A note on the effects of epidemic forecasts on epidemic dynamics

Nicholas R. Record, Andrew J. Pershing

The purpose of a forecast, in making an estimate about the future, is to give people information to act on. In the case of a coupled human system, a change in human behavior caused by the forecast can alter the course of events that were the subject of the forecast. In this context, the forecast is an integral part of the coupled human system, with two-way feedback between forecast output and human behavior. However, forecasting programs generally do not examine how the forecast might affect the system in question. This study examines how such a coupled system works using a model of viral infection – the susceptible-infected-removed (SIR) model – when the model is used in a forecasting context. Human behavior is modified by making the contact rate responsive to other dynamics, including forecasts, of the SIR system. This modification creates two-way feedback between the forecast and the infection dynamics. Results show that a faster rate of response by a population to system dynamics or forecasts leads to a significant decline in peak infections. Responding to a forecast leads to a lower infection peak than responding to current infection levels. Inaccurate forecasts can lead to either higher or lower peak infections depending on whether the forecast under- or over-estimates the peak. The direction of inaccuracy in a forecast determines whether the outcome is better or worse for the population. While work is still needed to constrain model functional forms, forecast feedback can be an important component of epidemic dynamics that should be considered in response planning.

Introduction

The field of forecasting is growing rapidly to include many systems (Payne et al. 2017). This growth has magnified many ethical considerations around forecast development, such as conflicts of interest, representation of uncertainty, equity for end users, and unintended consequences, to name a few (Hobday et al. 2019). One challenge that is becoming more common is that forecasts increasingly deal with systems that have human components. In conventional forecasts, such as weather forecasts, human responses do not measurably affect the system in question (Fig 1A). There are more and more cases, however, where human actions are coupled to the system dynamics. Examples include forecasts used in living resource management (Tommasi et al. 2017), endangered species management (Ross et al. 2020), and epidemic forecasts (Adam 2020). Historically, cases like these have often been framed as projections, which present scenarios that are contingent upon different human choices (Fig 1B).

In contrast to projections, forecasts provide specific predictions about future events. If humans are changing their behavior in response to information in the forecast, and if that change in behavior alters the outcome of the forecast target, then the forecast is no longer outside of the system, but is instead a dynamically connected component of the system (Fig 1C). This phenomenon, sometimes refered to as "forecast feedback" or "reflexive prediction" has been historically considered to some degree in economic and political forecasting (Galatin 1976), but is rarely considered in biological systems. According to the "Law of Forecast Feedback", this type of dynamic can hypothetically produce a recursion paradox, where predictability breaks down entirely (Smith 1964). The complexity of

41 dealing with forecast feedback or reflexive prediction is a subject of scientific debate, and
42 it's not clear whether a reflexive forecast could ever be verified empirically (Kopec 2011).
43 As forecasts are increasingly used within the systems they are forecasting, we need to
44 examine the effects that forecasts can have on the dynamics of the system in question.

45 Epidemic models represent a case where forecasts and human behavior can be very tightly
46 coupled. A forecast predicting a high infection peak can motivate measures like quarantine
47 or social distancing. These measures change the forecasted dynamics, ideally lowering the
48 predicted peak. A less severe outlook can then motivate an easing of measures, which in
49 turn can raise the peak again. This two-way feedback illustrates the difficulty in forecasting
50 systems coupled to human dynamics.

51 Epidemic models are conventionally used for projections, rather than for forecasts. They
52 can estimate the consequences of certain actions, potential dangers, or scenarios. However,
53 in the modern information-rich environment, there is a demand for real-time forecasts for
54 both management and general audiences, and such forecasts of epidemics are increasingly
55 common. Many of the modeling studies that have responded to the COVID-19 outbreak are
56 forecasts (COVID and Murray 2020; Roosa et al. 2020; Fanelli and Piazza 2020). The United
57 States Center for Disease Control has even issued an open call for COVID-19 forecasts
58 through a forecasting challenge (https://github.com/cdcepi/COVID-19-ILI-forecasting),
59 and many research teams and news sites serve forecasts to the public in real time. This
60 raises the question: what is the effect of a forecast on the epidemic dynamics? In most
61 biological forecasts, this type of feedback is not explicitly taken into account.

62 We examined this question using the standard susceptible-infected-removed (SIR)
63 epidemic model. The SIR framework underlies many projections and forecasts that form
64 the basis for response strategies for COVID-19 and other epidemics (Adam 2020). We built
65 forecast feedback into the SIR model by allowing the contact rate to change dynamically in
66 response to different information provided by the SIR equations. In turn, the SIR model
67 dynamics depend on the contact rate, so that there is two-way feedback between the
68 forecast and the other system dynamics. The purpose here is not to fully analyze or
69 characterize the global properties of a particular dynamical model, as there is a whole class
70 of well characterized versions of the SIR model that consider a wide range of additional
71 processes and details (Beretta and Takeuchi 1995; Anderson and May 1979; Takeuchi, Ma,
72 and Beretta 2000; Satsuma et al. 2004; Kyrychko and Blyuss 2005; Batista 2020) that one
73 could modify to explore these feedbacks. Rather, we use simulations of a few simple SIR
74 modifications to illustrate important implications of these feedbacks. Examining a system
75 in this way provides a critical analysis of the role of a forecast in a rapidly changing coupled
76 human system.

Methods

78 Our objective is to test the potential effects of an epidemic forecast on the epidemic itself.
79 The approach is to explore this question in its simplest form. To that end, we use the
80 standard susceptible-infected-removed (SIR) model:

$$\begin{aligned}
\frac{dS}{dt} &= -\alpha S I \\
\frac{dI}{dt} &= \alpha S I - \beta I \\
\frac{dR}{dt} &= \beta I
\end{aligned}$$

81

82   Here, S is the number of individuals in a population that are susceptible to infection, I is the
83   number of infected individuals, and R is the number of removed individuals (interpreted as
84   recovered/immune, dead, or otherwise removed); α is the contact rate, and β is the
85   removal rate. The SIR model has been one of the primary tools for making simulations on
86   which control and intervention measures are based, such as social distancing, and shelter
87   in place measures, though other statistical and machine learning tools are also used. There
88   are many ways to modify this system of equations to better approximate a particular
89   epidemic. Our interest is in the general effect that model output (either current or
90   forecasted) can have on the dynamics themselves, as mediated through changes in human
91   behavior. The contact rate α is what would likely change with the suggested response
92   measures. A high infection or a severe enough forecast are what motivates measures whose
93   aim is to reduce the contact rate. We therefore test the effect of allowing α to vary as a
94   function of the SIR model output, in a way that is dynamically linked to the other model
95   equations.

96   Our examination of this system asks two general questions:

97   (1) What if adoption of response measures depends on the current level of infection? This
98   simulates the scenario where the human response is different depending on whether
99   the level of infection is low or high. In this case, α depends on I at any given time.

100 (2) What if adoption of response measures depends on the forecasted peak infection?
101   Peak infection is a primary concern with major epidemics because of health care
102   capacity. In this case, α depends on the predicted peak infection I_*, with the
103   prediction made at any given time using a standard SIR solution.

104 Beginning with case (1), α is a dynamic function, dependent on I. We add a fourth equation
105 to our dynamical system, so that the full set of equations includes a dynamical equation for
106 α:

107

$$\begin{aligned}
\frac{dS}{dt} &= -\alpha S I \\
\frac{dI}{dt} &= \alpha S I - \beta I \\
\frac{dR}{dt} &= \beta I \\
\frac{d\alpha}{dt} &= r\alpha(1 - \alpha/K)
\end{aligned}$$

108   The fourth equation is formulated so that α approaches an asymptotic contact rate K. This
109   is a common functional form in ecological theory (Record, Pershing, and Maps 2014). There
110   are likely multiple possible functional forms for K. There is some evidence that the contact
111   rate is responsive to infection dynamics in an approximately monotonic way. For example,
112   when government response indices (Hale et al. 2020) are taken as a proxy for contact rate,
113   and the infection level is scaled to the maximum for each country, a negative relationship
114   appears (Fig 2A). To make the asymptotic contact rate responsive to the infection
115   dynamics, K is a function of I:

116
$$K(I) = \frac{\alpha_0 - \alpha_*}{N^2}I^2 + \alpha_*$$

117   The two parameters α_* and α_0 are respectively the unhindered contact rate, and the
118   reduced contact rate after response measures are in full effect. This gives a declining curve
119   in asymptotic contact rate K as a function of the infection level I (Fig 2B). Finally, we have
120   the parameter r, which determines how quickly people adopt response measures–i.e. how
121   quickly they move from one α to another. It is likely that from an empirical point of view, r
122   could have a wide range of values, depending on the community and other contextual
123   information. There are other possibilities for the shape of this curve and for the α equation,
124   with different functional forms and producing a wide range of possible dynamics. The
125   quadratic gives a simple curve where the response gets more intense as infections get
126   higher, which allows us to simulate some simple but realistic properties. We use the model
127   in normalized form to show general results, rather than those specific to a particular
128   outbreak (Parameter values: $\alpha_* = 1, \alpha_0 = 0.2, \beta = 0.1$; Initial conditions: $S = 0.999$,
129    $I = 0.001, R = 0, \alpha = 1$). With the equations normalized, the total population size is always
130    $N = 1$. As a diagnostic, we use I_{max}, the magnitude of the peak infection as the dynamics
131   play out, because of its relevance to health care capacity, as in the COVID-19 pandemic.

132   Question (2) requires having a forecast. For this, we use an analytical solution for the
133   infection peak (Weiss 2013) of the SIR model,

134
$$I_* = \left[1 - \frac{\beta}{\alpha N} - \frac{\beta}{\alpha N}\log\frac{\alpha N}{\beta}\right]N$$

135   where $I_*(t)$ is the predicted maximum I value–i.e. a forecast of the magnitude of the
136   infection peak, where the forecast is made at any time, t. Here, we suppose that people are
137   reacting to the forecasted peak, rather than the current level of infection, and that the
138   forecast is based on current information at any given time. The forecast solves the standard
139   SIR model, using the current parameter values, as a forecaster would do in real time. This is
140   modeled by replacing I with I_* in the equation for K. Again, we use the realized I_{max} as a
141   diagnostic.

142   The objective here is to illustrate potential dynamics of the feedback between forecast
143   output and human behavior, rather than to ananlyze the global properties of this particular
144   formulation. To this end, we step through simulations where we adjust the human
145   response rate parameter r and compare the diagnostic I_{max}. Each simulation represents a

146   different value for r. Additionally, the forecasted I_* value at any time represents a
147   hypothetical at time t, because the population is constantly responding, and so the forecast
148   is changing. Moreover, as with any forecast, there is the potential that the prediction is an
149   over- or under-estimation of what will happen, due to stochasticity and other forms of
150   uncertainty. Forecast error can potentially affect forecast feedback dynamics. We test this
151   effect by scaling the forecasted I_* value proportionally, from 0.4 to 1.6, and looking at the
152   effect on the infection peak I_{max} across a range of r values. Here, each simulation
153   represents a different accuracy offset.

Results

155   We evaluate question (1) by looking at how I_{max} depends on r (Fig 3A). Responding to the
156   current level of infection leads to a drop in the infection peak (approximately 8% using this
157   set of parameters), as compared to no response, if the response rate is sufficiently fast. If
158   the response rate is very slow, there is effectively no reduction in the infection peak. There
159   is a sharp transition between these two cases. In this example, a response rate slower than
160   about $r = 0.1$ – corresponding to a response time of about 10 time units – makes no notable
161   change in the infection peak. For different parameter values, the threshold levels can be
162   different, but the basic shape of these relationships is consistent across different
163   parameterizations.

164   When the contact rate is responsive to the forecasted infection peak rather than to the
165   instantaneous infection level (question 2), the shape of the curve is similar (Fig 3A). The
166   reduction in the peak infection is larger, (approximately ~12% drop using this set of
167   parameters, or roughly a 50% improvement over the former case). There is also a notable
168   difference in the needed response time. In this case, a response time of 10 time units (
169    $r = 0.1$) is sufficient for most of the drop to occur. Across parameter space, the magnitudes
170   of these differences change, but the pattern is consistent.

171   We tested the effects of an over- or under-estimate forecast (Fig 3B), with the forecasted
172   value I_* scaled proportionally in the range 0.4 to 1.6. If the forecast is an overestimate, and
173   if the response rate is fast enough, an inaccurate forecast can lower the peak even more
174   than an accurate forecast. An overestimated forecast also gives a larger window of time for
175   response – i.e. the response rate does not need to be as fast to see a lowering of the peak. If
176   the forecast is an underestimate, however, it leads to a higher peak and narrows the
177   response time window. Finally, if the response rate is very slow, inaccuracies in the
178   forecast in either direction make very little difference. In all of these cases, responding to a
179   forecast is better than not responding at all, due to how we have formulated $K(I)$ as a
180   decreasing function of I.

Discussion

182   Many new forecasting products are coming online. With the COVID-19 pandemic in
183   particular, studies and online tools with real-time or near-real-time preditions and

184   projections are produced and available rapidly (Biswas and Sen 2020; Batista 2020; Chen,
185   Lu, and Chang 2020; Simha, Prasad, and Narayana 2020; Teles 2020). People are generally
186   not accustomed to interpreting forecasts as being dynamically linked with their own
187   behavioural responses to the forecast, but such cases are more and more common, and
188   include epidemics, climate change, and endangered species management, to name a few.

189   One growing challenge is the blurring lines between forecasts and projections. For COVID-
190   19, early warnings of a potential global pandemic did not motivate early responses in many
191   places, allowing the virus to move from a local to a global problem. In places like the U.S.
192   and U.K., significant action at the national level did not take place until after Imperial
193   College released projections that millions would die in the absence of social distancing
194   (Adam 2020; Dyer 2020), and after signs of the epidemic were widespread. Once actions
195   were taken, the true trajectory began to deviate from the worst case scenarios, and the
196   projections no longer matched reality. This is typical of projections, which aren't intended
197   to be specific predictions, but rather play out different scenarios that depend on initial
198   actions. Climate projections are similar, calculating future conditions based on
199   Representative Concentration Pathways (RCPs) (Taylor, Stouffer, and Meehl 2012). The
200   RCPs each depict a scenario of future carbon such as aggressive emission reductions
201   (RCP2.6) or business as usual (RCP8.5). There is no weighting placed on which pathway
202   society is likely to select. The goal of the projections is to evaluate the consequences of
203   actions and to contrast action with inaction.

204   Forecasts, on the other hand, do represent specific predictions. We are more accustomed to
205   weather forecasts, where human responses do not change the outcome. Many epidemic
206   models are now offering forecasts (e.g. COVID and Murray 2020; Roosa et al. 2020; Fanelli
207   and Piazza 2020), and in systems like these, humans are a dynamic component, responding
208   to ongoing changes. The human actions depend on the state of the system and the
209   information in forecasts. In reality, not all scenarios are equally available – the likelihood
210   that humans will act depends on the state of the system and the information in forecasts.
211   Examining this dynamic within an SIR model framework illustrates some significant points.

212   First, as might be expected, using information from a forecast can reduce the magnitude of
213   the infection peak. Additionally, using the forecast also grows the window of time in which
214   a response has an effect. This could give more room to allow for missteps during times
215   when uncertainty is high. Second, inaccuracies in the forecast have an asymmetrical effect
216   on the outcome. An overestimate in the forecast can improve the outcome, in this case
217   lowering the infection peak, but an underestimate in the forecast can actually make things
218   worse. By underestimating the potential danger, response is diminished. Similarly, if the
219   response rate is too slow, a forecast makes very little difference, but an over-estimate
220   forecast can buy more response time. These asymmetries raise the difficult ethical question
221   of whether it is better to give an accurate forecast if a more dire forecast could actually
222   motivate a stronger response. This question becomes even more complex if the forecast is
223   one member in an ensemble that is used for decision making, or is one member in a
224   sequence of forecasts where trust in the forecast is cumulative. If the goal of a forecast is to
225   alter human behavior, then a self-defeating forecast might actually be desirable (Sabetta
226   2019). In this broader view, accuracy should be considered only one part of a forecast's
227   performance.

Conclusion

We have to be cautious of using forecasts that do not take into account the effects of forecast feedback on the system dynamics. This is especially important in systems where human health depends on the forecast, as is the case with SIR and other epidemic models. The examples shown here represent just one possible formulation for this type of dynamic. Future work is required to better constrain the possible functional forms, both empirically and theoretically. There is a whole class of models with forecast feedback modifications to examine – nearly any dynamical model where human decision making potentially plays an integrated role – producing a wide range of model behaviors. Forecast feedback creates certain challenges and limitations for predictions, possibly paradoxical, but at a minimum forecasters should try to understand the effects this feedback can have on the systems we are trying to predict.

Acknowledgements

We would like to acknowledge the institutions around the world that are working hard to make epidemic data and forecasts freely available. We thank the editor and two reviewers for helpful comments.

References

Adam, D. 2020. "Special Report: The Simulations Driving the World's Response to Covid-19." *Nature.*

Anderson, Roy M, and Robert M May. 1979. "Population Biology of Infectious Diseases: Part I." *Nature* 280 (5721). Nature Publishing Group: 361–67.

Batista, Milan. 2020. "Estimation of the Final Size of the Covid-19 Epidemic." *Preprint. medRxiv.*

Beretta, Edoardo, and Yasuhiro Takeuchi. 1995. "Global Stability of an Sir Epidemic Model with Time Delays." *Journal of Mathematical Biology* 33 (3). Springer: 250–60.

Biswas, Kathakali, and Parongama Sen. 2020. "Space-Time Dependence of Corona Virus (Covid-19) Outbreak." *arXiv Preprint arXiv:2003.03149.*

Chen, Yi-Cheng, Ping-En Lu, and Cheng-Shang Chang. 2020. "A Time-Dependent Sir Model for Covid-19." *arXiv Preprint arXiv:2003.00122.*

COVID, IHME, and Christopher JL Murray. 2020. "Forecasting Covid-19 Impact on Hospital Bed-Days, Icu-Days, Ventilator-Days and Deaths by Us State in the Next 4 Months." *medRxiv.* Cold Spring Harbor Laboratory Press.

261 Dyer, Owen. 2020. "Covid-19: US Testing Ramps up as Early Response Draws Harsh
262 Criticism." British Medical Journal Publishing Group.

263 Fanelli, Duccio, and Francesco Piazza. 2020. "Analysis and Forecast of Covid-19 Spreading
264 in China, Italy and France." *Chaos, Solitons & Fractals* 134. Elsevier: 109761.

265 Galatin, Malcolm. 1976. "Optimal Forecasting in Models with Uncertainty When the
266 Outcome Is Influenced by the Forecast." *The Economic Journal* 86 (342). JSTOR: 278–95.

267 Hale, Thomas, Anna Petherick, Toby Phillips, and Samuel Webster. 2020. "Variation in
268 Government Responses to Covid-19." *Blavatnik School of Government Working Paper* 31.

269 Hobday, Alistair J, Jason R Hartog, John P Manderson, Katherine E Mills, Matthew J Oliver,
270 Andrew J Pershing, and Samantha Siedlecki. 2019. "Ethical Considerations and
271 Unanticipated Consequences Associated with Ecological Forecasting for Marine Resources."
272 *ICES Journal of Marine Science* 76 (5). Oxford University Press: 1244–56.

273 Kopec, Matthew. 2011. "A More Fulfilling (and Frustrating) Take on Reflexive Predictions."
274 *Philosophy of Science* 78 (5). University of Chicago Press Chicago, IL: 1249–59.

275 Kyrychko, Yuliya N, and Konstantin B Blyuss. 2005. "Global Properties of a Delayed Sir
276 Model with Temporary Immunity and Nonlinear Incidence Rate." *Nonlinear Analysis: Real
277 World Applications* 6 (3). Elsevier: 495–507.

278 Payne, Mark R, Alistair J Hobday, Brian R MacKenzie, Desiree Tommasi, Danielle P
279 Dempsey, Sascha MM Fässler, Alan C Haynie, Rubao Ji, Gang Liu, Patrick D Lynch, Daniela
280 Matei, Anna K Miesner, Katherine E Mills, Kjersti O Strand and Ernesto Villarino. 2017.
281 "Lessons from the First Generation of Marine Ecological Forecast Products." *Frontiers in
282 Marine Science* 4. Frontiers: 289.

283 Record, Nicholas R, Andrew J Pershing, and Frédéric Maps. 2014. "The Paradox of the
284 'Paradox of the Plankton'." *ICES Journal of Marine Science* 71 (2). Oxford University Press:
285 236–40.

286 Roosa, K, Y Lee, R Luo, A Kirpich, R Rothenberg, JM Hyman, P Yan, and G Chowell. 2020.
287 "Real-Time Forecasts of the Covid-19 Epidemic in China from February 5th to February
288 24th, 2020." *Infectious Disease Modelling* 5. Elsevier: 256–63.

289 Ross, Camille, Nicholas R Record, Benjamin Tupper, David Brickman, and Daniel E
290 Pendleton. 2020. "Predicting Regions of North Atlantic Right Whale, Eubalaena Glacialis,
291 Habitat Suitability in the Gulf of Maine in 2050." *Elementa: Journal of the Anthropocene* in
292 review.

293 Sabetta, Lorenzo. 2019. "Self-Defeating Prophecies: When Sociology Really Matters." In
294 *Anticipation, Agency and Complexity*, 51–59. Springer.

295 Satsuma, Junkichi, R Willox, A Ramani, B Grammaticos, and AS Carstea. 2004. "Extending
296 the Sir Epidemic Model." *Physica A: Statistical Mechanics and Its Applications* 336 (3-4).
297 Elsevier: 369–75.

298 Simha, Ashutosh, R Venkatesha Prasad, and Sujay Narayana. 2020. "A Simple Stochastic Sir
299 Model for Covid 19 Infection Dynamics for Karnataka: Learning from Europe." *arXiv*
300 *Preprint arXiv:2003.11920*.

301 Smith, George Cline. 1964. "The Law of Forecast Feedback." *The American Statistician* 18
302 (5). Taylor & Francis Group: 11–14.

303 Takeuchi, Yasuhiro, Wanbiao Ma, and Edoardo Beretta. 2000. "Global Asymptotic
304 Properties of a Delay Sir Epidemic Model with Finite Incubation Times." *Nonlinear Analysis:*
305 *Theory, Methods & Applications* 42 (6). Pergamon: 931–47.

306 Taylor, Karl E, Ronald J Stouffer, and Gerald A Meehl. 2012. "An Overview of Cmip5 and the
307 Experiment Design." *Bulletin of the American Meteorological Society* 93 (4). American
308 Meteorological Society: 485–98.

309 Teles, Pedro. 2020. "Predicting the Evolution of Covid-19 in Portugal Using an Adapted Sir
310 Model Previously Used in South Korea for the Mers Outbreak." *medRxiv*. Cold Spring Harbor
311 Laboratory Press.

312 Tommasi, Desiree, Charles A Stock, Alistair J Hobday, Rick Methot, Isaac C Kaplan, J Paige
313 Eveson, Kirstin Holsman, Timothy J. Miller, Sarah Gaichas, Marion Gehlen, Andrew
314 Pershing,Gabriel A Vecchi, Rym Msadek, Tom Delworth, C Mark Eakin, Melissa A Haltuch,
315 Roland Séférian,Claire M Spillman, Jason R Hartog, Samantha Siedlecki, Jameal F Samhouri,
316 Barbara Muhling,Rebecca G Asch, Malin L Pinsky, Vincent S Saba, Sarah B Kapnick, Carlos F
317 Gaitan,Ryan R Rykaczewski, Michael A Alexander, Yan Xue, Kathleen V Pegion, Patrick
318 Lynch,Mark R Payne, Trond Kristiansen, Patrick Lehodey, Francisco E Werner. 2017.
319 "Managing Living Marine Resources in a Dynamic Environment: The Role of Seasonal to
320 Decadal Climate Forecasts." *Progress in Oceanography* 152. Elsevier: 15–49.

321 Weiss, Howard Howie. 2013. "The Sir Model and the Foundations of Public Health."
322 *Materials Mathematics*, 0001–0017.

323

324   Figure 1. *(A) The conventional forecasting scheme, where a system informs a forecast, which*
325   *informs some human response. (B) The conventional scheme for projection, where a range of*
326   *possible actions produce multiple scenarios (i.e. projections), which can inform action. (C) The*
327   *forecasting scheme where the human response is part of the system dynamics – i.e. forecast*
328   *feedback or reflexive prediction.*

329   Figure 2. *(A) Evidence of a relationship between the magnitude of infection and a contact rate*
330   *index. The contact rate is the inverse of the government response index from Hale et al.*
331   *(2020), so that a higher index corresponds to a higher contact rate. Infection magnitude is*
332   *scaled to the maximum for each country. (B) The dependence of the asymptotic contact rate*
333   *(K) on the population size (I).*

334   Figure 3. *(A) The dependence of the infection peak magnitude on the rate (r) at which the*
335   *population reduces the contact rate (i.e. adopts response measures). The population*
336   *responding to current infection levels (black); the population responding to forecasted*
337   *infection peaks (grey). (B) The dependence of the infection peak levels (contours) on the rate*
338   *(r) at which the population reduces the contact rate (e.g. adopts social distancing behaviors)*
339   *and the accuracy of the forecast. In this simulation, the population is responding to forecasted*
340   *peak infection levels.*

341

Figure 1

Forecasting schematic diagram

(A) The conventional forecasting scheme, where a system informs a forecast, which informs some human response. (B) The conventional scheme for projection, where a range of possible actions produce multiple scenarios (i.e. projections), which can inform action. (C) The forecasting scheme where the human response is part of the system dynamics -- i.e. forecast feedback or reflexive prediction.
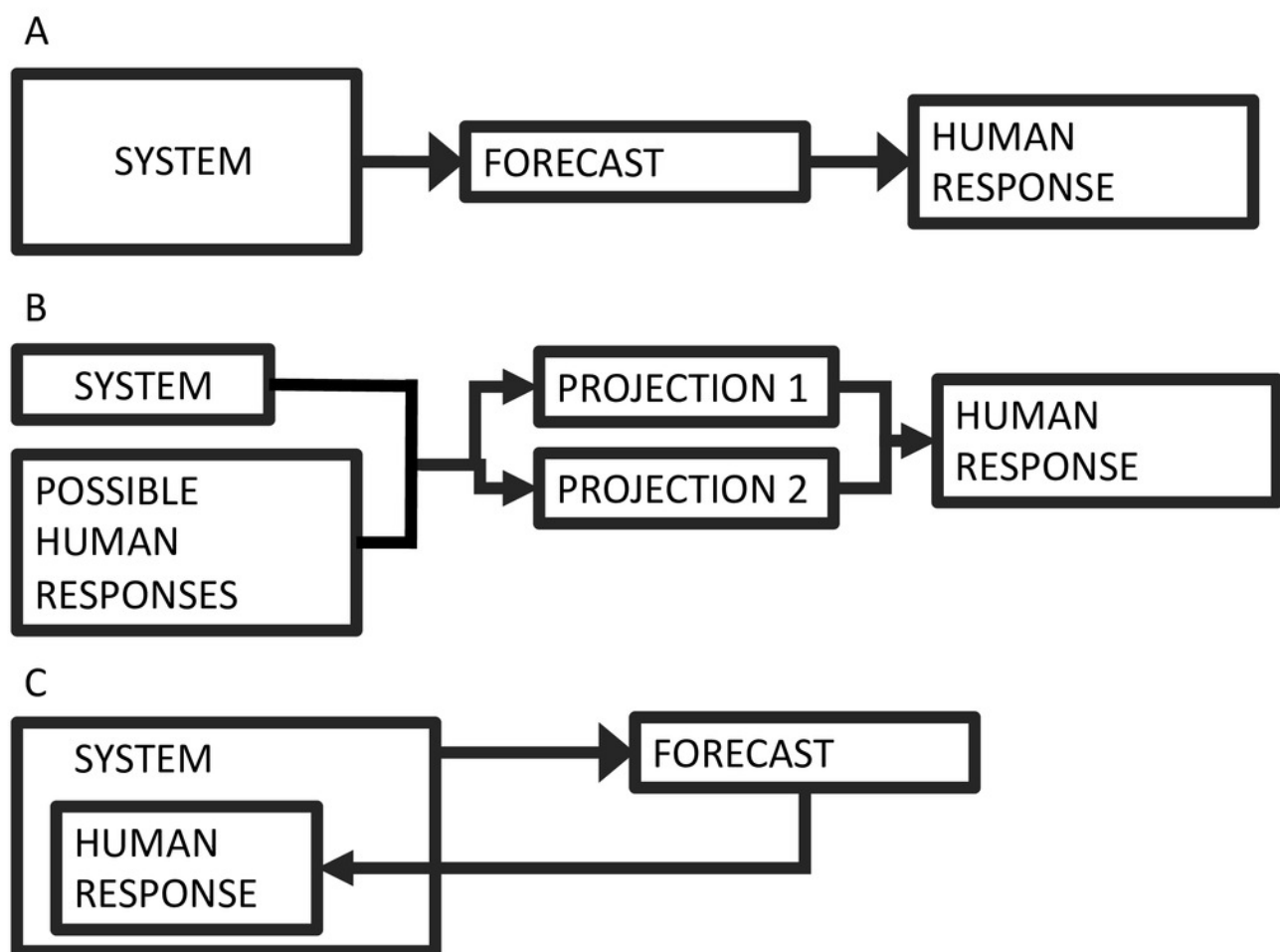
Figure 2

Plots informing the model structure.

(A) Evidence of a relationship between the magnitude of infection and a contact rate index. The contact rate is the inverse of the government response index from Hale et al. (2020), so that a higher index corresponds to a higher contact rate. Infection magnitude is scaled to the maximum for each country. (B) The dependence of the asymptotic contact rate (K) on the population size (I).
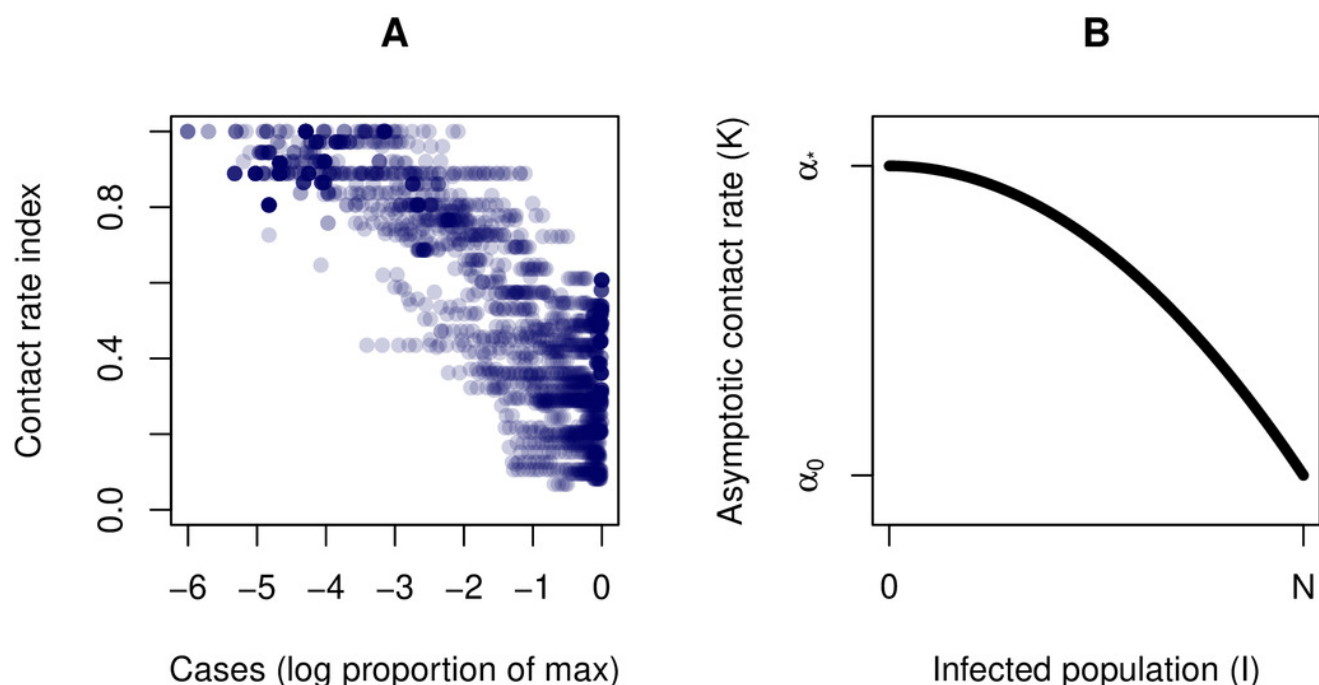
Figure 3

Results of model analysis.

(A) The dependence of the infection peak magnitude on the rate (r) at which the population reduces the contact rate (i.e. adopts response measures). The population responding to current infection levels (black); the population responding to forecasted infection peaks (grey). (B) The dependence of the infection peak levels (contours) on the rate (r) at which the population reduces the contact rate (e.g. adopts social distancing behaviors) and the accuracy of the forecast. In this simulation, the population is responding to forecasted peak infection levels.