plots the distribution of a trajectory of selected compartment(s)/variable(s) by plotting the median, 95^{th} percentile, and 5^{th} percentile for each compartment.
- plotCompList = the set of compartments to plot.
- rollM = the number of days to average if a rolling average is used to smooth the projections.
- dateBreaks = how to show dates on the x-axis: month, week, day, etc.
- titleString, xString, yString, lString = Names of the title, x-axis, y-axis, and legend, respectively.

Key parameters, holding total population and disease dynamics constant

The following parameters are very important to the disease dynamics:

- Number of nodes and transfer parameters. The number of nodes and transfer parameters model how mixed the population is. A simulation with many nodes/low transfers represents a highly segmented population, where small epidemics burn out quickly. Few nodes/high transfers represent a well-mixed population, where epidemics can grow much more. Decreasing the number of nodes will increase the size of epidemics. Increasing transfer parameters will increase the size of epidemics.
- Effect of interventions/physical distancing. The more effective an intervention, the smaller the peak. Reducing the effectiveness of the intervention will allow the epidemic to grow larger.
- Prevalence thresholds. The higher the prevalence threshold, the less likely an intervention will be used. This will create a sharper curve, but also reduce the likelihood of multiple peaks and the total length of time an intervention is used.
- Contact tracing effectiveness. The more effective the contact tracing, the more individuals move to Is instead to I, reducing the epidemic spread.

Four example scenarios

Baseline Scenario

- No seasonality of coronavirus infectiousness
- No student return in September 2020
- Stay-at-home will be re-imposed in response to increased COVID-19 prevalence, at two levels

Best guess scenario

- Seasonality of coronavirus infectiousness
- Students return in September 2020
- Stay-at-home will be re-imposed in response to increased COVID-19 prevalence

Counterfactual scenario

- Seasonality of coronavirus infectiousness
- Students return in September 2020
- *No more stay-at-home whatsoever after July 15th 2020*

Enhanced Contact Tracing scenario

- Seasonality of coronavirus infectiousness
- Students return in September 2020
- Stay-at-home will be re-imposed in response to increased COVID-19 prevalence
- Contact tracing finds 4 times as many exposed individuals compared to baseline (half of all exposed individuals are isolated before they become infectious)

Baseline Scenario parameters (1)

Simulation

numTrials = 100	100 simulations
tSpan = 365	One year trajectory
startOfSimDay = 05/01/2020	Simulation starts on May 1st, 2020

Population

N = 500	500 segments of the population
trialPop = 65,000	Total population
I0Pop = 150, all other pop in S	Initial infectious (from TRACE)
maxINodeProp = 0.1	Up to 50 nodes with an initial infectious
trialPop/N = 130	Approximately 130 individuals per node

Phasing out current stay-at-home

kbDay1, kbDay2, kbDay3	5/25/2020, 6/20/2020, 7/15/2020

Disease Dynamics

R0 = 2.9	Transmissibility
RIsolated = .125	Transmissibility of isolated individuals
exposedPeriod = 1/4	1/(exposed period)
infectiousPeriod = 1/8	1/(infectious period)
isoRate = .125	1 in 8 exposed individuals are isolated by contact tracing
isoPeriod = 1/10	Reciprocal of isolated period (covers infectious period)
hospRate = .033	Proportion of infectious+isolated that are hospitalized
hospPeriod = 1/14	Reciprocal of hospitalization period
nonHospDeathRate = 0	Case fatality rate for non-hospitalized
hospDeathRate = .125	Fatality rate for hospitalized
reSuscepRate = .1	Proportion of recovereds who eventually become susceptible again
tempImmPeriod = 1/100	Reciprocal of temporary immune period
mu = 0	Natural birth rate
nu = 0	Non-COVID death rate
Initial phi --> Rt = .9	phi at beginning of sim (effective Rt = .9)
cosAmp = 0	No seasonal variation
R0Spread = .1	Uniform spread of R0 between trials

Transfer events

transferRate = 1/7	One transfer event approximately every 7 days
transferNodeNum = .05	5% of nodes transfer at every transfer event
transferMinProp = .01	At least 1% of population of node transfers every event
transferMaxProp = .1	At most 10% of population of node transfers every event

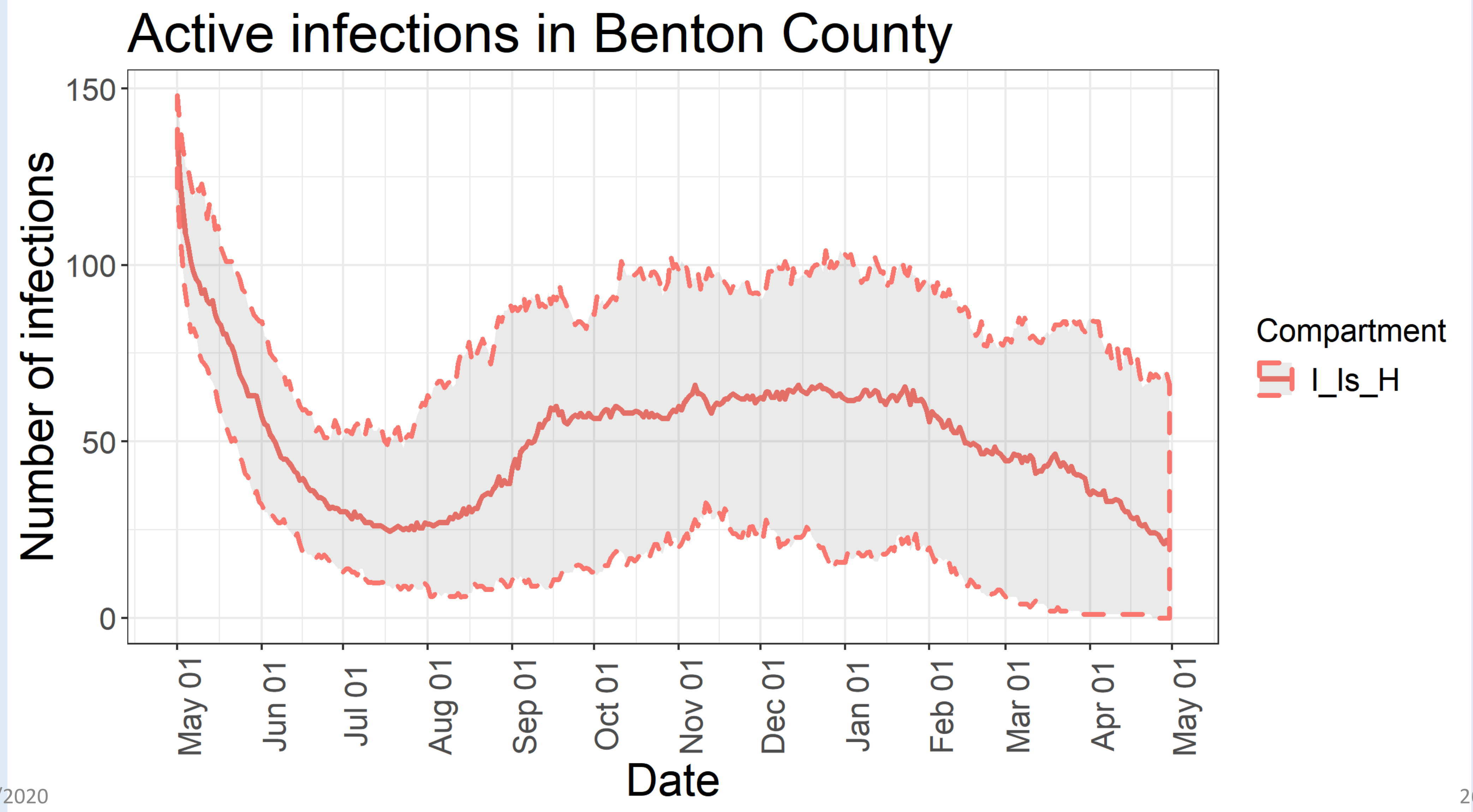
Baseline Scenario parameters (2)

Physical distancing	
maxPrev1 = .001	If prevalence rises above 1 in 1000, institute minor stay-at-home
maxPrev2 = .002	If prevalence rises above 2 in 1000, institute major stay-at-home
phiFactor1 --> R0 = 1.5	Minor stay-at-home reduces R0 to 1.5
phiFactor2 --> R0 = .9	Major stay-at-home reduces R0 to .9
upDelay = 10	Takes 10 days to identify uptick in prevalence
downDelay = 28	Wait 28 days after prevalence drops before lifting a stay-at-home policy
phiMoveUp = .25	Moderate speed of response to levying in stay-at-home policies
phiMoveDown = .1	Slow return to normal when lifting stay-at-home policies
kbSwitch = 0	Current (March 23rd) stay-at-home in place at beginning of simulation
RPhysicalDistancing = 2	Effective Rt with physical distancing but no interventions
RNoAction = 2.9	Effective Rt without interventions or physical distancing
pdDecay = 30	Number of days it takes for RPhysicalDistancing to rise to RNoAction

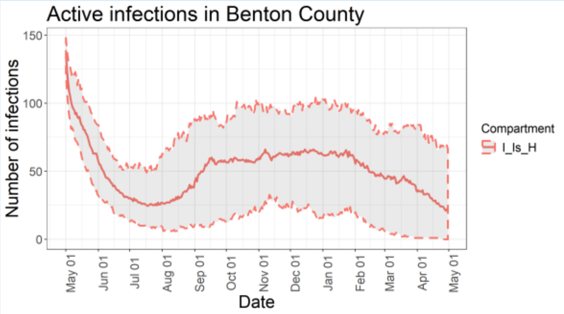
Parachuting events	
parachuteRate = 1/30	1 parachute event approximately every 30 days
parachuteNum = 1	1 infected individual in each parachute event
paraChi_df = 4	More parachute events in months 2 through 7 then in other months

No Student Events

Projections of active COVID-19 infections under the baseline scenario



Baseline scenario - interpretations



The baseline scenario projects that the phased lifting of stay-at-home orders will reduce the prevalence to below 20 by mid summer.

However, the relaxation of stay-at-home will allow COVID-19 to persist in the community and support new infections as they parachute in. The prevalence will begin to rise again after the current stay-at-home policies are completely lifted in July.

Nevertheless, continued effective contact tracing, physical distancing, and a lack of seasonality will lead the epidemic to dwindle through the winter and spring of 2021.

Note: In this scenario, the small wave from September-October is not dependent on returning students: the baseline scenario specifically excludes the return of students.

Note: This scenario does not represent a laissez-faire approach to pandemic control. Extensive contact tracing and physical distancing are key control measures.

Best-Guess Scenario parameters (1)

Simulation	
numTrials = 100	100 simulations
tSpan = 365	One year trajectory
startOfSimDay = 05/01/2020	Simulation starts on May 1st, 2020

Population	
N = 500	500 segments of the population
trialPop = 65,000	Total population
I0Pop = 150, all other pop in S	Initial infectious (from TRACE)
maxINodeProp = 0.1	Up to 50 nodes with an initial infectious
trialPop/N = 130	Approximately 130 individuals per node

Phasing out current stay-at-home	
kbDay1, kbDay2, kbDay3	5/25/2020, 6/20/2020, 7/15/2020

Disease Dynamics			
R0 = 2.9	Transmissibility	tempImmPeriod = 1/100	Reciprocal of temporary immune period
RIsolated = .125	Transmissibility of isolated individuals	mu = 0	Natural birth rate
exposedPeriod = 1/4	1/(exposed period)	nu = 0	Non-COVID death rate
infectiousPeriod = 1/8	1/(infectious period)	Initial phi --> Rt = .9	phi at beginning of sim (effective Rt = .9)
isoRate = .125	1 in 8 exposed individuals are isolated by contact tracing	cosAmp = .25	Moderate seasonal variation in transmissibility of the coronavirus
isoPeriod = 1/10	Reciprocal of isolated period (covers infectious period)	R0Spread = .1	Uniform spread of R0 between trials
hospRate = .033	Proportion of infectious+isolated that are hospitalized		
hospPeriod = 1/14	Reciprocal of hospitalization period		
nonHospDeathRate = 0	Case fatality rate for non-hospitalized		
hospDeathRate = .125	Fatality rate for hospitalized		
reSuscepRate = .1	Proportion of recovereds who eventually become susceptible again		

Transfer events	
transferRate = 1/7	One transfer event approximately every 7 days
transferNodeNum = .05	5% of nodes transfer at every transfer event
transferMinProp = .01	At least 1% of population of node transfers every event
transferMaxProp = .1	At most 10% of population of node transfers every event

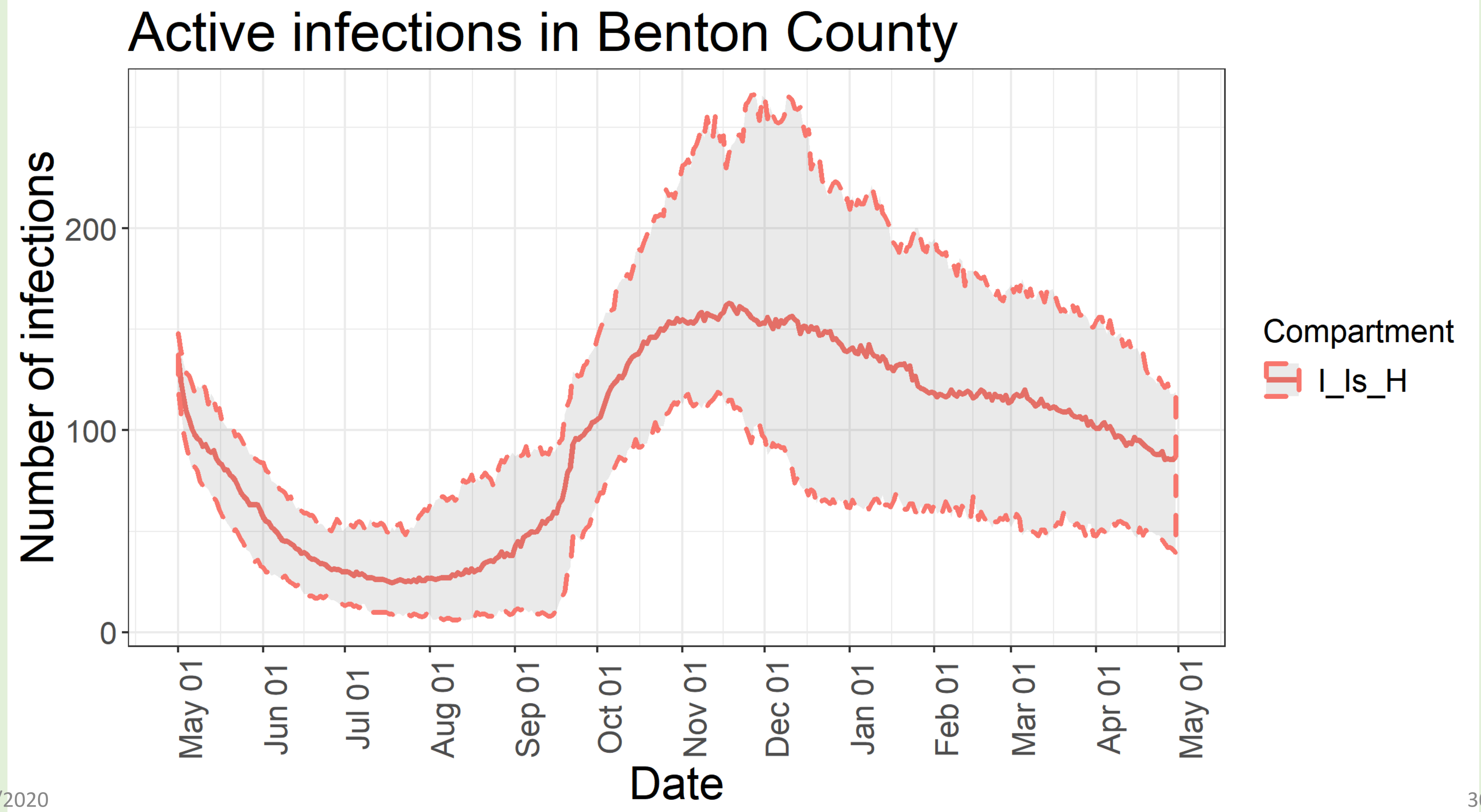
Best-Guess Scenario parameters (2)

Physical distancing	
maxPrev1 = .001	If prevalence rises above 1 in 1000, institute minor stay-at-home
maxPrev2 = .002	If prevalence rises above 2 in 1000, institute major stay-at-home
phiFactor1 --> R0 = 1.5	Minor stay-at-home reduces R0 to 1.5
phiFactor2 --> R0 = .9	Major stay-at-home reduces R0 to .9
upDelay = 10	Takes 10 days to identify uptick in prevalence
downDelay = 28	Wait 28 days after prevalence drops before lifting a stay-at-home policy
phiMoveUp = .25	Moderate speed of response to levying in stay-at-home policies
phiMoveDown = .1	Slow return to normal when lifting stay-at-home policies
kbSwitch = 0	Current (March 23rd) stay-at-home in place at beginning of simulation
RPhysicalDistancing = 2	Effective Rt with physical distancing but no interventions
RNoAction = 2.9	Effective Rt without interventions or physical distancing
pdDecay = 30	Number of days it takes for RPhysicalDistancing to rise to RNoAction

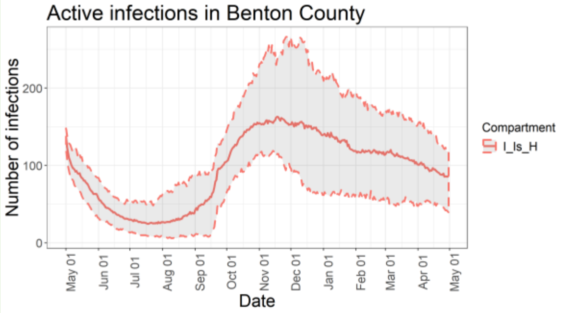
Parachuting events	
parachuteRate = 1/30	1 parachute event approximately every 30 days
parachuteNum = 1	1 infected individual in each parachute event
paraChi_df = 4	More parachute events in months 2 through 7 then in other months

Student Events	
studentPop = 25,000	Student population is 25,000
studentReturnDate = 09/21/2020	Students return around 9/21/2020
maxStudentNodes = 100	Students distribute across 100 nodes (1/5 of the total nodes)
sSProp = .9, sEProp = .0001, sIProp = .0015, sRProp = .9*remaining, sImProp = .1*remaining	90% of students are susceptible; with a few exposed, a few more infectious, and the rest recovered/immune

Projections of active COVID-19 infections under the best-guess scenario



Best-guess scenario - interpretations



The best-guess scenario matches the baseline scenario through September. Then, when students return in September, they will bring with them about 40 new infections.

The import of infected students immediately starts a minor intervention, which slows the epidemic in October and November. The minor intervention in this scenario would maintained through March 2021, then gradually lifted over the next month. Note – this model does not include students leaving for Winter Break.

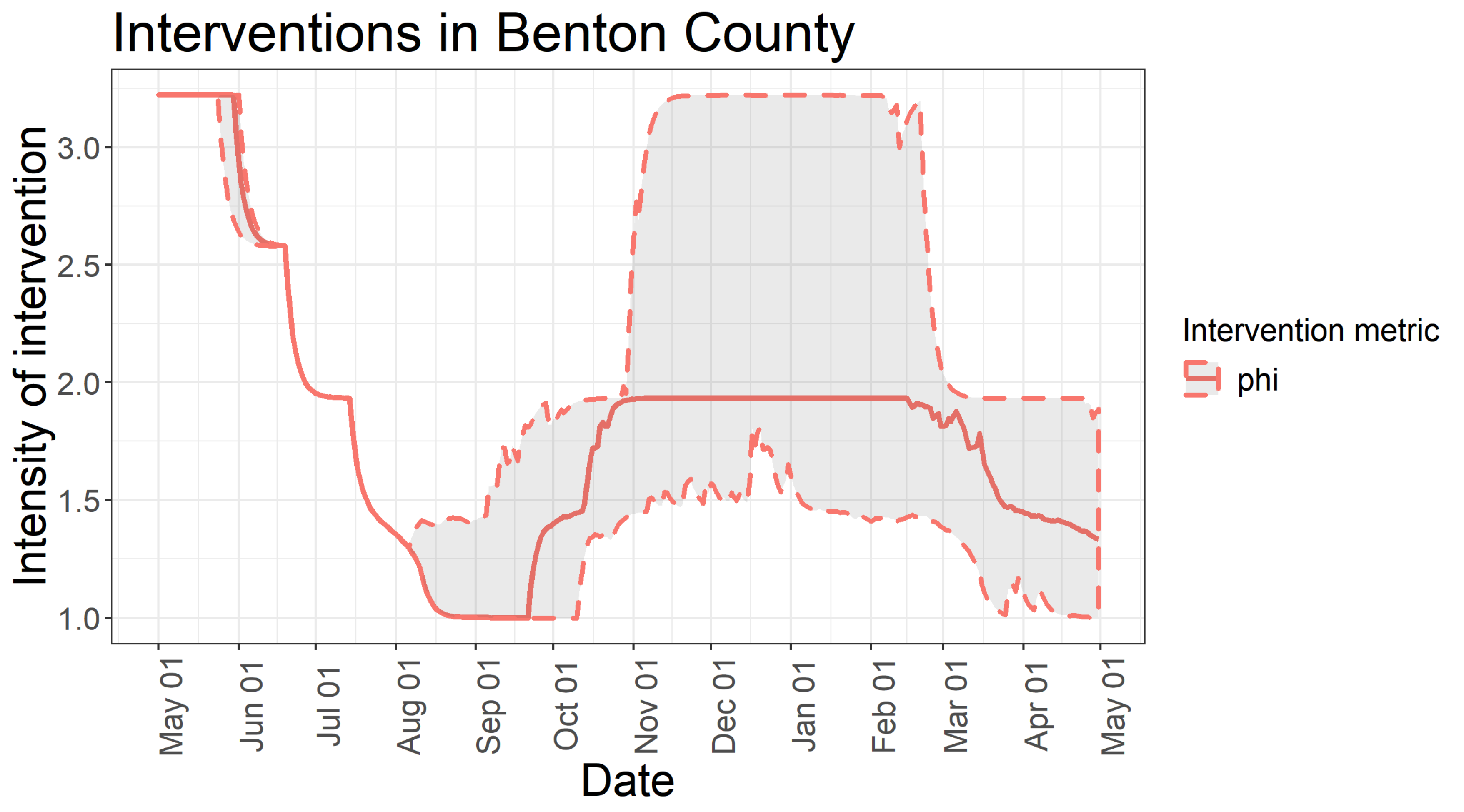
Daily active infections would peak at around 150 (similar to the beginning of May 2020) in November 2020, then slowly decrease over the next six months.

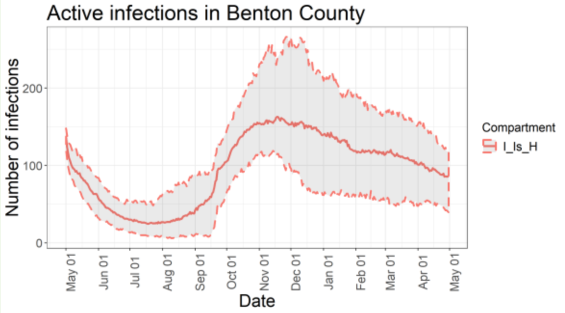
Minor stay-at-home interventions, continued effective contact tracing, and the seasonal effect will lead the epidemic to dwindle through the spring of 2021.

Note: This scenario does not represent a laissez-faire approach to pandemic control. A six months of minor stay-at-home orders are needed and extensive contact tracing and physical distancing are key control measures.

Note: If the prevalence threshold for a major intervention was lowered, we could see a sharper drop-off in cases after November 2020.

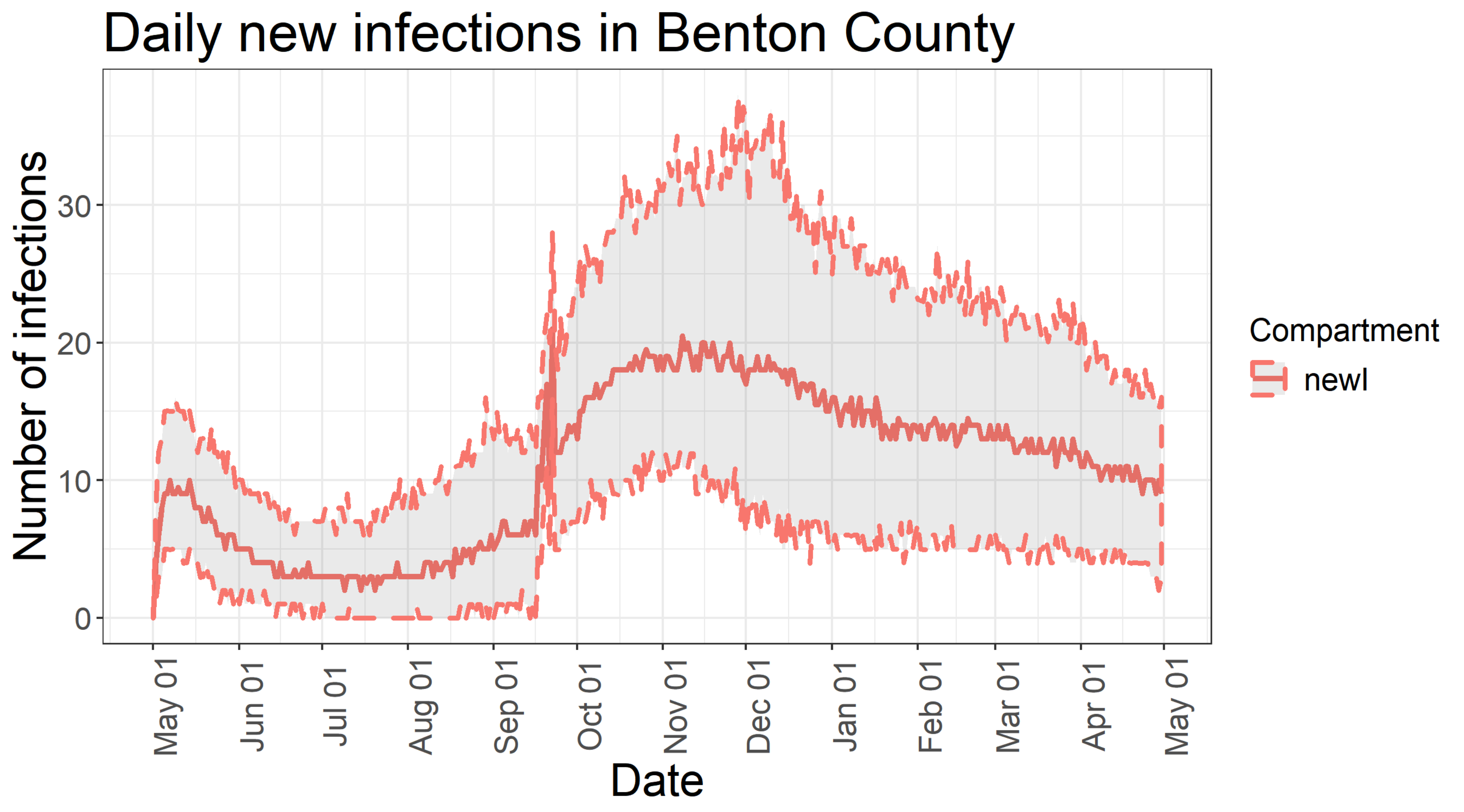
Best-guess scenario – interventions

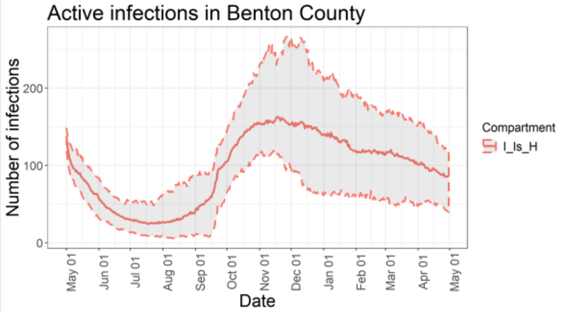




This graph visualizes stay-at-home policies and physical distancing. At the beginning of the simulation, the current major stay-at-home policies are in effect. They are fully removed on July 15th. By September, people have stopped physical distancing. In response to the import of infected students in September, minor stay-at-home is re-imposed on September 28th. Epidemic pressure requires the more-or-less continual use of minor stay-at-home policies until April 2021.

Best-guess scenario – Daily new cases





This graph visualizes daily new infections. With the current high prevalence, May has about 10 new infections per day. During summer of 2020, the daily new infections drops to close to 1 or 2. When the students return across the course of a week, daily new cases spike to as many as 20 per day, and as the epidemic pressure pushes the newly seeded infections through the population, new infections only slowly drop from 20 to 10 over the next 8 months.

Counterfactual Scenario parameters (1)

Simulation		Disease Dynamics			
numTrials = 100	100 simulations	R0 = 2.9	Transmissibility	tempImmPeriod = 1/100	Reciprocal of temporary immune period
tSpan = 365	One year trajectory	RIsolated = .125	Transmissibility of isolated individuals	mu = 0	Natural birth rate
startOfSimDay = 05/01/2020	Simulation starts on May 1st, 2020	exposedPeriod = 1/4	1/(exposed period)	nu = 0	Non-COVID death rate
Population		infectiousPeriod = 1/8	1/(infectious period)	Initial phi --> Rt = .9	phi at beginning of sim (effective Rt = .9)
N = 500	500 segments of the population	isoRate = .125	1 in 8 exposed individuals are isolated by contact tracing	cosAmp = .25	Moderate seasonal variation in transmissibility of the coronavirus
trialPop = 65,000	Total population	isoPeriod = 1/10	Reciprocal of isolated period (covers infectious period)	R0Spread = .1	Uniform spread of R0 between trials
I0Pop = 150, all other pop in S	Initial infectious (from TRACE)	hospRate = .033	Proportion of infectious+isolated that are hospitalized	**Transfer events**	
maxINodeProp = 0.1	Up to 50 nodes with an initial infectious	hospPeriod = 1/14	Reciprocal of hospitalization period	transferRate = 1/7	One transfer event approximately every 7 days
trialPop/N = 130	Approximately 130 individuals per node	nonHospDeathRate = 0	Case fatality rate for non-hospitalized	transferNodeNum = .05	5% of nodes transfer at every transfer event
Phasing out current stay-at-home		hospDeathRate = .125	Fatality rate for hospitalized	transferMinProp = .01	At least 1% of population of node transfers every event
kbDay1, kbDay2, kbDay3	5/25/2020, 6/20/2020, 7/15/2020	reSuscepRate = .1	Proportion of recovereds who eventually become susceptible again	transferMaxProp = .1	At most 10% of population of node transfers every event

Counterfactual Scenario parameters (2)

Physical distancing	
maxPrev1 = .001	If prevalence rises above 1 in 1000, institute minor stay-at-home
maxPrev2 = .002	If prevalence rises above 2 in 1000, institute major stay-at-home
phiFactor1 --> R0 = 1.5	Minor stay-at-home reduces R0 to 1.5
phiFactor2 --> R0 = .9	Major stay-at-home reduces R0 to .9
upDelay = 10	Takes 10 days to identify uptick in prevalence
downDelay = 28	Wait 28 days after prevalence drops before lifting a stay-at-home policy
phiMoveUp = .25	Moderate speed of response to levying in stay-at-home policies
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kbSwitch = 0	Current (March 23rd) stay-at-home in place at beginning of simulation
RPhysicalDistancing = 2	Effective Rt with physical distancing but no interventions
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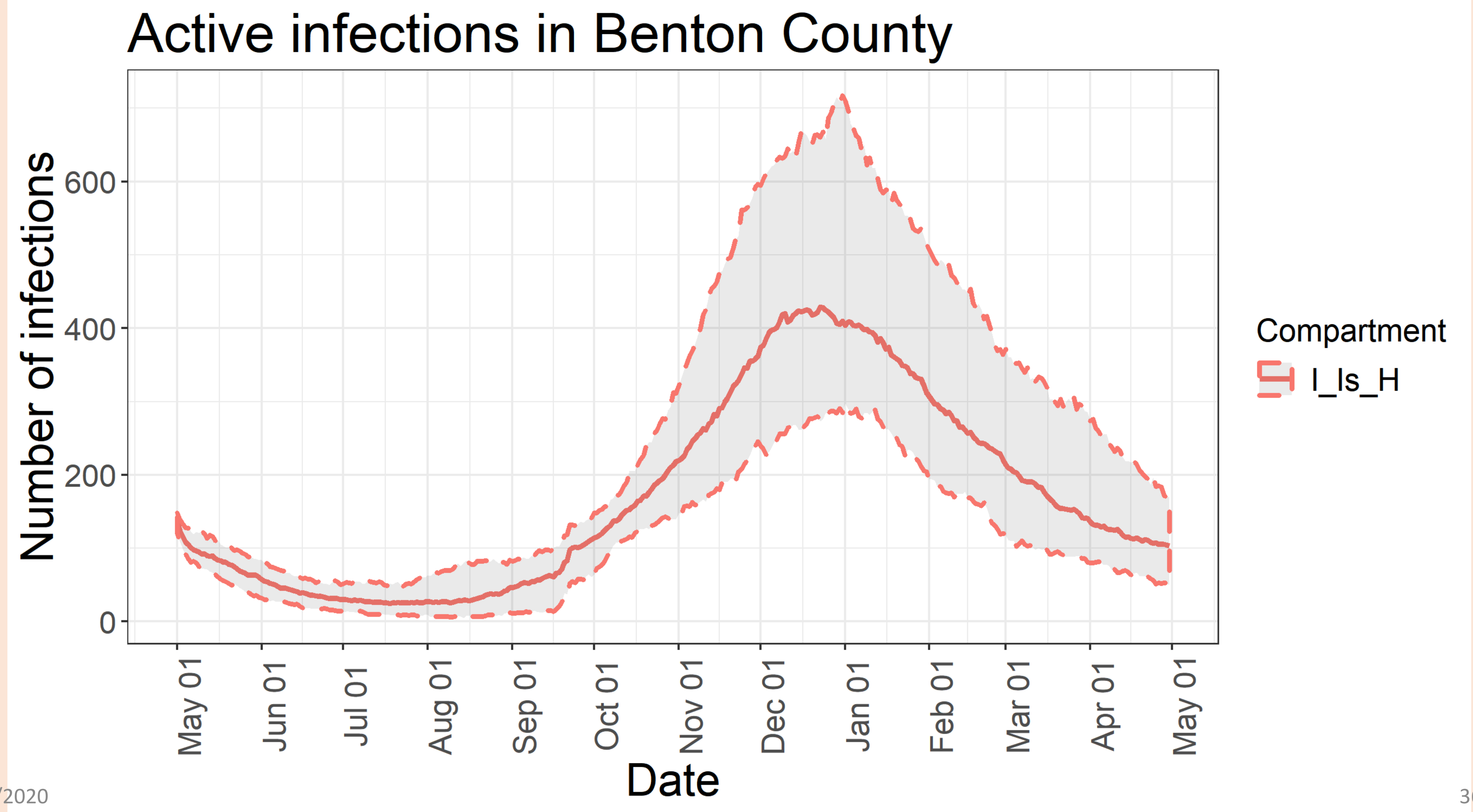
pdDecay = 30	Number of days it takes for RPhysicalDistancing to rise to RNoAction

Parachuting events	
parachuteRate = 1/30	1 parachute event approximately every 30 days
parachuteNum = 1	1 infected individual in each parachute event
paraChi_df = 4	More parachute events in months 2 through 7 then in other months

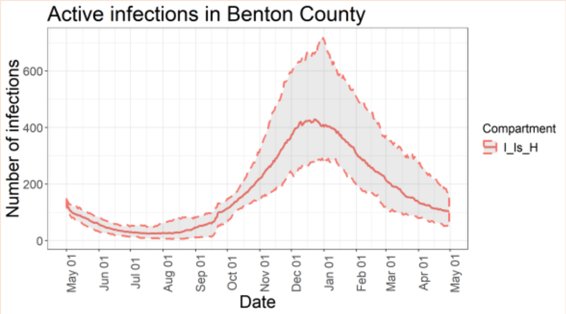
Student Events	
studentPop = 25,000	Student population is 25,000
studentReturnDate = 09/21/2020	Students return around 9/21/2020
maxStudentNodes = 100	Students distribute across 100 nodes (1/5 of the total nodes)
sSProp = .9, sEProp = .0001, sIProp = .0015, sRProp = .9*remaining, sImProp = .1*remaining	90% of students are susceptible; with a few exposed, a few more infectious, and the rest recovered/immune

Switch off policies
Beginning on 07/01/2020, no stay-ate-home policy interventions will be used in response to prevalence. Physical distancing and contact tracing will be the only response measures.

Projections of active COVID-19 infections under the counterfactual scenario



Counterfactual scenario - interpretations



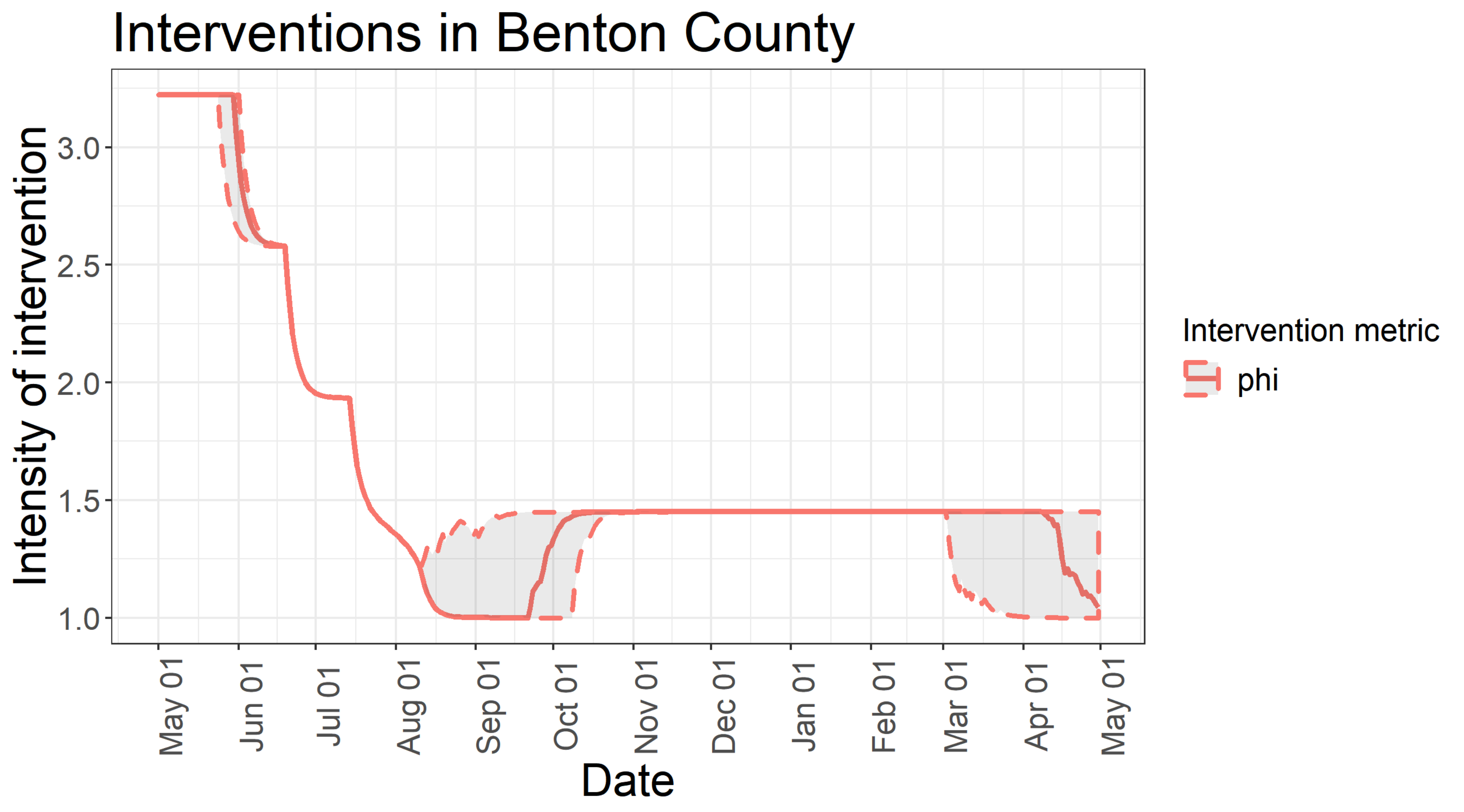
The counterfactual scenario predicts a slow resurgence but unstoppable recurrence of COVID-19 cases that starts basically immediately after the current stay-at-home policies are fully lifted. Without stay-at-home policies, the return of students would be a drop in the bucket as far as additional infections are concerned. The students would increase the susceptible population by about 22,000, but that doesn’t materially change the shape of the curve.

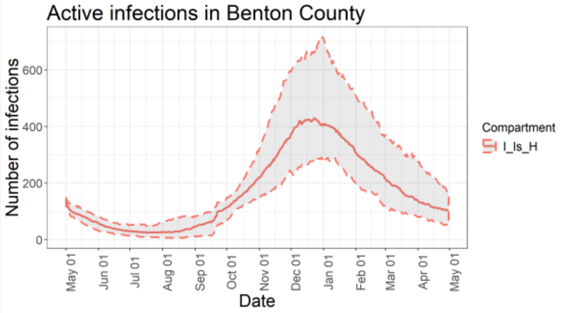
This model predicts that the epidemic would peak in December 2020.

Under this counterfactual scenario, the epidemic would burn through Benton County in one wave, after which enough of the population would have been infected that the epidemic would die out.

Note:
Given the successful control of COVID-19 through the March 23rd stay-at-home policies, enough susceptible people will remain in Benton County that this scenario is likely to play out if we ever stop using stay-at-home policies as a response to resurging cases before the development and widespread use of an effective vaccine. All it would take would be one or two super-spreaders (analogous to parachuting in 40 infected students).

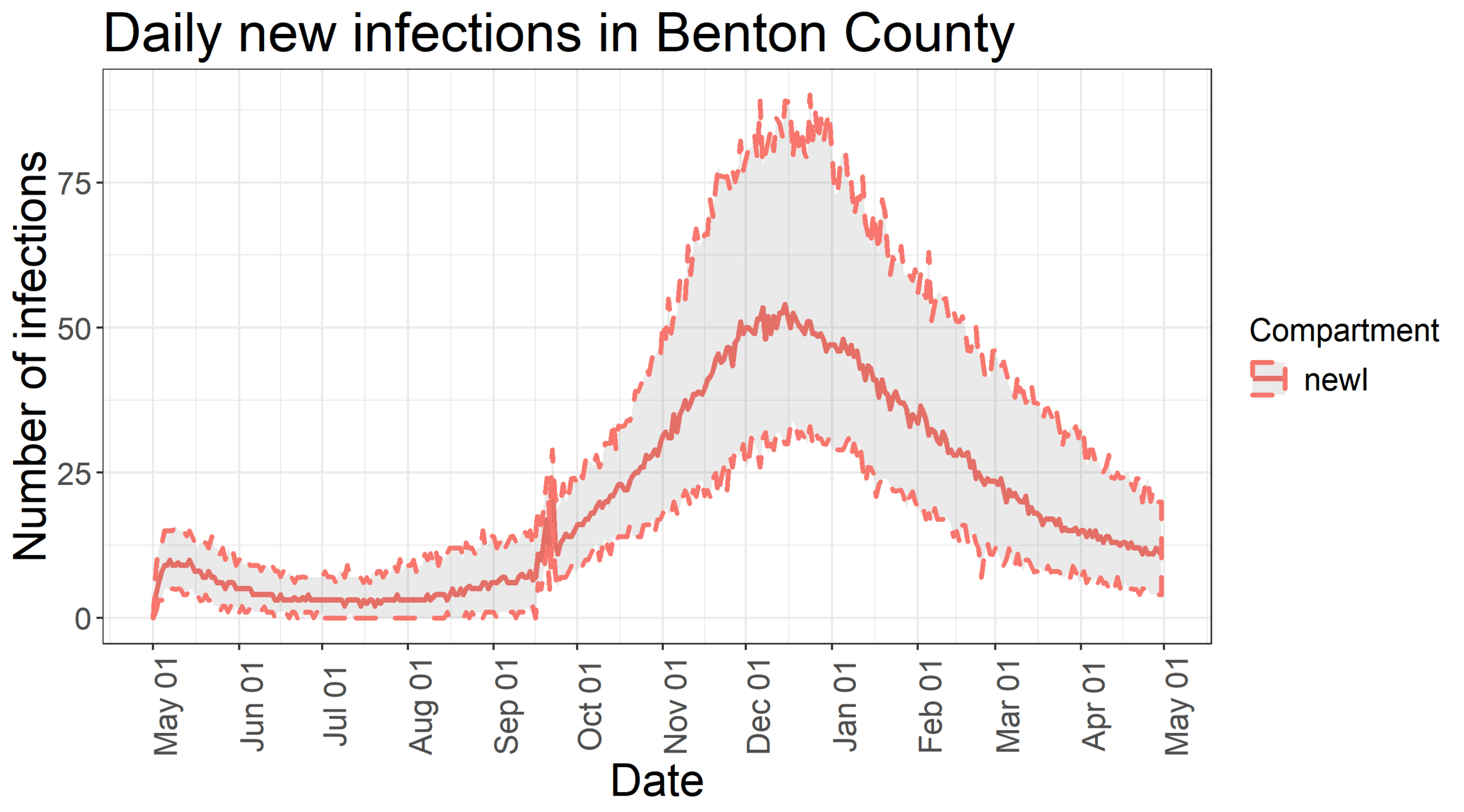
Counterfactual scenario – interventions

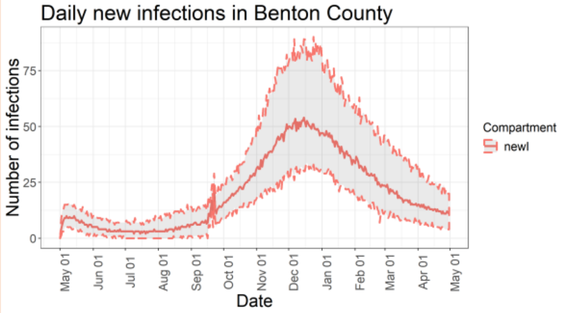




This graph visualizes stay-at-home policies and physical distancing. At the beginning of the simulation, the current major stay-at-home policies are in effect. They are fully removed on July 7th. Under this counterfactual scenario, no more stay-at-home policies will be used. Individuals practicing physical distancing is the reason that phi is close to 1.5 from October 2020 through April 2021.

Counterfactual scenario – daily new infections





This graph visualizes daily new infections. During summer of 2020, the daily new infections drops to close to 0 or 1. When the students return across the course of a week, daily new cases reach up to 20. Without stay-at-home orders, new cases continue to climb, peaking at close to 50 new cases each day in December 2020. Daily new cases decline toward 10 per day by May 2021.

Enhanced contact tracing parameters (1)

Simulation

numTrials = 100	100 simulations
tSpan = 365	One year trajectory
startOfSimDay = 05/01/2020	Simulation starts on May 1st, 2020

Population

N = 500	500 segments of the population
trialPop = 65,000	Total population
I0Pop = 150, all other pop in S	Initial infectious (from TRACE)
maxINodeProp = 0.1	Up to 50 nodes with an initial infectious
trialPop/N = 130	Approximately 130 individuals per node

Phasing out current stay-at-home

kbDay1, kbDay2, kbDay3	5/25/2020, 6/20/2020, 7/15/2020

Disease Dynamics

R0 = 2.9	Transmissibility	templmmPeriod = 1/100	Reciprocal of temporary immune period
RIsolated = .125	Transmissibility of isolated individuals	mu = 0	Natural birth rate
exposedPeriod = 1/4	1/(exposed period)	nu = 0	Non-COVID death rate
infectiousPeriod = 1/8	1/(infectious period)	Initial phi --> Rt = .9	phi at beginning of sim (effective Rt = .9)
isoRate = .5	Half of all exposed individuals are isolated by contact tracing	cosAmp = .25	Moderate seasonal variation in transmissibility of the coronavirus
isoPeriod = 1/10	Reciprocal of isolated period (covers infectious period)	R0Spread = .1	Uniform spread of R0 between trials
hospRate = .033	Proportion of infectious+isolated that are hospitalized		
hospPeriod = 1/14	Reciprocal of hospitalization period		
nonHospDeathRate = 0	Case fatality rate for non-hospitalized		
hospDeathRate = .125	Fatality rate for hospitalized		
reSuscepRate = .1	Proportion of recovereds who eventually become susceptible again		

Transfer events

transferRate = 1/7	One transfer event approximately every 7 days
transferNodeNum = .05	5% of nodes transfer at every transfer event
transferMinProp = .01	At least 1% of population of node transfers every event
transferMaxProp = .1	At most 10% of population of node transfers every event

Enhanced contact tracing parameters (2)

Physical distancing	
maxPrev1 = .001	If prevalence rises above 1 in 1000, institute minor stay-at-home
maxPrev2 = .002	If prevalence rises above 2 in 1000, institute major stay-at-home
phiFactor1 --> R0 = 1.5	Minor stay-at-home reduces R0 to 1.5
phiFactor2 --> R0 = .9	Major stay-at-home reduces R0 to .9
upDelay = 10	Takes 10 days to identify uptick in prevalence
downDelay = 28	Wait 28 days after prevalence drops before lifting a stay-at-home policy
phiMoveUp = .25	Moderate speed of response to levying in stay-at-home policies
phiMoveDown = .1	Slow return to normal when lifting stay-at-home policies
kbSwitch = 0	Current (March 23rd) stay-at-home in place at beginning of simulation
RPhysicalDistancing = 2	Effective Rt with physical distancing but no interventions
RNoAction = 2.9	Effective Rt without interventions or physical distancing
pdDecay = 30	Number of days it takes for RPhysicalDistancing to rise to RNoAction

Parachuting events	
parachuteRate = 1/30	1 parachute event approximately every 30 days
parachuteNum = 1	1 infected individual in each parachute event
paraChi_df = 4	More parachute events in months 2 through 7 then in other months

Student Events	
studentPop = 25,000	Student population is 25,000
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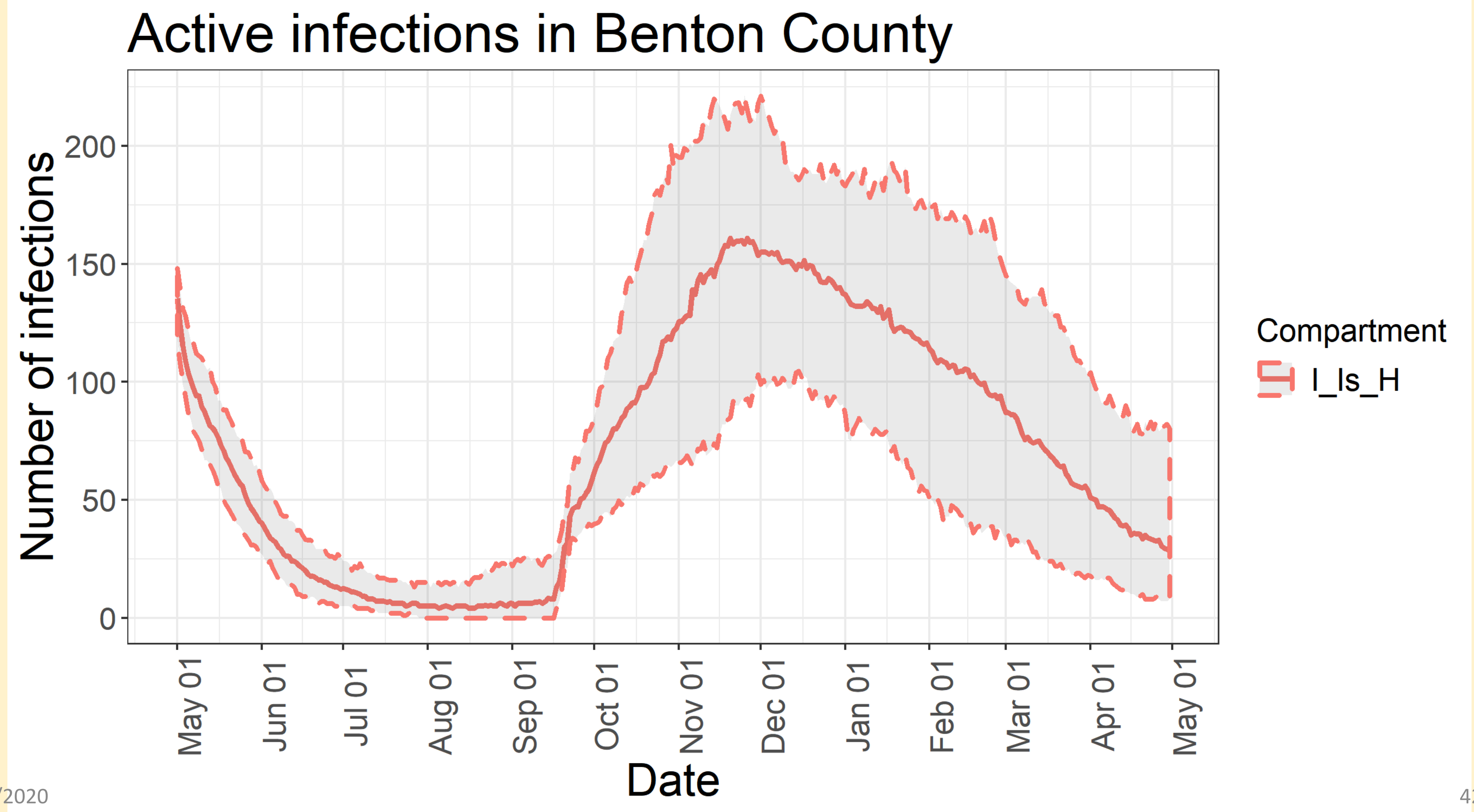
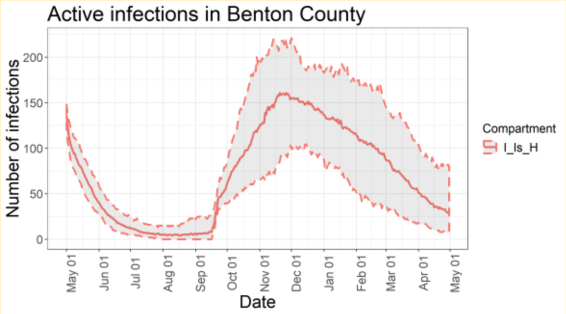
Projections of active COVID-19 infections under enhanced contact tracing



Enhanced contact tracing - interpretations



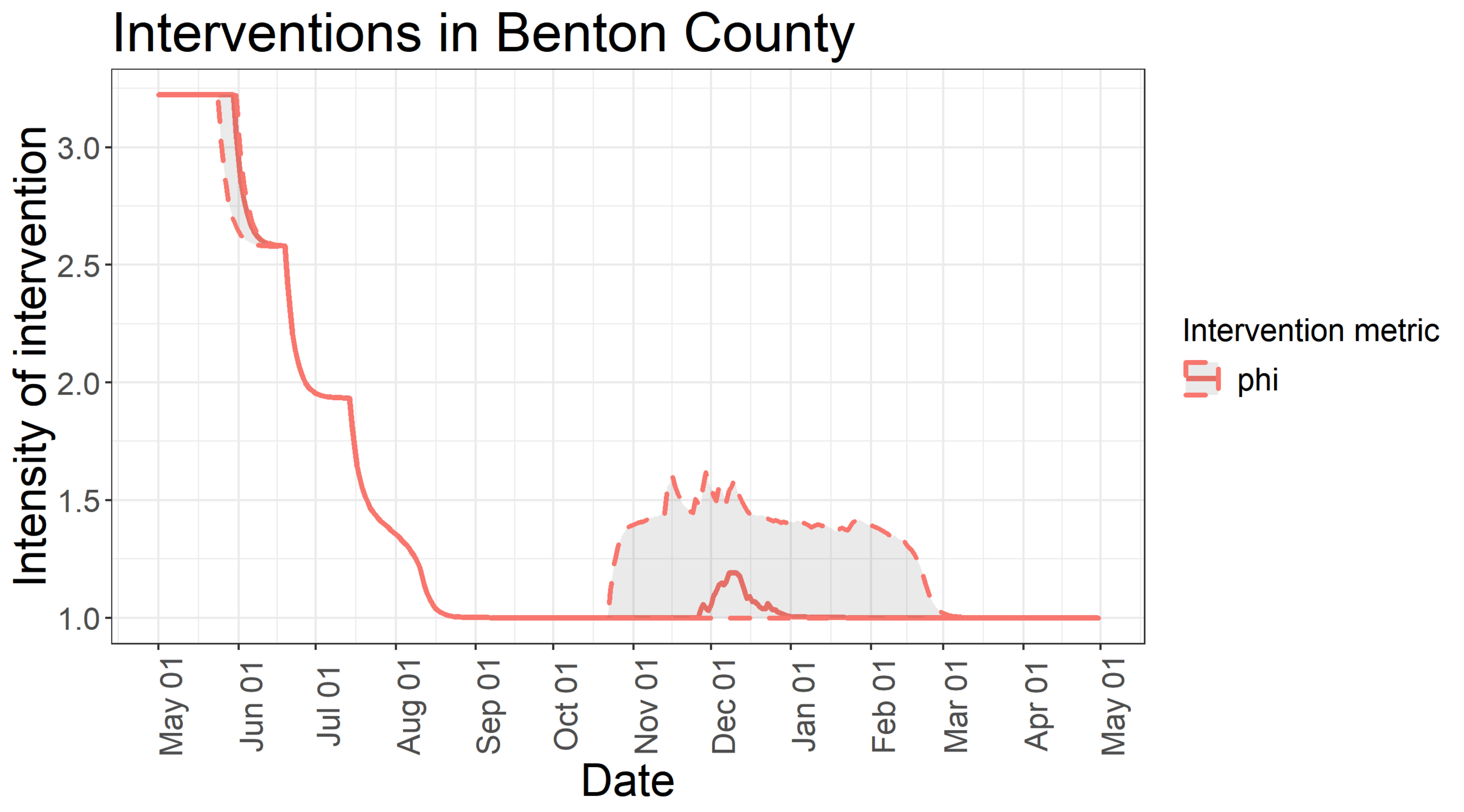
The enhanced contract tracing scenario closely resembles the best-guess scenario in terms of active infections. The major difference is a sharper drop-off of active infections beginning in December 2020.

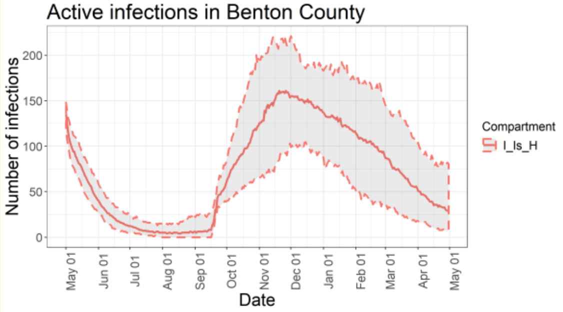
However, this plot conceals a major difference – because of enhanced contact tracing, stay-at-home orders will not be needed to control the second wave of the infection at the same level as in the best-guess scenario (see the next slide for the interventions). This can be interpreted as a much lower shock to society/economy when the students return.

Daily active infections would peak at around 150 (similar to the beginning of May 2020) in November 2020, then decrease over the next six months to around 30 active infections in May 2021.

Note: This scenario does not represent a laissez-faire approach to pandemic control. Extensive and wildly successful contact tracing is a key control measure. “Contact tracing” can be understood to also include widespread testing, individual willingness to seek care for Covid-like-illness, and general awareness of the importance of responding as a community. It goes far beyond a narrow definition of contract tracing to encompass everything we can do as a community to find future and current cases and isolate them to reduce spread of the disease.

Enhanced contact tracing – interventions

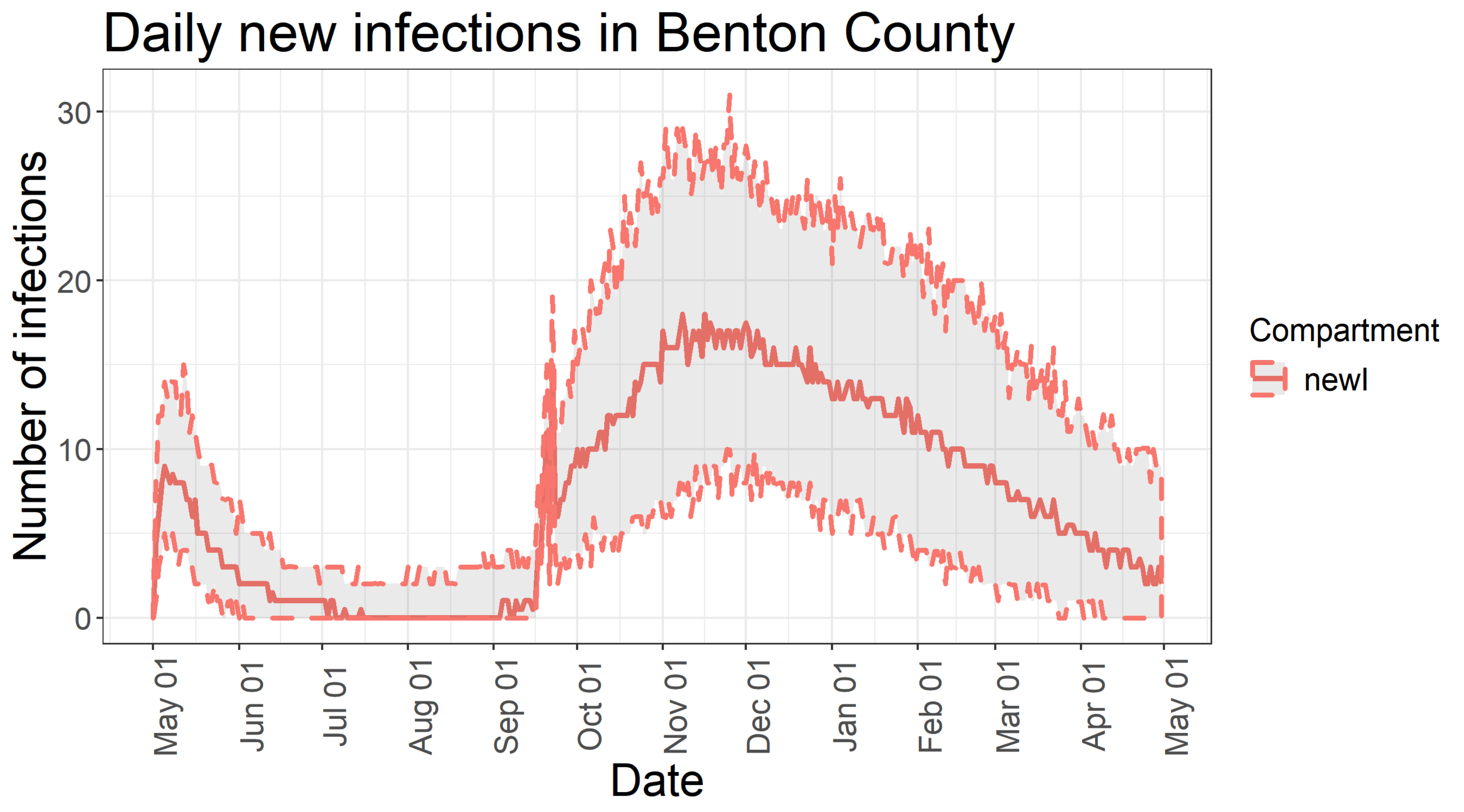


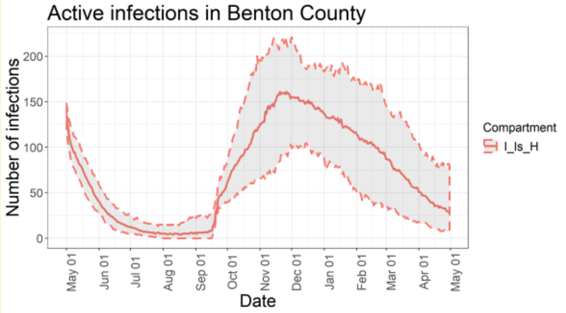


This graph visualizes stay-at-home policies and physical distancing. At the beginning of the simulation, the current major stay-at-home policies are in effect. They are fully removed on July 7th.

Enhanced contact tracing reduces the epidemic pressure so much that, even when students return in September, stay-at-home policies will not be needed to keep the second wave at or below current infection levels (i.e. less than 150 active infections).

Enhanced contact tracing – daily new infections





This graph visualizes daily new infections. During summer of 2020, enhanced contact tracing reduces the epidemic pressure enough to lower new infections to close to 0 or 1. When the students return across the course of a week, daily new cases reach up to 20. Enhanced contact tracing finds many of the new cases before they become infectious, which reduces the epidemic pressure and slows the spread of disease, so that new cases drop to about 2 per day by May 2020.