

# The Ebola Outbreak in West Africa: Important Lessons about Modeling & Simulating Uncertain Dynamic Issues

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**ABSTRACT:** *During the first half of 2014, the Ebola outbreak in West Africa was severely underestimated. But during the second half of the year, many modelling studies showed catastrophic projections of cumulative Ebola cases and deaths. Recently, these modelling studies have been criticized for severely overestimating the outbreak. As a consequence, the usefulness of simulation models during outbreaks has even been questioned, even in Nature. This study exposes some of the causes for overestimation as well as for underestimation when using simulation models for current uncertain dynamic issues. Addressing some of these causes by calibrating more complex instead of less complex transmission models to more, or more recent, data is shown to reduce the Ebola projections from millions to tens of thousands of cases. This study also shows that the current outbreak was likely to be curbed by the current massive deployment and behavioural changes before accelerated vaccination campaigns can even be rolled out. It is shown that the quality of the model and results can be improved substantially, but also that some uncertainty cannot be reduced, and that communicating results under uncertainty to decision makers, the media, and other scientists remains problematic*

**Keywords:** Modelling, Ebola Virus, Policy , Model-based Policy Analysis, Deep Uncertainty

**THIS IS AN EXTREMELY ABBREVIATED VERSION OF THE ARTICLE IN ORDER TO BE ABLE TO PUBLISH IT AS A JOURNAL ARTICLE. THE FULL ARTICLE IS AVAILABLE UPON REQUEST.**

## **1. INTRODUCTION**

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The remainder of this article is structured as follows. First, methods and models used in this research are briefly presented. Second, simulation results from several models and from multiple post-processing rounds are presented and discussed. Finally the consequences of these results are discussed and conclusions are drawn.

## **2. METHODS AND MODELS**

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The models used and policies simulated here are discussed in (Pruyt et al., 2015). See Figure 1.

## **3. RESULTS**

### **3.1 Omission versus consideration of uncertainty**

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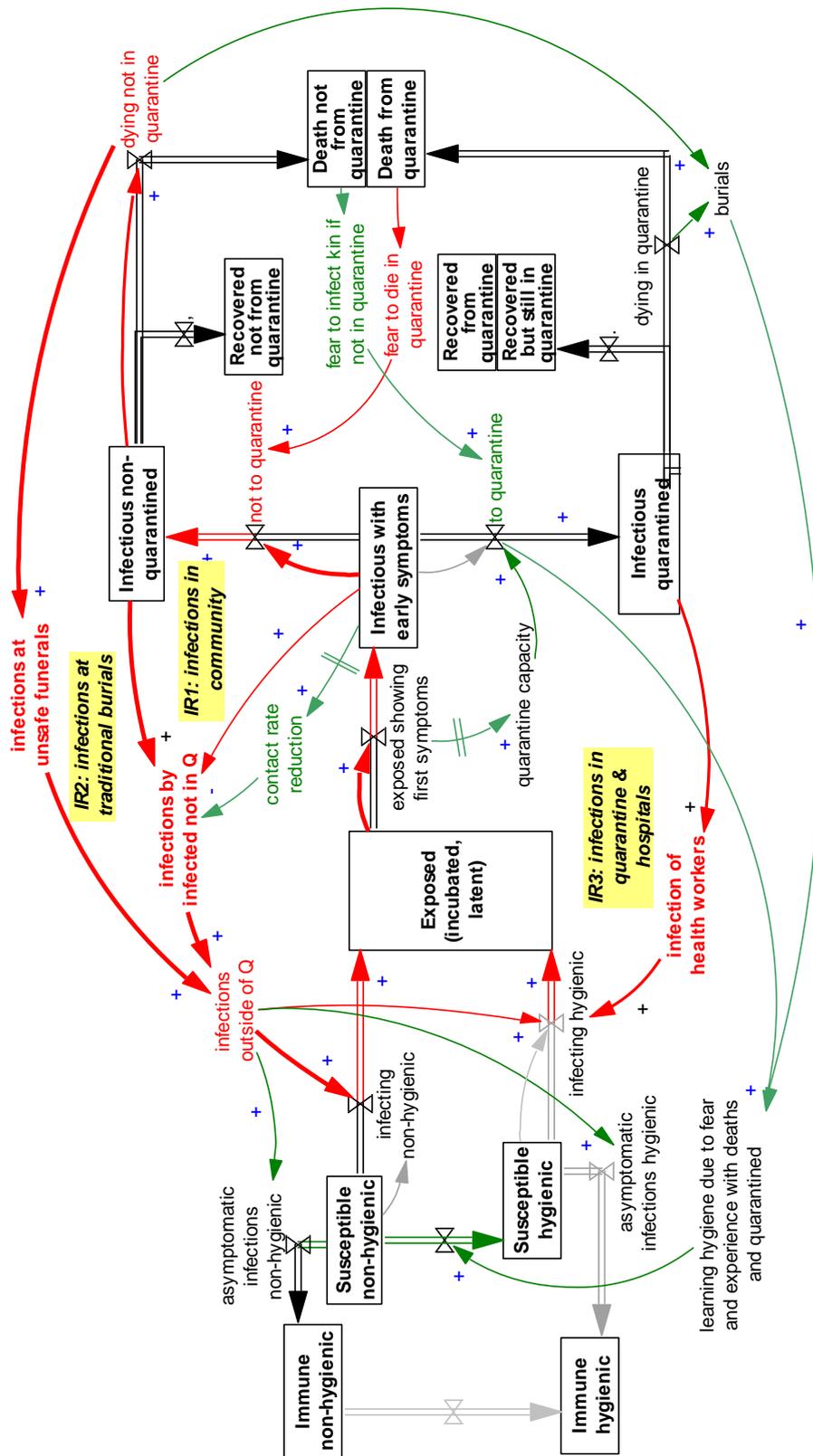


Figure 1: Simplified diagram of the core simulation model showing compartments, infective routes, and some endogenous social psychological effects

Table 2: Uncertainties with pre-calibration and post-calibration ranges (calibrated values in bold)

Parameter	Units	Initial	Calibr 1 (28/09)	Calibr 2 (28/09;17/10;4/11)	Sources/Remarks
average recovery time	[d]	(7,12)	(7, <b>10.48</b> )	<b>(9.36,10.15)</b>	(WRT14), +detec.time + saf.time in Q, calibrated
detection time	[d]	(4,6)	<b>(5.88, 6)</b>	(4,6)	(Gomes 2014, Schieffelin 2014, WRT14), calibrated
initial incubated	[p]	(5,10)	<b>(6.64,10)</b>	(5,10)	(Baize et al. 2014), calibrated
repr. nمبر non hyg. susc. pop.	[p/p]	(1.50,2)	<b>(1.89, 2)</b>	<b>(1.63,1.77)</b>	(Gire 2014, Gomes 2014, Rivers 2014) , calibrated
fraction repr. nمبر [/] funeral	[-]	(0.3,0.6)	idem	(0.3, <b>0.58</b> )	fraction infections due to unsafe funerals, calibrated
relative infectivity 1 <sup>st</sup> symptoms	[-]	(0.3,0.9)	idem	<b>(0.56,0.64)</b>	assumed, calibrated
adequacy endo. building Q cap	[-]	(0.2,0.3)	idem	idem	assumed based on WHO situation reports
average incubation time	[d]	(10,13)	idem	idem	(WRT14, Schieffelin 2014, Lekone and Finenstädt 2006, Towers et al. 2014)
average decease time	[d]	(4,5)	idem	idem	(WRT14, Gomes 2014), +‘detect t’ -> death
average Q disinfection time	[d]	(0.5,1.5)	idem	idem	assumed quarantine bed turnaround time
CFR (case fatality ratio)	[-]	(0.6,0.8)	idem	idem	(WRT14)
contact rate factor	[-]	(1, 4)	idem	idem	effect infectious fraction on contact rate reduction
delay on endo adaptation Q cap	[d]	(21,45)	idem	idem	assumed based on WHO situation reports
factor learning hyg. [f(contact)]	[-]	(0,5)	idem	idem	assumed
fraction to Q if not endo.	[-]	(0.25,0.5)	idem	idem	assumed
infections of hygienic infected	[1/d]	(10 <sup>-3</sup> ,0.04)	idem	idem	assumed, infections of hyg.Susc. by Infectious in Q.
safety time in Q	[d]	(2,4)	idem	idem	additional time in quarantine before discharge
size kin	[p/p]	(50, 200)	idem	idem	assumed to calculate fear of infecting kin
size rumour quarantine fear	[p/p]	(500,2 10 <sup>3</sup> )	idem	idem	assumed to calculate fear of quarantine
time from non hyg. to hyg.	[d]	(2,14)	idem	idem	assumed
factor asymptomatic	[-]	(0.2,1.2)	idem	idem	(Bellan ea. 2014, Leroy ea. 2000); fraction = factor/2
reduction RN by hygienic	[-]	(0.5,0.9)	idem	idem	assumed, % reduction in reproductive number
Order Incubation Delay	[-]	2, 3	idem	idem	categorical, (WRT14)
OrderDeceaseDelay	[-]	2, 3	idem	idem	categorical, assumed
OrderRecoveryDelay	[-]	2, 3	idem	idem	categorical, assumed

(WRT14):= (WHO Ebola Response Team 2014); [d] := [day]; [p] := [person]; [-] := dimensionless; Q:= quarantine

### 3.2 Omission versus inclusion of psychological and sociocultural effects

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### 3.3 Including Interventions

See Fig. 3. **STRONGLY ABBREVIATED HERE.**

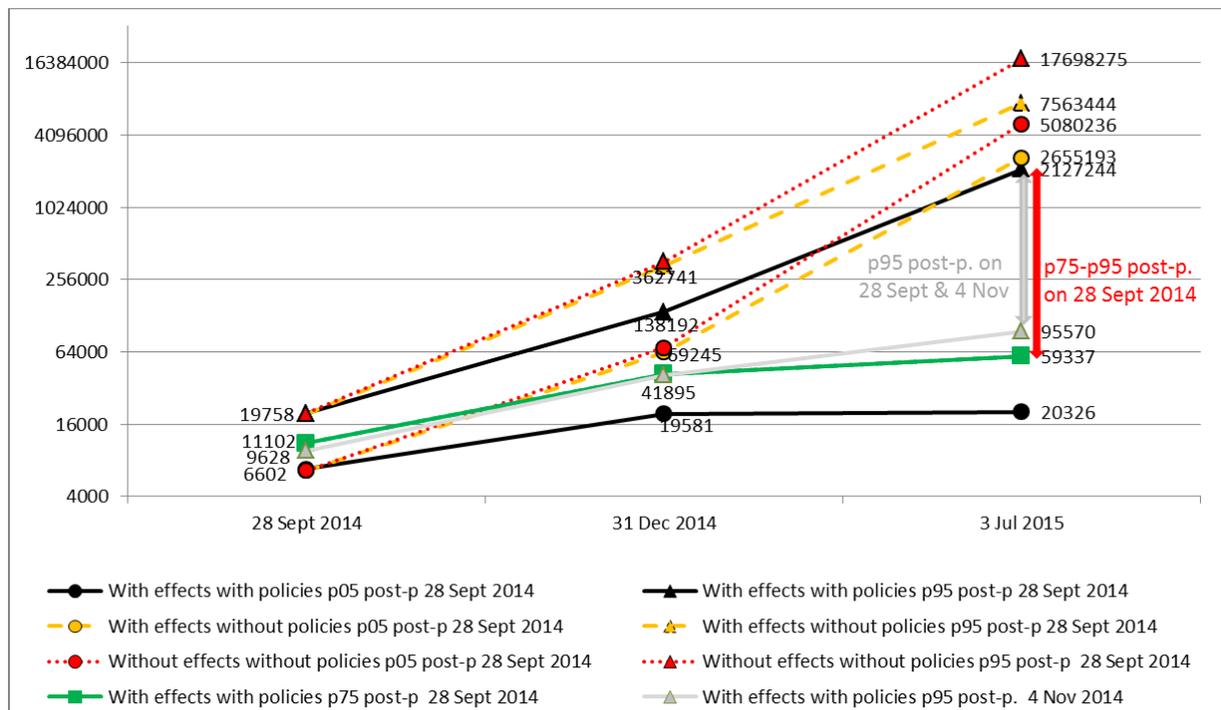


Fig. 3: Simulated total cases on 28 September, 31 December, 3 July calibrated with 28 September data

### 3.4 Communicating Ensembles of Uncertain Results

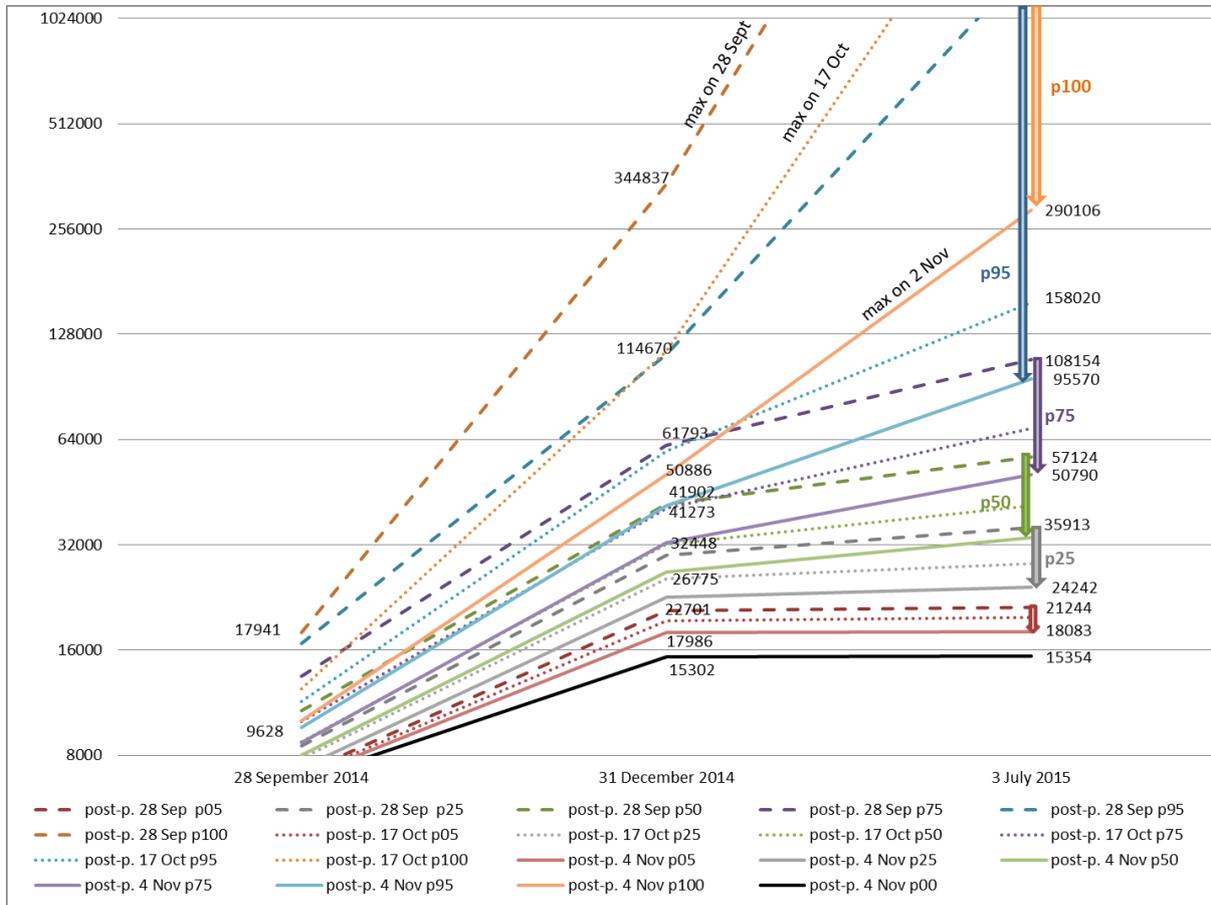
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### 3.5 Time Reduces Some Uncertainty

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### 3.6 Accounting for surprises and changes

See Figure 4. **STRONGLY ABBREVIATED HERE.**



**Fig. 4:** Reduction of percentiles due to post-processing over time (28 Sep -> 17 Oct -> 4 Nov)

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A second online notebook<sup>1</sup> documents the calibration in which changing sociocultural psychological effects and past surprises are accounted for and the simulation results. The newly calibrated ranges are listed in the fifth column of table 5. Calibration with superspreading and shift in underlying model actually improves the fit between the simulated ensemble and the real data: instead of 1/3 now 1/2 of the runs survive post-processing.

<sup>1</sup> See <http://nbviewer.ipython.org/gist/ep77/f2108a3bf5941b4392e5>

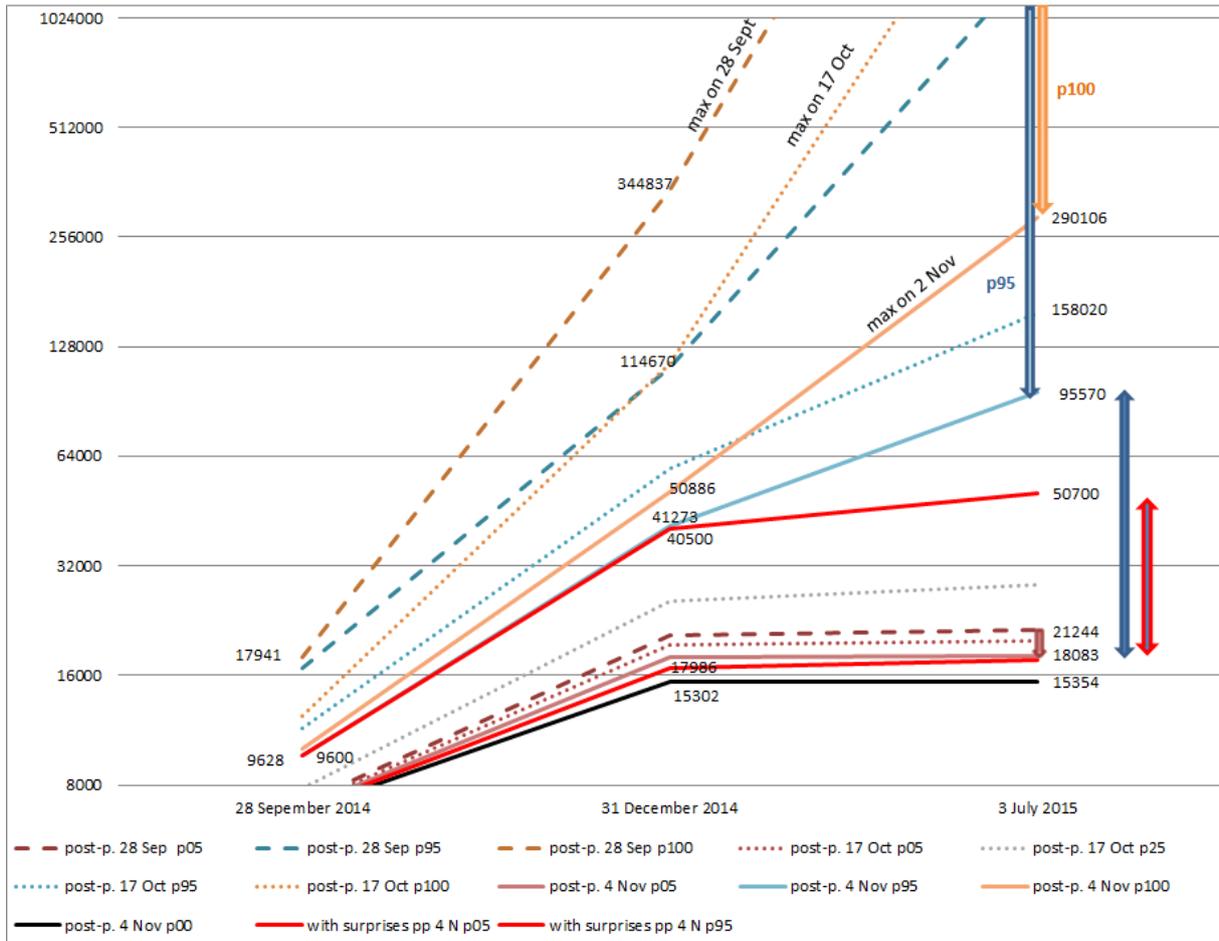


Figure 5: Ensembles with surprises (superspreading) and changing social-psychological behaviour

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### 3.7 With Shrinking Uncertainty Bounds

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### 3.8 With Future Surprises and Geo-Spatially Specific Models

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## 4. DISCUSSION

Although social and psychological feedback effects are important and should therefore be included in models, massive quarantine deployment with effective supporting policies is much more important for curbing the Ebola epidemic in West Africa. Massive intervention with good supporting policies and better estimates over a longer period of time, even without underlying behavioural changes, already reduce estimates of total Ebola cases from between 20 thousand and 2.1 million cases (90% CI) to 18-96 thousand cases (90% CI), or to 17-42 thousand cases (90% CI) if more recent estimates (4 November 2014) are believed to be more accurate (95%-150%). Note, however, that this does not mean that massive interventions can be stopped or scaled down early on. These “best case projections” are only valid with massive interventions being implemented on time. In case of Ebola, a pro-active ‘overkill’ intervention policy is most effective. Given the outbreak and mass interventions implemented, it was clear that the outbreak could be curbed before a mass vaccination campaign could be rolled out.

In this article, it was argued and shown that uncertainty bounds of early projections should be very wide to properly reflect the uncertainty. However, projections should not be implausible as was the case with some projections of the Ebola outbreak in West Africa. It was shown that these wide uncertainty bounds automatically shrink over time with new real-world information becoming available.

It was also shown that models with the necessary social-psychological complexity generate better estimates than overly simplistic models. In the case of the Ebola outbreak in West Africa, But it was especially the shift from adverse behaviours to normal behaviours.

Adverse social effects matter especially in 2014 whereas the lack of social effects matters in especially in 2015, and asymptomatic infections matter especially in 2015.

Interestingly, the overly simplistic models used early on may have drawn attention to the worst case outcomes, and may therefore have created the necessary sense of urgency to plan for the worst, i.e. to deploy massively. (Early) planning for the worst in turn results in robust interventions that would

be excessive for most, but not all, plausible futures. Thus, early projections with high worst case projections, and even with inadequate models, may have provoked the right response. However, inadequate models are easily criticized. But even adequate models may generate projections that are judged to be 'wrong' in hindsight. Especially if forecasted evolutions are defeated by the action taken to prevent it.

From the above, it is possible to identify multiple reasons why the models got it 'wrong'. One, the Ebola outbreak was a moving target with new information becoming available every few days. Two, the transmission models used early on lacked social & psychological feedback effects. Three, even the most complex models were too simplistic. Four, simulations without interventions were communicated. Five, models were calibrated to poor uncertain data without accounting for surprises. Six, models were simulated at a time the future was still very uncertain. Seven, simulation under uncertainty is hard to communicate, hence, uncertainty is not properly discussed. And eight, dramatic estimates receive(d) more attention than reasonable estimates.

Hence, there are many causes for overestimation, including: the omission of effects of interventions, the omission of dynamic social-psychological effects, the uncertainty of early data/info, a fundamental misunderstanding of uncertainty, the treatment of poor data as good data, hard overfitting with deterministic models, not considering enough heterogeneity, not considering past surprises like past superspreading, the fear to underestimate, and the fact that catastrophic news sells better.

Hence, there are many causes for underestimation, including: the assumption that interventions are effective and certain, the omission of (super-) adverse effects, uncertainty of data/info, a fundamental misunderstanding of uncertainty, the treating of poor data as good data, overfitting with deterministic models, too much homogeneity (region, agent), and the omission of *future* superspreading / surprises. Note that many causes could lead to overestimation as well as underestimation.

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