FROM MODELLING UNCERTAIN SURPRISES TO SIMULATING BLACK SWANS

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Abstract

Exploratory System Dynamics Modelling and Analysis is useful for dealing with dynamically complex issues that are characterized by deep uncertainty. So far, this approach has not been used for uncertain surprises or recognized ignorance, aka black swans. It could nevertheless be stretched to issues, systems and analyses beyond deep uncertainty. Combining (System Dynamics) modelling and simulation approaches, cross-impact approaches, Exploratory Modelling and Analysis, adaptive sampling techniques, and scenario discovery techniques may help to turn potential black swans into grey swans that may be dealt with. This new multi-method approach, which extends the exploratory System Dynamics approach to the boundary of recognized ignorance, and even total ignorance, is illustrated on a current/recent issue, namely the Ebola epidemic in West Africa and the development of Ebola drugs and vaccines. Moreover, a new approach is shown to generate and discover the most surprising types of behaviours a model, or a set of models, could possibly generate.

Keywords: uncertainty, black swans

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1 Introduction

This paper focusses on simulating surprises in complex systems that are highly uncertain. The Ebola outbreak in West Africa and the development of drugs and vaccines for Ebola outbreaks is used as an example throughout this paper.

System Dynamics (SD) modelling and simulation (Forrester, 1961; Sterman, 2000; Pruyt, 2013) is commonly used to simulate complex systems characterized by different levels of uncertainty, from marginal and statistical uncertainty all the way to deep uncertainty (see Figure 1). Deep uncertainty relates to those situations in which experts and parties do not agree upon models to represent these situations, probabilities associated to their inputs and outcomes, and the desirability of outcomes (Lempert *et al*., 2003). But that does not mean that issues and systems characterized by deep uncertainty cannot be modelled and simulated. To the contrary. They can be represented, simulated, and analysed using sets of plausible simulation models – not a single model. Until recently it was too difficult to simultaneously deal with alternative plausible models about complex issues (Oreskes *et al*. 1994), and thus deal with deep uncertainty and higher levels of uncertainty related to complex systems.

Marginal Uncertainty -> Statistical uncertainty -> Deep Uncertainty -> Recognized Ignorance -> Total Ignorance

Figure 1: Typology of Levels of Uncertainty. [original figure not included here -> journal article]

Over the last two decades, approaches have been developed for dealing with deep uncertainty related to complex systems. Exploratory Modelling and Analysis (EMA), aka Robust Decision-Making (RDM), is one of these approaches. EMA was first proposed by Bankes (1993) and further developed into different strands for different purposes (scenario discovery, robust decision making) by a group of policy scientists at RAND Corporation (Lempert and Schlesinger 2000; Bankes, 2002; Lempert *et al*., 2003; Lempert et al. 2006; Groves and Lempert, 2007; Bryant and Lempert, 2010; Weaver et al. 2013). Today, EMA is applied and further developed by a much larger group of policy and computer scientists across the world. EMA is also commonly combined with systems approaches such as SD modelling and simulation. Examples of EMA combined with SD, aka ESDMA, include (Lempert *et al*., 2003; Pruyt and Hamarat 2010; Kwakkel and Pruyt 2013, 2015; Pruyt and Kwakkel 2014; Pruyt *et al*. 2015). Moorlag *et al*. (2015) combine EMA with both System Dynamics and Agent Based Modelling (Eipstein 2007, van Dam *et al*. 2013).

ESDMA enables one to deal simultaneously with dynamic complexity and deep uncertainty. That is, it enables one to generate many plausible dynamics, some of which are surprising. In traditional SD and Agent-Based modelling, surprising dynamics are often generated by non-linear feedback effects or interactions between agents from which highly non-linear behaviour emerges at the systems level. New sampling methods like the one presented by Islam and Pruyt (2014) allow to search specifically for the largest diversity of behaviours, and thus, for the full breath of unanticipated evolutions and surprising dynamics. These surprising dynamics generated by systems models are not due to exogenously modelled surprises like unexpected events, major disruptions, or unanticipated radical changes. These exogenous surprises are generally not included, and therefore not focussed on. However, including exogenous or semi-endogenous surprises and treating them as deeply uncertain would in many cases provide interesting opportunities and complement the endogenous SD perspective.

For example, Ebola drugs and vaccines would not be at the point of being mass produced if a surprising combination of “exogenous” surprises would not have triggered a systemic response with largely endogenous dynamics. That is, if 9/11 would not have occurred, if the Ebola virus would not have been particularly useful as a carrier for genetic treatment due to its aggressiveness, if the 2014 Ebola outbreak in West Africa would not have been of unprecedented size, and if it would have been known the outbreak would largely be curbed by the time the vaccine would be ready for use. Moreover, the 2014 outbreak would not have been out of control for months if unanticipated superspreading events (i.e., the infection of dozens of individuals at the funeral of healers) would not have occurred, the virus would have been recognized early on, the initial response would have been adequate, etc. The outbreak would have been hard to curb at all if adverse social psychological effects would not have turned into ‘normal’ social psychological effects. These effects can be simulated with exploratory SD models extended with discrete elements and switches. Adding discrete elements and switches would make systems models more realistic if simulated both with and without these effects. Doing this well requires combining modelling and simulation approaches, cross-impact approaches, stochastic approaches, Exploratory Modelling and Analysis, adaptive sampling methods, innovations in time series classification, and advanced statistical and data science techniques.

This approach could even be stretched to issues, systems and analyses of higher degrees of uncertainty. That is, to what is sometimes referred to as recognized ignorance or black swans (Taleb 2007). Combining these methods and techniques may enable one to simultaneously consider all sorts of evolutions and surprises, even unknown ones. Doing so, one may be able to turn black swans into grey swans, and discover new plausible futures. This paper shows and discusses, in other words, how recognized ignorance –and to some extent– total ignorance may be addressed.

This paper consists of three distinct examples. The first example illustrates the added value of explicitly including "known" or "knowable" surprises – both past surprises and future surprises – in order to deal with "uncertain" surprises. The second example illustrates how "unknown" and even "unknowable" surprises could be simulated to deal with recognized ignorance. The third example demonstrates the newest techniques to generate and discover really surprising behaviours. In each of these examples, Exploratory Modelling and Analysis is combined with System Dynamics modelling. In the first two examples, System Dynamics models are 'polluted' with discrete surprises and/or switches. How this is done is first addressed in a methodology section (section 2). Section 3 illustrates how known but uncertain surprises could be dealt with in case of a deeply uncertain issue, the Ebola outbreak in West Africa. Section 4 illustrates how unknown uncertain surprises could be dealt with. Section 5 consists of a discussion and concluding remarks.

2 Methodology, Methods, Techniques, and Tools

The approach for dealing with recognized ignorance and total ignorance proposed here builds on the methodology, techniques, and tools developed over the last two decades for dealing with deep uncertainty. **STRONGLY ABBREVIATED HERE.**

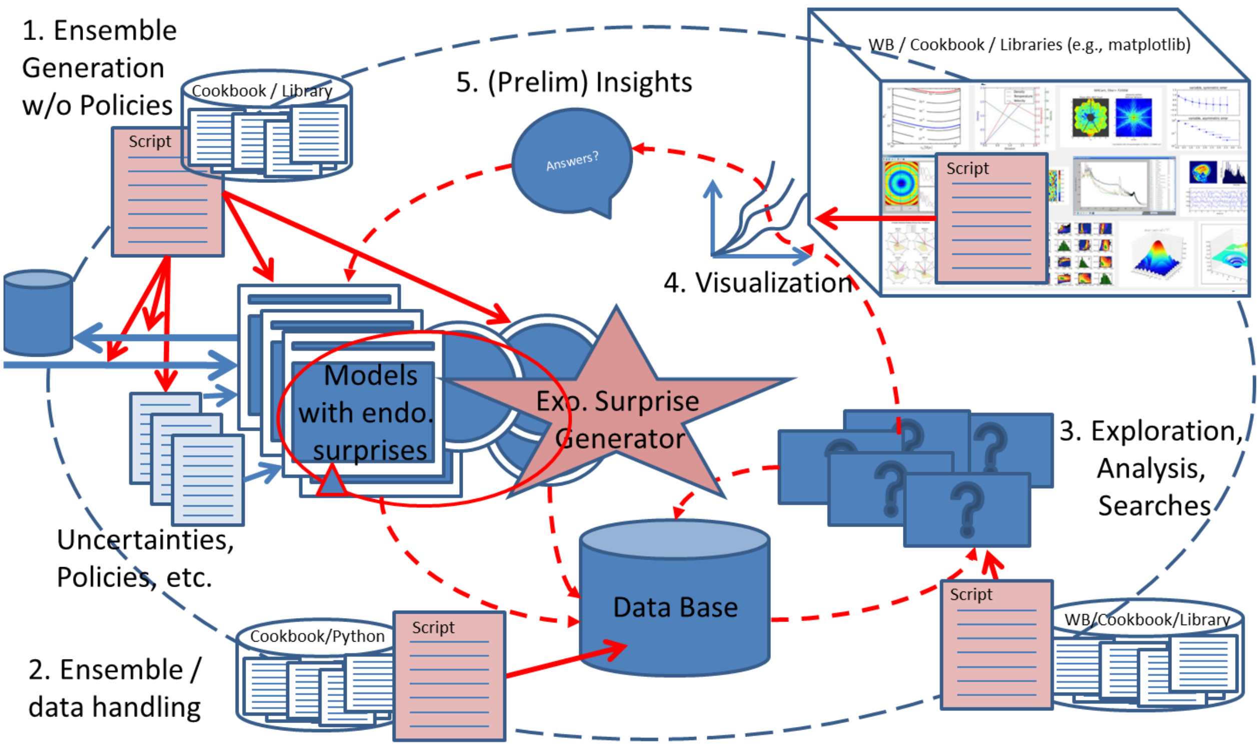

Figure 2: EMA process / approach / workbench for dealing with deep uncertainty

Figure 2 displays the EMA process and TU Delft's EMA Workbench[1] for doing so. **STRONGLY ABBREVIATED HERE.**

[1] See http://simulation.tbm.tudelft.nl . The EMA workbench can be downloaded from Git and other sites.

3 The Ebola Outbreak in West Africa: Including Uncertainty Leads to Fewer Surprises

A set of Ebola models, based on one and the same core model, was developed end of September 2014 (Pruyt *et al*. 2015a) and further refined until mid-November (Pruyt 2015a). **STRONGLY ABREVIATED HERE.** In the full article, I discuss and show how adding uncertainty as well as "known" surprises and important changes, significantly reduces the uncertainty bounds of the ensemble forecast obtained with these models (18-95 thousand to 18-50 thousand cases in Figure 4). Adding surprises and uncertainty thus leads to fewer surprises.

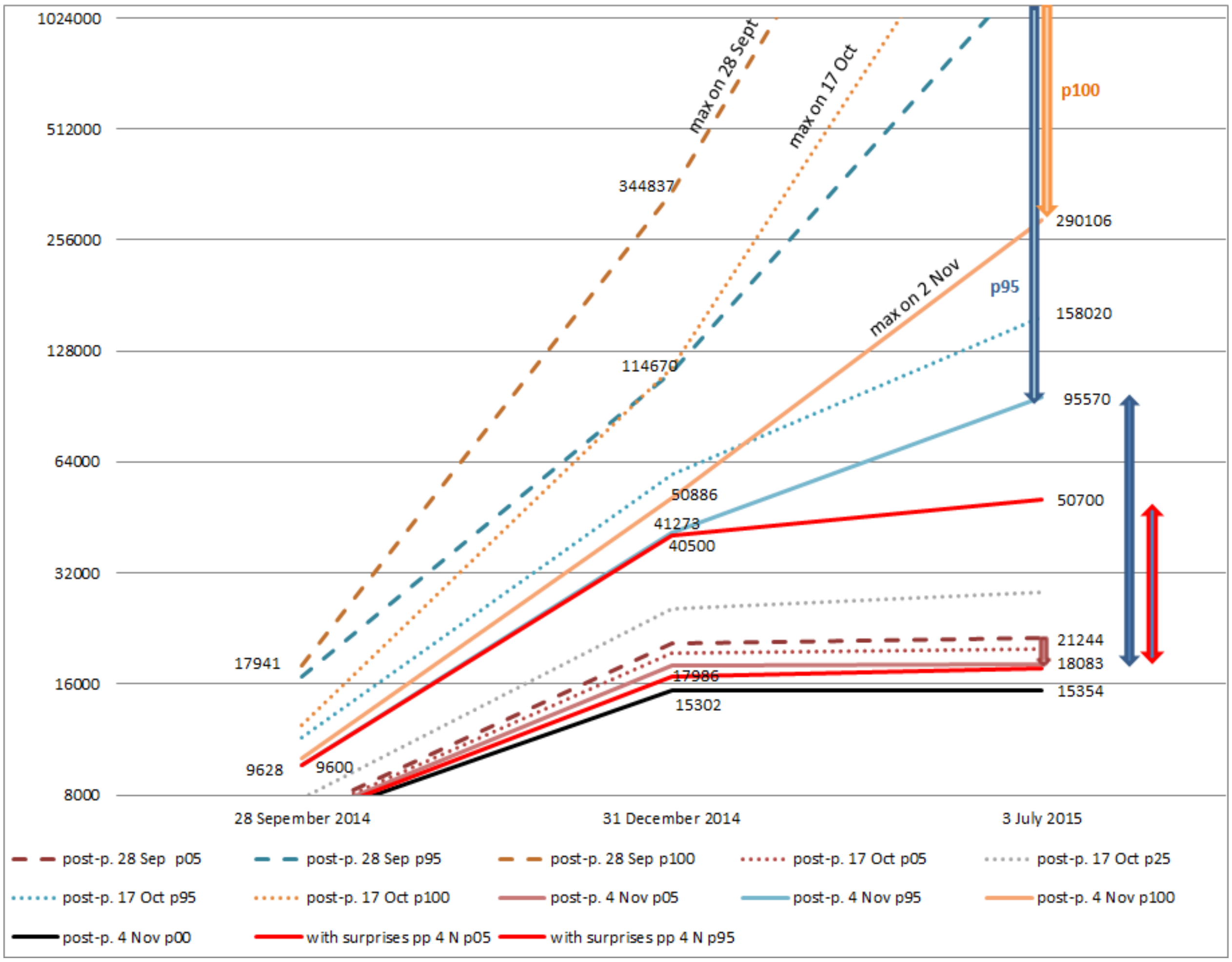

Figure 4: Percentile 5 and percentile 95 of ensembles post-processed on 28 September, 17 October, and on 4 November (data from 2 November 2014) and ensemble post-processed with surprises (superspreading and social-psychological changes) post-processed on 4 November

4 Including Changes & Surprises Leads to Less Uncertainty: The Development of Ebola Drugs and Vaccines

The second example represents the sequence of surprises in the development of Ebola drugs and vaccines. It illustrates the use of this exploratory simulation approach for situations characterized by surprises under deep uncertainty up to recognized ignorance. In the example included here, values are purely fictitious.

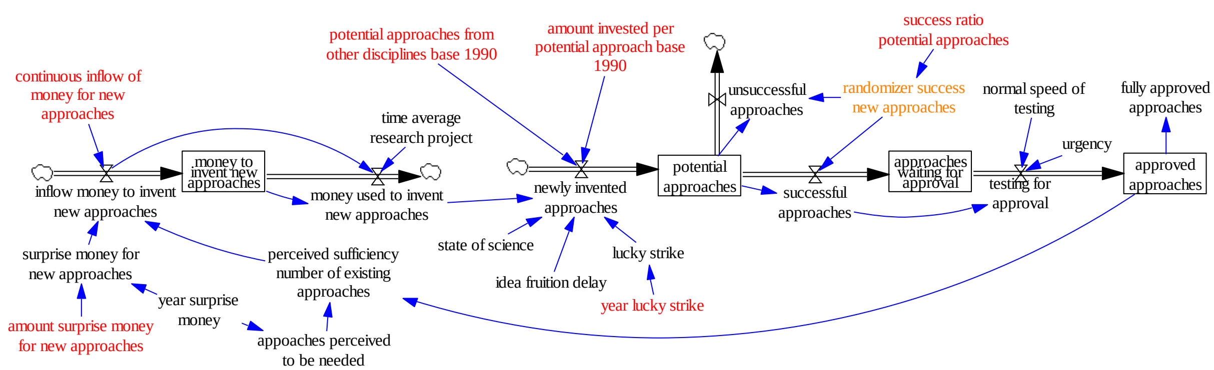

Fig. 5: Simulation model of the development of Ebola vaccines and drugs

In the didactic model used here and displayed in Figure 5, research money is spent via research projects to invent new approaches, which are subsequently mixed and tested. Successful approaches are then queued. Urgency determines how much time the approval process takes: we assume that urgency rises dramatically in 2014 due to the Ebola outbreak in West Africa. This model comprises uncertainties, discrete surprises, and randomized surprises.

This model was simulated 1000 times under uncertainty for two scenarios, one in which a generative event (in this case 9/11) results in a considerable amount of additional money for BSL-4 related research including research related to the Ebola virus, and one in which the 2014 Ebola outbreak in West Africa first results in a considerable amount of additional money for Ebola research. Note that in both cases there is also base funding, that there are more and more spill-overs from other disciplines, and that there could be unexpected discoveries (‘lucky strikes’).

Figures 6 and 7 display the envelopes of the ensemble of simulation runs and some randomly selected simulation runs (left), and the Kernel Density Estimates of the 2020 values (right). It is clear that, given the uncertainty ranges and surprises modelled, the scenario with the generative event (displayed in Figure 6) results in significantly more approved approaches for the development of Ebola vaccines and drugs than without generative event (displayed in Figure 7).

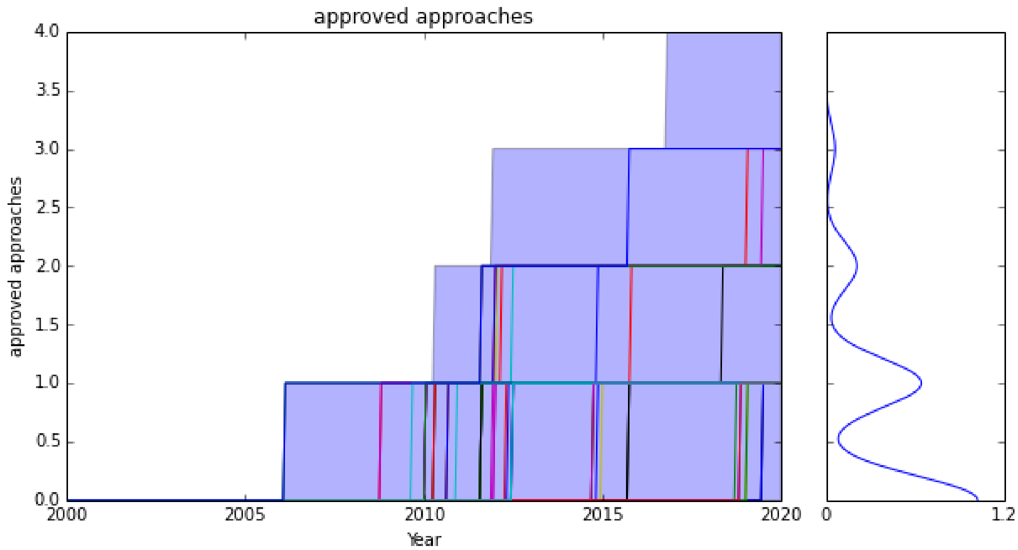

Fig. 6: Development of Approved Approaches with additional funding after 9/11

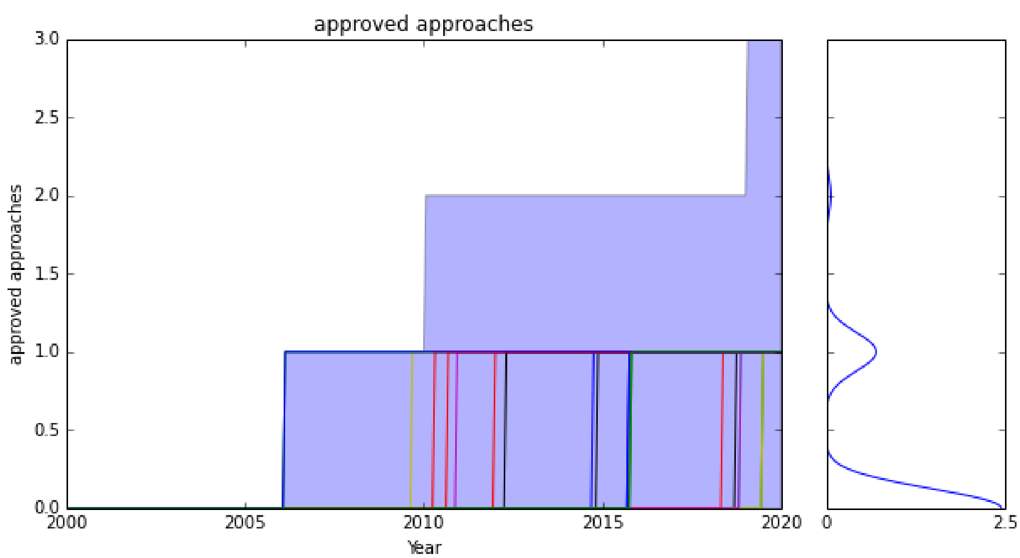

Fig. 7: Development of Approved Approaches for additional money in 2014

These results could be further explored using time series clustering and machine learning algorithms. Note however that the results only make sense at the level of the ensemble. In the case of a generative event, there would still be many instances at the ensemble level without approved vaccines an drugs, although there would also be quite some instances with 1, 2, 3 and very exceptionally even 4 approved approaches by 2020. Without generative event, there would be fewer approved approaches on the ensemble level, possibly 1 and very exceptionally 1 or 2 by 2020. What this means is that with cross-fertilisation and substantial investments from 2002 on, the chances of success are much higher.

Note that surprises included in the model do not necessarily need to be specified and accurate to be useful for exploratory analysis to be useful for policy making. The information that spill-overs from other disciplines make a considerable difference may, under uncertainty, be almost as valuable as accurate information regarding the spill-over that makes a considerable difference under certainty. Innovation policy and vaccine development require substantial seed money together with sufficient cross-linkages. Although it does not necessarily leads to successful outcomes, it is more likely to lead to successful outcomes than innovation policies and situations with too few resources, with concentrated funding, where cross-fertilization is not nurtured, and without perceived urgency.

Hence, including changes and surprises leads to less uncertainty.

5 New Methods to Discover Surprising Behaviours/Scenarios

New approaches and methods were shown at the Conference. These approaches and methods are currently under review for publication. **STRONLY ABBREVIATED HERE.** As a consequence, they are not included here. They will also be submitted for presentation at the 2016 ISDC at Delft, the Netherlands.

6 Discussion, Implications, Conclusions

This paper deals with uncertainty, changes, and surprises. It was argued that modelling uncertainty and analysing the resulting dynamics often leads to surprises. The first model-based study discussed here, also shows that some uncertainty can be reduced, and that some uncertainty may reduce over time. Embracing uncertainty and reducing the uncertainty that can be reduced then leads to fewer real surprises. But uncertainty is not the same as surprises and changes. Including surprises and changes leads in fact to a better fit between model-generated outcomes and real-world evolutions, and hence, to less uncertainty.

Indeed, the first model-based study shows that the fit between systems models and reality improves if past and present surprises and unexpected changes are included explicitly in models under deep uncertainty. Calibration then results in more realistic model parameters and outcomes, and in better foresight with better ensemble forecasts.

The second model-based study shows how the degree dealt with could shift from deep uncertainty to total ignorance. In practice, recognized ignorance is often caused by a combination of surprises and deep uncertainty. Using the second model, it was shown that different kinds of surprises could be modelled and simulated. What-if analysis and exploration of the resulting ensembles may then generate valuable information about what matters on the systems level. The latter approach could be further developed into an approach to explore issues that are characterized by recognized ignorance, for it may not be necessary to know exactly what surprises are caused by. Multiple models could then be developed to span the widest variety of plausible mechanisms and surprises. Although there may be a substantial loss of accuracy and degree of detail though, the analyses and conclusions may still be very informative for high level policy makers.

Note however that adding many plausible mechanisms and surprises may also result in a combinatorial explosion of the uncertainty space that would need to be generated and explored. This in turn necessitates the use of new techniques such as adaptive sampling (Islam and Pruyt 2014) that allow to sample from those areas of the multi-dimensional uncertainty space that generate the most interesting dynamics. Moving towards recognized ignorance may also require more robust policy designs, and thus, robust optimization to design more robust policies (Hamarat *et al*. 2013, 2014).

But the main message is that, since surprises and deep uncertain can be dealt with in modelling and simulation, recognized ignorance and even total ignorance are within reach.

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7 Appendix A:

FIGURE NOT INCLUDED HERE.

Fig A.1: Core Ebola model with compartments (rectangles), flows between compartments, causal relations (all arrows), social-psychological switches (blue), & policy switches (green). Source: (Pruyt *et al*. 2015)