Developing Scenarios for Uncertain Complex Risks: Using SD to Explore Futures of Lyme Disease in the Netherlands

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July 30, 2012

Abstract

Lyme disease due to infection with Lyme borreliosis poses an uncertain dynamic threat to the Dutch and their public health system. This risk was used to develop and illustrate two variants of a National Risk Assessment approaches for slumbering/latent risks. This paper explains and illustrates the System Dynamics-based variant using the societal risk posed by Lyme disease. Thousands of plausible evolutions of lyme disease are generated using a System Dynamics model in order to assess the societal risk posed by Lyme disease. The risk is scored in the Dutch National Risk Assessment framework adapted to deeply uncertain dynamically complex risks, and mapped in a new type of risk diagram developed for uncertain complex risks in order to compare the risk posed by Lyme disease to other plausible risks. Finally, scenario discovery techniques are used to identify a small set of representative scenarios that could be used in a capability analysis.

Keywords: Slumbering scenarios, System Dynamics, ESDMA, NRA, Lyme Disease

1 Introduction

1.1 Integrated Risk Capability Analysis and Scenarios

Today, many governments use national risk assessment (NRA) methods as well as capability-based planning or capability analysis methods (CA). Many recently developed NRA approaches –like the Dutch NRA approach– all-hazard (for natural hazards as well as for malicious threats), multi-dimensional, and scenario-based (Pruyt and Kwakkel year). They were first and foremost developed for incident-type risks characterized by low levels of uncertainty and dynamic complexity – not for risks characterized by high levels of uncertainty and/or dynamic complexity. Scenarios developed and used in these approaches are consequently only truly appropriate for risks characterized by low levels of complexity and uncertainty. However, risks with low levels of complexity and/or uncertainty may well be the least catastrophic risks modern societies may face today and in the future. And treating dynamically complex and/or deeply uncertain risks as simple incident-risks –for example, using three short-term weather scenarios to capture and represent an uncertain complex phenomenon such as climate change– leads to self-deception, underestimation, and narrow fire-fighting policies that address symptoms of underlying phenomena instead of the underlying phenomena or all effects. So, in spite of the fact that most approaches attempt to be all-hazard, few really are because they only properly allow for developing scenarios of simple risks of –at most– medium uncertainty.

That is precisely why two complementary scenario building approaches were added to the Dutch NRA: one qualitative procedural approach extending the incident risk approach to risks of

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medium uncertainty and little dynamic complexity, and one approach based on System Dynamics (SD) for dealing with risks characterized by medium to deep uncertainty and some to extreme degrees of dynamic complexity. Both approaches were developed using the risk posed to Dutch society by Lyme Disease –a risk that at first seemed to be characterized by little to some dynamic complexity and medium uncertainty– as test/pilot case. This paper first and foremost illustrates the SD-based NRA approach, using this case of Lyme Disease. But it is more than just an illustration: it is also a first attempt to explore and understand the uncertain risk posed by lyme disease.

Although Lyme Disease was chosen as pilot case for the Dutch NRA because initially it looked as though it would be a good example of a risk with little to some dynamic complexity and medium uncertainty, hence, appropriate for illustrating both the qualitative and the quantitative variant of the NRA approach for slumbering/latent risks, later it became gradually clear that the risk of Lyme Disease is actually characterized by deep uncertainty, making the computational SD-based approach used in this paper even more relevant. This will also be shown here.

1.2 Organization

Section 2 starts with a discussion of risk scenarios, the method(ologie)s used, and steps in the Dutch model-based NRA. The application of the SD-based NRA variant to Lyme disease is illustrated in section 3. Concluding remarks and current and future research related to this topic are dealt with in section 4.

2 Methodology: Risks, Method(ology), Steps in the NRA Model-Based Scenario Building Approach

2.1 Risks: From Simple & Certain to Complex & Uncertain

Many scenario development methods exist. Mostly used are qualitative process-based scenario generation approaches relying heavily on inputs from experts. The incident-risk approach tailor made initially for the Dutch NRA belongs to this class of methods (Bergmans et al. 2009; Pruyt and Wijnmalen 2010; Pruyt and Kwakkel year). These procedural/expert-based scenario methods work fine for many risks – especially for risks that are relatively well known and (are expected to) have relatively simple time-evolutionary behaviors. Model-based scenario development methods also exist, but seem to be used less frequently for NRA. They may nevertheless be more useful than traditional procedural/expert-based methods for scenario development for uncertain risks with complex dynamics. Hence, the choice of scenario method to be used should depend on the risk.

Issues –and therefore risks– could be classified in many different ways. Kwakkel and Pruyt (2011)[1] classify systems and issues, and thus risks, according to following levels of uncertainty:

- Level 1 or ***marginal uncertainty***: the issue or risk is considered to be as good as certain – uncertainty is at most marginally influential on the outcomes and conclusions, and therefore of minor importance.
- Level 2 or ***shallow uncertainty***: it is possible to simulate or enumerate all alternative scenarios and provide their (subjective or objective) probabilities.
- Level 3 or ***medium uncertainty***: it is possible to simulate or enumerate all alternatives and rank order the alternatives in terms of their perceived likelihood.
- Level 4 or ***deep uncertainty***: it is possible to enumerate multiple plausible alternatives or build multiple plausible models and simulate them, but it is impossible to order the alternatives or outcomes according to their likelihood or plausibility.

[1] See also Kwakkel and Pruyt (year).

- Level 5 or ***recognized ignorance***: it is impossible to simulate or enumerate alternatives in such a way that surprising outcomes are largely excluded, in other words, one cannot know or anticipate the future due to fundamental ignorance.

	None to little **dynamic complexity**	Some to extreme **dynamic complexity**
L1: Marginal Uncertainty	1 scenario for well-known risk wo DC *Known case or static model with SA*	1 scenario for well-known DC risk *Known case or dynamic model with SA*
L2: Shallow Uncertainty	multiple scenarios or models wo DC with subjective or objective probabilities *Prob. case(s) or static model(s)*	multiple scenarios or models for a DC risk with subjective or objective probabilities *Prob. case(s) or dynamic model(s)*
L3: Medium Uncertainty	**alternative scenarios wo DC with ordinal likelihoods** *Latin Hypercube on static model*	alternative scenarios with ordinal likelihoods for DC risk *Latin Hypercube on dynamic model*
L4: Deep Uncertainty	**multiple alternative scenarios wo likelihoods for risk wo DC** *EMA on static models, or morph. box*	**multiple alternative scenarios wo LHs for a very DC risk** *EMA on dynamic models (ESDMA)*
L5: Recognized Ignorance	unable to enumerate alternatives wo possibly being surprised by risk wo DC *EMA and/or creative process*	**unable to enumerate alternatives wo possibly being surprised by DC risk** *Extreme EMA on dynamic models*

Table 1: Levels of uncertainty and dynamic complexity, and suggested scenario generation approaches – Legend: DC:= dynamically complex ; LHs:= likelihoods

Combining these levels of uncertainty with two levels of dynamic complexity (*none to little* and *some to extreme*) gives the eight combinations in Table 1. Lyme disease was initially perceived –and therefore selected– as a risk of medium uncertainty and little to some dynamic complexity. Risks of medium uncertainty require at least alternative scenarios with associated likelihoods or the use of (either static or dynamic) models used in a probabilistic sense. However, most important societal risks are at least deeply uncertain – likelihoods cannot truly be assigned nor can outcomes be interpreted probabilistically. Deeply uncertain risks require method(ologie)s to enumerate/generate all plausible scenarios (before selecting a set of scenarios that are representative or of particular interest). Either the method(ologie)s used for deeply uncertain risks pushed to their limits or processes focussed on stimulating creativity could be used to some extent for dealing with recognized ignorance by identifying grey swans, by generating the broadest possible set of risk scenarios (ie from least surprising to wildest possible), or by developing an artificial set of scenarios spanning the widest plausible outcome space.

All cells in the right hand side column of Table 1 would benefit from the use of dynamic models, e.g. System Dynamics simulation models, because human beings are unable to derive the dynamics of complex systems without resorting to computer models. Computational models are also very useful for generating scenarios of medium to deep uncertainty. Hence, risks characterized by more than medium uncertainty (the bottom two rows) may all benefit from the use of some form of model-based approach, e.g. Exploratory Modeling and Analysis (EMA).

But the major advantage of developing and/or using simulation models for NRAs relates to its use for both NRA and CA: Not only does scenario generation for risks characterized by some to extreme dynamic complexity benefit from developing and/or using dynamic simulation models, e.g. exploratory SD models (see subsection 2.2), it also facilitates the ensuing capability analysis in the sense that policies with regard to capabilities could be tested using these models.

2.2 Methodology: Exploratory *System Dynamics* Modeling & Analysis

System Dynamics. Traditionally, System Dynamics (SD) is used for modeling and simulating dynamically complex issues and analyzing their resulting non-linear behaviors over time in order to develop and test the effectiveness of structural policies (Forrester 1961; Ford 1999; Sterman 2001). Traditional SD modeling and simulation could be used in isolation to generate transient scenarios –as indicated in Table 1– for risks characterized by some to extreme dynamic complexity and by shallow uncertainty. A combination of traditional SD and sampling (e.g Latin Hypercube) could be used to generate transient scenarios –as indicated in Table 1– for risks characterized by some to extreme dynamic complexity and by medium uncertainty.

Exploratory System Dynamics. SD models may also be built specifically for the purpose of exploring the potential influence of uncertainties on dynamically complex issues. Such Exploratory SD (ESD) models are preferably fast-to-build and easily-manageable, and consequently, rather simple and highly aggregated. ESD is an interesting approach for exploring uncertainties, generating all sorts of behaviors, and testing the effectiveness of policies in the face of these uncertainties. Many ESD models are also partly open models (ie, partly endogenous, partly exogenous) with elements from Trend Impact Analysis and Cross Impact Analysis[2]. But irrespective of the type of ESD model, using ESD in isolation may lead to insufficiently broad and systematic exploration of (all plausible modes of) behavior(s), and firmly base policymaking under deep uncertainty on. So if plausible scenarios need to be generated and exhaustiveness is not required, then ESD could be used for generating scenarios for risk characterized by some to extreme dynamic complexity under medium uncertainty, deep uncertainty, and recognized ignorance. However, the combination of ESD with Exploratory Modeling and Analysis (see following paragraph) may be useful and sufficient for broadly and systematically generating scenarios, and analyzing plausible dynamics under deep uncertainty, and for testing the effectiveness and robustness of policies without neglecting deep uncertainty and dynamic complexity.

Exploratory Modeling and Analysis Exploratory Modeling and Analysis (EMA) is a methodology for exploring deep uncertainty and testing policy robustness. It consists of using exploratory models (not necessarily ESD models) for generating tens of thousands of scenarios (called an 'ensemble of futures' or an 'ensemble of scenarios'), analyzing the ensemble of scenarios, and testing the robustness of policy options across the ensemble of scenarios. As shown in table 1, EMA is useful for dealing with deep uncertainty (Lempert et al. 2003; Agusdinata 2008) and in an extremely exploratory mode also to some extent for dealing with recognized ignorance –for all degrees of dynamic complexity. EMA consists of the following steps: (*i*) developing 'exploratory' –fast and relatively simple– models of the issue of interest; (*ii*) generating an ensemble (tens of thousands) of scenarios by sweeping uncertainty ranges and varying uncertain structures, boundaries, mechanisms, models, and modeling methods; (*iii*) time-series clustering and analysis of the ensemble of scenarios; (*iv*) and/or specifying a variety of policy options (preferably adaptive ones), and simulating, calculating, and comparing the performance of various options across the ensemble.

EMA is still under development: researchers of several institutes are currently improving, extending and contributing to EMA theory, EMA methodology, and EMA tools, and are working on a plethora of EMA applications, often in combination with adaptive policymaking. See for example (Bankes 1993; Lempert and Schlesinger 2000; Lempert et al. 2003; Lempert et al. 2006; Bryant and Lempert 2009) for RAND related EMA work. And see (Walker and Marchau 2003; Van der Pas et al. 2007; Van der Pas et al. 2008; Agusdinata 2008; Agusdinata et al. 2009) and (Kwakkel et al. 2010a; Kwakkel et al. 2010b; Kwakkel and Pruyt 2011) for Delft University of Technology related EMA work.

Exploratory System Dynamics Modeling and Analysis Since EMA requires handy models for generating (thousands of) plausible scenarios, and ESD requires methods for exploring deep uncertainty, they are actually natural complementary allies (Pruyt 2007), and could be combined as Exploratory System Dynamics modeling and Analysis (ESDMA).

ESDMA could be used for: (*i*) ensemble generation, (*ii*) ensemble exploration, (*iii*) direct searches, (*iv*) scenario discovery and selection, (*v*) advanced analysis, (*vi*) adaptive policy design,

[2]Cross Impact Analysis could be used as a systemic scenario development approach for dynamically complex issues in which transient, nonrecurrent events play an important role. It is an extension of the Delphi forecasting technique and could be seen as an the equivalent of the previous approach but then for event-based dynamics. It combines trends, events, their probabilities and Monte Carlo simulation. Cross-impact analysis concentrates on the way in which external or internal events or trends may interact to produce new effects or magnified effects. Trend Impact Analysis is similar to Cross Impact Analysis but focusses on trends.

(*vii*) policy robustness testing, and (*viii*) deep validation (model verification and validation) and triangulation between experts/models (Pruyt and Kwakkel 2012). Many of these uses have nevertheless not been explored and developed to their full potential yet, since ESDMA is relatively new[3]. For the classification displayed in Table 1, ESDMA is most appropriate for generating all (sorts of) plausible scenarios for risks characterized by some to extreme dynamic complexity under deep uncertainty and recognized ignorance (two bottommost cells on the right hand side of table 1).

2.3 Steps of the Model-Based NRA Scenario Building Approach

The quantitative variant of the scenario development approach of the Dutch NRA makes use of SD modeling to simulate and analyze the underlying phenomenon, and distill plausible scenarios of interest. The SD models developed for the NRA could also be used post-NRA, for example in a capability analysis. Since deep uncertainty needs to be taken into account, ESDMA is used here:

1. identifying a potential risk, its character (degree of uncertainty, risk, time horizon), and plausible evolutions,
2. identifying possible variables and key performance indicators, plausible causal relations between them, and major uncertainties (parametric as well as structural uncertainties),
3. specifying the plausible relations between the variables and key performance indicators, and specifying values or uncertainty ranges for parameters,
4. simulating the SD model(s) –note the plural form: step 2 may result in more than one model– while varying the uncertainties in order to generate an ensemble of plausible behaviors, i.e. transient scenarios, and displaying the ensemble of scenarios for different dimensions,
5. analyzing and exploring the ensemble of scenarios, and plotting the total impact scores of the ensemble in a risk envelopes diagram,
6. distilling different representative scenarios of interest based on total impact scores, their origin in the multi-dimensional uncertainty space, and their time-evolutionary behavior.

This quantitative variant requires sufficient modeling expertise, i.e. at least one SD expert, preferably a SD expert specialized in making 'quick and dirty' models on the spot, during workshops with domain experts.

[3]Although the first EMA related paper goes back to 1993, progress was rather slow given the few scientists working on it. ESDMA is of even more recent date: as far as we know, Lempert et al. (2003) provided the first illustration of ESDMA on a single SD model, the modified wonderland model, immediately illustrating a set of ESDMA uses (ensemble generation, ensemble exploration, policy robustness testing). Picking up from there, the first attempts or our research team included ensemble generation and policy testing on an oversimplified bank crisis model (Pruyt and Hamarat 2010a), and a H1N1 flu model (Pruyt and Hamarat 2010b). The flu model developed into a test case for our software tool[4]. Our first multi-model ESDMA was performed on simplistic radicalization models, presented in (Pruyt and Kwakkel 2011). The first Exploratory Group Model Specification and Simulation workshop was organized for our work related to societal aging, reported on in (Pruyt, Logtens, and Gijsbers 2011; Logtens 2011; Logtens et al. 2012). Special ESDMA model structures were developed for and described in (Pruyt et al. 2011; de Groen 2011; de Groen and Pruyt 2012; Auping 2011; Auping et al. 2012). Our first EMA on an Agent-Based Model was performed using an ABM of the transition of the Dutch electricity system by Kwakkel and Yucel (2011). Scenario discovery and selection was applied almost simultaneously in (Kwakkel et al. 2012; Pruyt et al. 2012). Using ESDMA with robust optimization for designing adaptive policies was first implemented in (Hamarat, Kwakkel, and Pruyt 2012a; Hamarat, Kwakkel, and Pruyt 2012b; Hamarat, Pruyt, and Kwakkel 2012). All of the above was applied simultaneously across many risks in (Pruyt and Kwakkel year; Pruyt et al. 2012). Kwakkel and Timmermans (2012) performed, in the ESDMA context, the first direct search with Active Non-linear Testing (Miller 1998). And a first attempt at using Formal Model Analysis in ESDMA is reported on in (Keijser et al. 2012).

3 A Model-based Risk Assessment of Lyme Disease

3.1 STEP 1: Risk Identification – The Risk of Lyme Borreliosis

Lyme disease is caused by bites from ticks infected with the Borrelia bacteria. These bites are incurred in (natural) areas with high or low vegetation, but also in city parks. Increasingly, ticks are infected with this bacteria. Hence, more and more people are bitten by more and more infected ticks, not only in the Netherlands but also in Western Europe and elsewhere in the world. There are no foolproof methods for diagnosis unless a characteristic red stain (erythema migrans) is observed. The number of infections based on the adoption of this red stain in the past 15 years in the Netherlands increased from 6500 in 1994 to 22000 in 2009. Also, the treatment is still not effective enough. Initially, the disease often remains unobserved, and is only diagnosed in an advanced stage. The health consequences can be (very) severe, resulting not only in individual suffering, but also in pressures on the health system and the economy. More information on Lyme disease in general and specifically for the Netherlands is available in (Coumou et al. 2011) – note that the information available in that paper was not available in 2010, when the SD model presented in section 3 was developed, but that it is used for developing the models referred to in section **??**.

Lyme disease is a public health risk of which the public at large is largely unaware, which is insufficiently under control, and which is still deeply uncertain (stages and state transitions of Lyme disease, . . .). The prevalence of ticks with Lyme borreliosis, the rate of tick bites, and the number of cases of Lyme disease (in the different stages of the disease) could increase mildly to strongly, and preventive and curative measures could range from adequate and timely to inadequate and late. Scenarios related to Lyme borreliosis should also take the development of medical knowledge, and public awareness into account. Referring to Table 1, dynamic models would thus be useful.

Classifying risks in terms of the level of uncertainty and binary classes of dynamic complexity they are characterized by as in Table 1, Lyme is an example of a deeply uncertain risk (phase transitions are not well known, diagnosing is uncertain because of false positives and false negatives) with little to some dynamic complexity (mainly stock-flow structures, very few true feedback loops, forced seasonality, and a few non-linear relationships). The presence of some dynamic complexity may justify the development and use of dynamic simulation models, and the presence of deep uncertainty may justify the use of these models within the EMA methodology. But those who argue that there is little dynamic complexity and only medium to deep uncertainty may as well opt for non-model-based development of scenarios with or without corresponding likelihoods – the type of scenario that could be developed with the qualitative variant. Hence, the choice of this topic for developing both the qualitative and quantitative variant for slumbering risks.

As argued in (Pruyt 2010), SD modeling and Exploratory SD Modeling and Analysis are appropriate for different types of deeply uncertain dynamically complex safety and security issues. They could be used –but to various extents– for (i) acute crises, (ii) imminent crises, (iii) chronic crises, and (iv) slumbering phenomena as potential breeding ground for acute and/or chronic crises. The threat of Lyme Disease to the health system is –as we will see below– of the fourth type: the spread of Lyme borreliosis could lead to a potential chronic burden with additional seasonal stress on the health system. The latter being deeply uncertain. ESDMA may then be used for:

- generating an ensemble of plausible scenarios (10000+ scenarios) and exploring it;
- testing the robustness/flexibility/resilience of the systems or system designs (second line of defense) and designing monitoring and early detection systems for potential but unanticipated problems;
- helping to design mitigation/preventive policies to fight future crises by attacking the slumbering phenomena (which may be easier and less costly than dealing with the consequences of crises) (first line of defense);

- helping to decide about building capabilities for crisis management and adaptation (third line of defense).

In the current version of this paper, only the first use is illustrated here by means of the model developed to generate scenarios for the Dutch NRA.

3.2 STEP 2: Conceptual Model

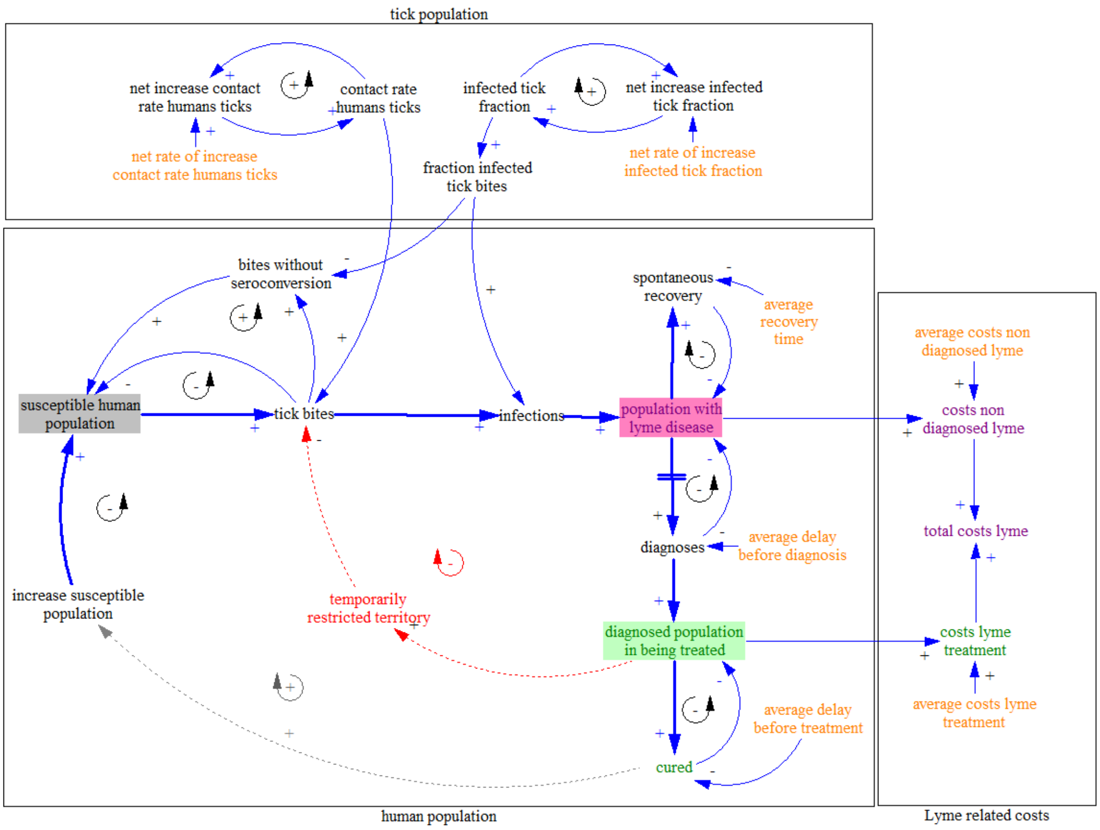


Figure 1: Causal loop diagram corresponding to the simplistic SFD in Figure 2

The important variables for an insidious Lyme scenario are the infected ticks fraction, the human-tick contact rate, the number of tick bites and infections, the population with (undiagnosed) Lyme disease, the diagnosis times, transition rates, etc. Key performance indicators to monitor (and relate to NRA criteria) are the diagnosed population in treatment and the ongoing costs of Lyme treatment (both in green). Key performance indicators one cannot monitor (but simulate and relate to NRA criteria) are the undiagnosed population with Lyme disease, the running costs of undiagnosed Lyme, and the total running costs due to Lyme (in purple). Figure 1 shows these variables, performance indicators, the relationships between them, and the resulting feedback loops[5] qualitatively in a causal loop diagram. Figure 2 shows the corresponding stock-flow diagram of the first iteration simulation model. The exogenous variables (in orange) in these diagrams are uncertain. And of all stocks, only the diagnosed population being treated stock is known for real, although the percentage of the real diagnosed population being treated truly being infected is

[5]These loops generate non-linear effects (exponential growth, oscillations,...), even if all the relationships in these loops are linear. In isolation positive or self-reinforcing loops generate exponential growth or decay, and negative or balancing loops generate convergent behavior. In case of multiple, interconnected loops, and changing loop dominance, computer programs are needed to calculate resulting system behavior.

fundamentally uncertain too. The stocks in this first model are also too aggregate: the stock-flow structure requires extension in subsequent iterations since different stages of lyme disease are not considered yet. This model is nevertheless interesting as a first approximation developed in group. SD models are preferably constructed interactively, from the mental models of the experts or actors, and iteratively, starting small and extending. Hence, the entire NRA scenario group or knowledgeable experts could and should be engaged actively in this first stage of the modeling process.

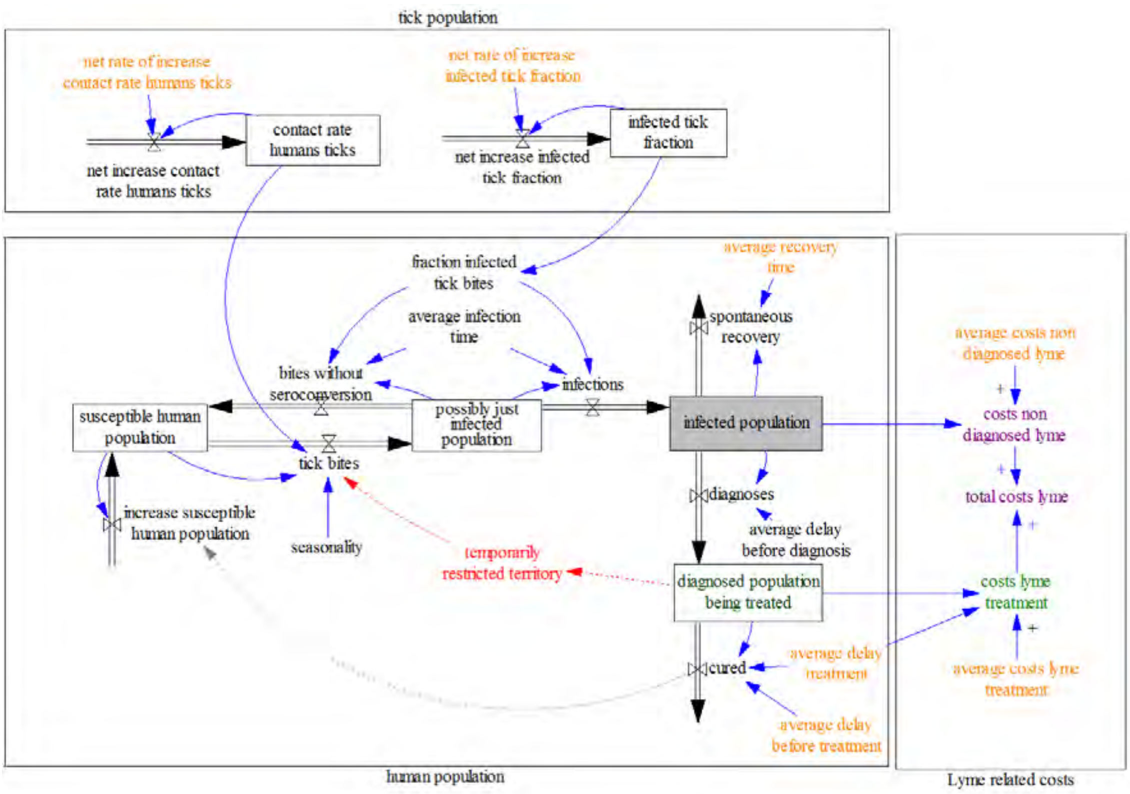


Figure 2: Simplistic Stock-Flow diagram / First iteration simulation model related to Lyme

3.3 STEP 3: Simulation Model and ESDMA Settings

The model is subsequently gradually expanded and specified (either the modeler with input from experts or the modeler together with the scenario group in a Group Model Specification session similar to the session described in (Pruyt, Logtens, and Gijsbers 2011)). Experts and scenario group members only need a minimum amount of information to understand SD modeling, more precisely that (i) the rectangles represent 'stock variables' (∼ bathtubs, state variables), the double arrows 'inflow variables' (∼ tap) and 'outflow variables' (∼ drain) and all other variables are auxiliary variables or constants, and that (ii) stock variables are integrals (accumulations) of all inflows minus all outflows over time. In the case of the development of the Lyme model displayed in Figure 3, the detailed modeling and specification of the different phases of Lyme disease and the difference between diagnosed and undiagnosed was not performed in group, nor was the extension of this model with ESDMA uncertainty structures (in red) and scripts, nor was the modeling of the NRA criteria (in orange).

The model is fairly simple: It consists first and foremost of a detailed stock-flow structure for infected persons, whether visible, invisible, or being treated for Lyme. Knowledge about infections will lead to temporary restrictions of the territory (dunes, national parks, et cetera). Switches

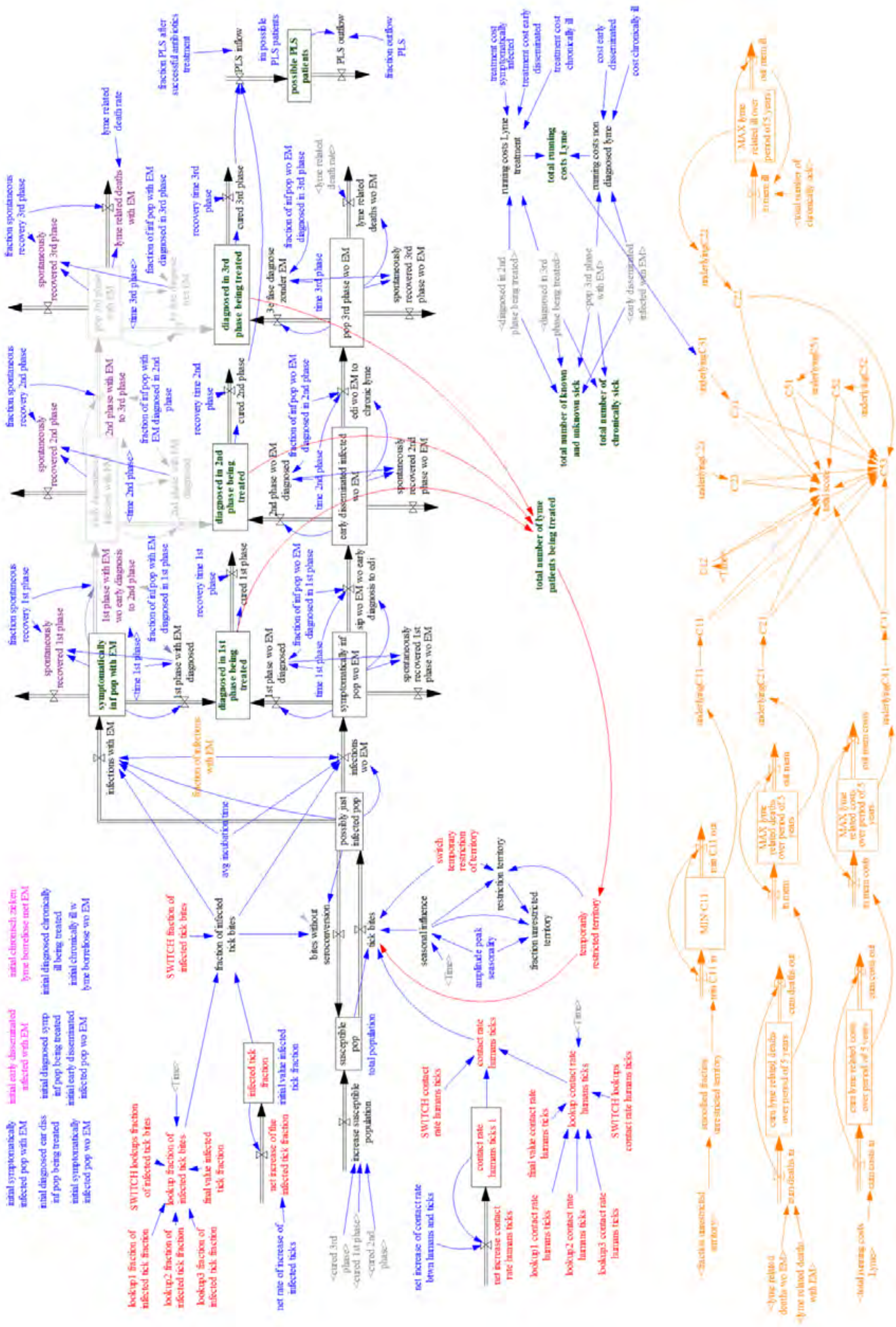


Figure 3: Simulation model related to Lyme with structures to translate the simulation results into NRA scores (orange), and ESDMA structures (red). Note: not all relations are visualized in this diagram

in the model allow to switch between structures or between different exogenous time-series, e.g. related to the fraction of infected ticks.

And the orange bottom-most structures translates the continuous key performance indicators related to Lyme disease into discrete NRA criteria scores for each of 10 NRA criteria and the NRA total score (see (Bergmans et al. 2009; Pruyt and Wijnmalen 2010; Pruyt and Kwakkel year)). These NRA total scores are the (equally) weighted sum of the scores (displayed in Figure 4) on the following ten criteria:

C1.1 Infringement of the Dutch territorial integrity

C1.2 Infringement of the integrity of the Dutch international position

C2.1 Number of fatalities

C2.2 Number of seriously injured and chronically ill

C2.3 Physical suffering (lack of fulfilment of basic needs)

C3.1 Economic costs and structure

C4.1 Long-term damage to the environment

C5.1 Disruption of everyday life (schools, work public transport, etc.)

C5.2 Violation of the democratic system (political, financial, etc.)

C5.3 Psychological impact (public outrage and anxiety/fear)

3.4 STEP 4: Computational Experiments and Visualization

The settings for the uncertainty analyses (Latin Hypercube, 1000 and 10000 runs) and the uncertainty ranges displayed in Table 2 lead to the behaviors over 300 months and the corresponding end-state histograms displayed in Figure 4 and corresponding NRA scores in Figure 5. Note that the continuous lyme related behaviors are translated by these NRA criteria in discrete outputs (maximum values or cumulative values over five years). The risk envelopes diagram in Figure 7 shows that almost half of these runs correspond to 'very serious' NRA scenarios ($0.33 > D \geq 0.11$), the other half being 'serious'.

If the parameter values / intervals and structures even come close to the actual risks, then the graphs above show that Lyme is a much greater risk than the visible part of it (ie the total number of Lyme patients in treatment) would suggest. The monthly total running costs attributed to Lyme would then be multiples of the amounts directly spent monthly on Lyme treatment.

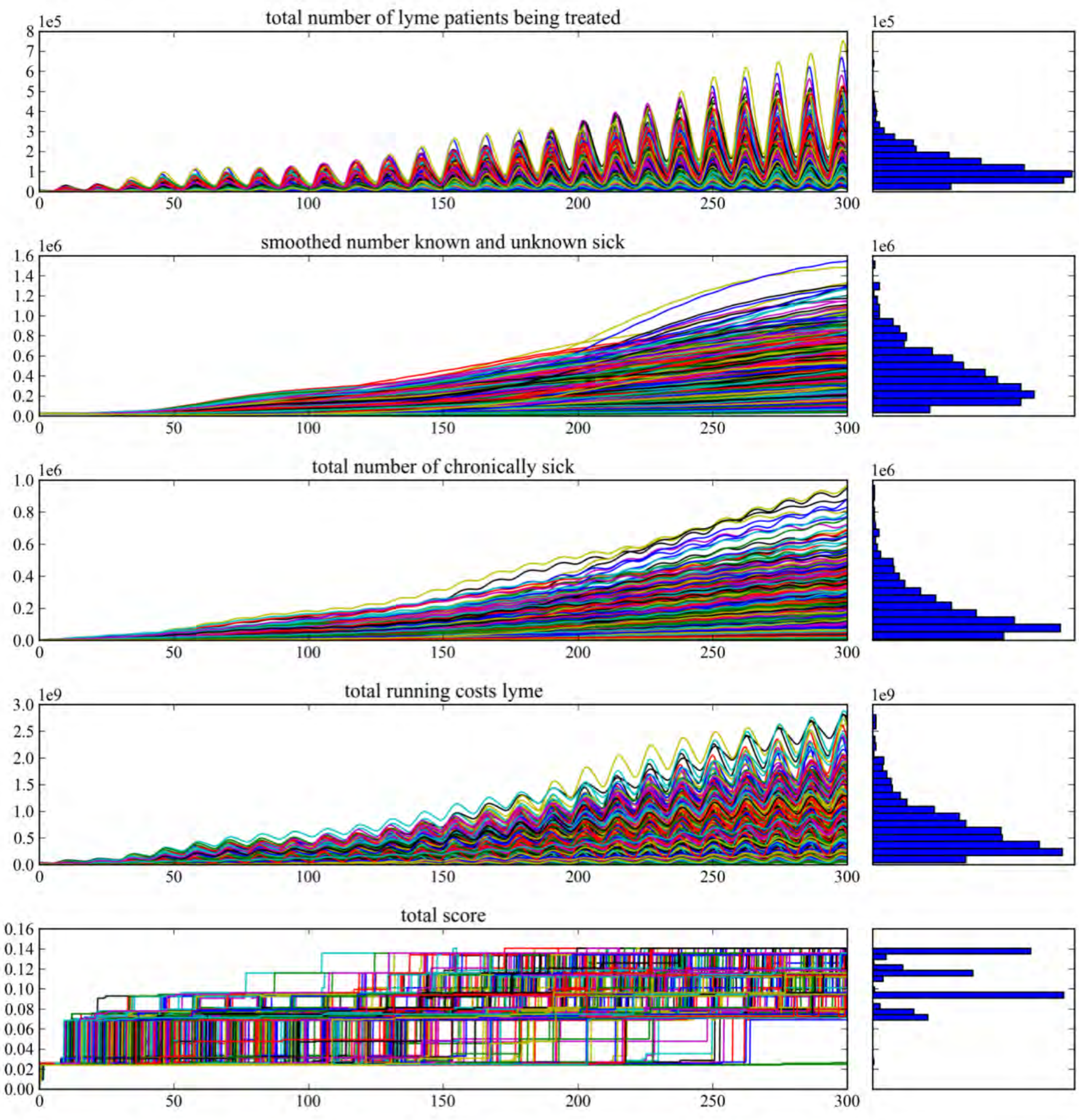


Figure 4: Lines for 1000 runs over 300 months (LH sampling over the uncertainties in Table 1)

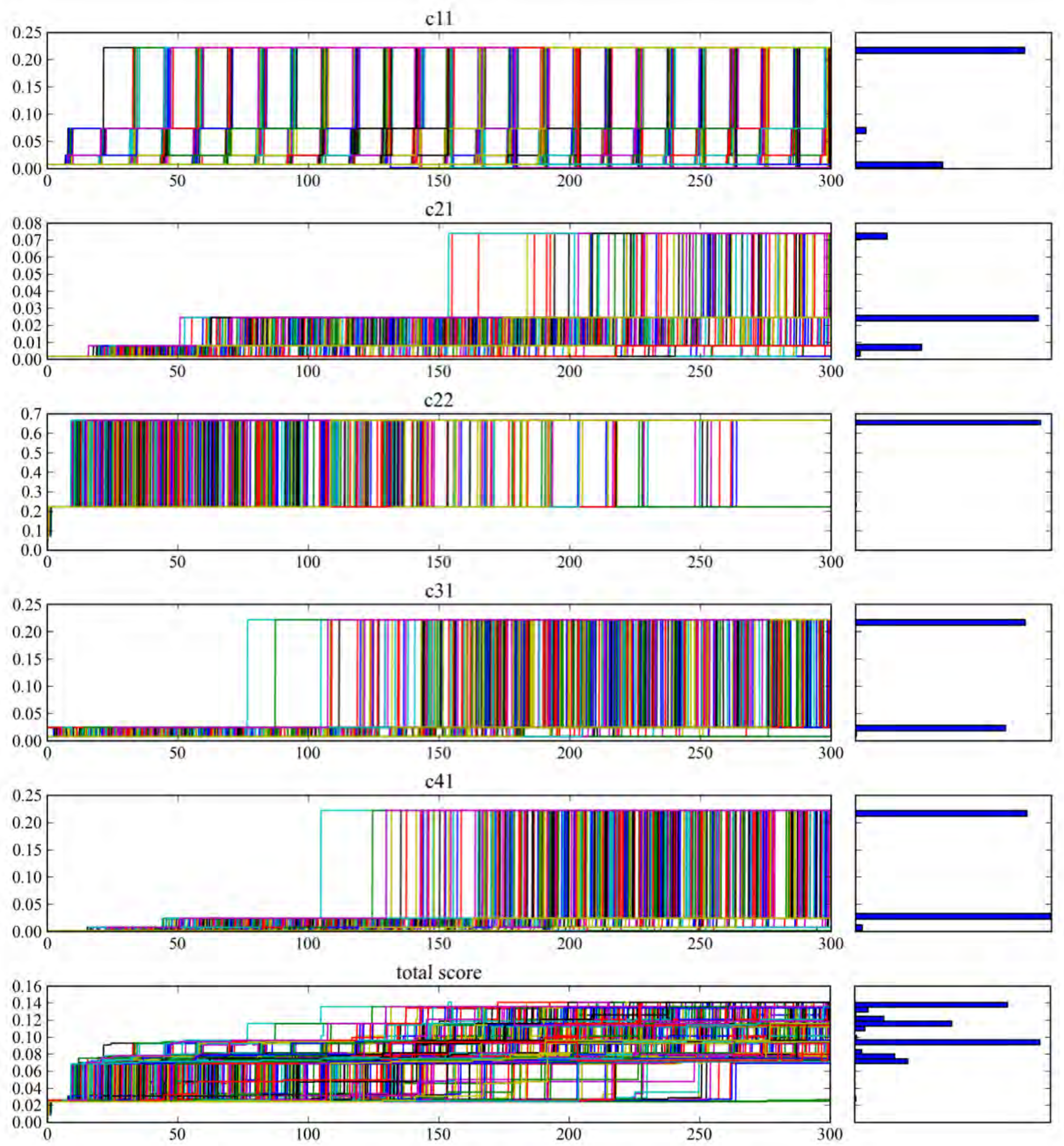


Figure 5: Discrete NRA scores of the runs displayed in Figure 4 on 5 relevant criteria ($1 \geq E \geq 0.33 > D \geq 0.11 > C \geq \ldots$ with E $\sim$ catastrophic, D $\sim$ very serious, C $\sim$ serious, etc.)

Parametric uncertainty	lower bound	upper bound
initial symptomatically infected pop wo EM	800	1000
initial early disseminated infected pop wo EM	13000	15000
initial chronically ill w lyme borreliose wo EM	0	1000
initial symptomatically infected pop with EM	800	1000
initial diagnosed symp inf pop being treated	5000	7000
initial diagnosed ear diss inf pop being treated	900	1100
initial diagnosed chronically ill being treated	0	1000
net rate of increase of infected ticks	0.003	0.007
net increase of contact rate btwn humans and ticks	0.003	0.007
avg incubation time	0.5	2
amplitude peak seasonality	1	2
ini possible PLS patients	0	1000
fraction of infections with EM	0.4	0.9
time 1st phase	0.5	1.5
time 2nd phase	5	17
time 3rd phase	6	18
fraction of inf pop with EM diagnosed in 1st phase	0.5	0.9
fraction of inf pop with EM diagnosed in 2nd phase	0.3	0.7
fraction of inf pop with EM diagnosed in 3rd phase	0.1	0.3
fraction of inf pop wo EM diagnosed in 1st phase	0.05	0.2
fraction of inf pop wo EM diagnosed in 2nd phase	0.3	0.5
fraction of inf pop wo EM diagnosed in 3rd phase	0.05	0.2
recovery time 1st phase	1	3
recovery time 2nd phase	1	3
recovery time 3rd phase	3	9
fraction PLS after successful antibiotics treatment	0.05	0.2
fraction outflow PLS	0.05	0.2
lyme related death rate	0.0000001	0.00001
treatment cost symptomatically infected	500	2000
treatment cost early disseminated	1000	3000
treatment cost chronically ill	1000	3000
cost early disseminated	500	2000
cost chronically ill	1000	3000
initial value infected tick fraction	0.01	0.05
fraction spontaneous recovery 1st phase	0.4	0.9
fraction spontaneous recovery 2st phase	0.04	0.09
fraction spontaneous recovery 3st phase	0.005	0.02
initial value infected tick fraction	0.01	0.05
final value infected tick fraction	0.2	0.6
SWITCH fraction of infected tick bites (Cathegorical)	0,1	default = 0
SWITCH lookups fraction of infected tick bites (Cath.)	1,2,3	default = 1

Table 2: Parameters treated as uncertain and the uncertainty ranges used

3.5 STEP 5: Analyzing & exploring the ensemble of scenarios, and plotting total impact scores of the ensemble in a risk envelopes diagram

A new type of risk visualization technique –a risk envelope diagram– is used here instead of a traditional risk diagram (or risk landscape) as displayed in Figure 10. The blue risk envelope in Figure 7 corresponds to 10000 model-based risk scenarios generated with the SD model. This risk envelope should be read as follows: all simulation runs result in at least a C score ('serious'), almost 50% of the runs result in a D score ('very serious'), and none of the 2000 runs generated an E score (catastrophic).

When different risks are plotted in the same envelope diagram, then envelopes that are higher and more to the right represent larger risks in terms of plausible impact and percentage of runs with high impact scores.

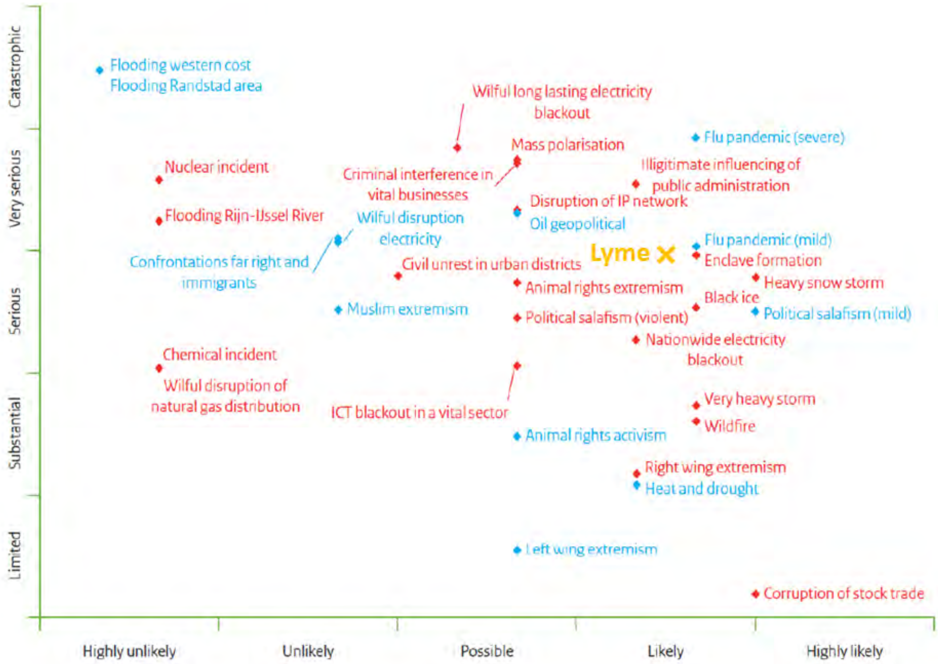


Figure 6: Traditional risk diagram with lyme according to the non-model-based variant

3.6 STEP 6: Distilling different representative scenarios of interest based on total impact scores, their origin in the multi-dimensional uncertainty space, and their time-evolutionary behavior

Applying scenario discovery and selection algorithms is particularly useful at this point *(i)* if a very small number of interesting scenarios is needed as is the case in the traditional Dutch NRA, or *(ii)* if a subset of scenarios representative for the larger set is desirable as is the case for model-based CA under deep uncertainty (Pruyt et al. 2012). Depending on the goal and the issue, different exemplary runs, exemplars in short, would be desirable: ideally, exemplars are representative for many other scenarios in terms of multi-dimensional impacts, time-evolutionary behavior (i.e. the dynamics), and the origins in the multi-dimensional uncertainty space. Although selecting exemplars based on all three of these aspects is rather complicated, selecting exemplars based on one of these aspects is straightforward and could be supported by:

- data set splitting to select representative exemplars in terms of multi-dimensional impacts.
- using a time-series clusterer algorithm –in our case a more advanced version of the one proposed by Yucel and Barlas (2011) with a metric proposed by Yucel (2012)– with dendrogram and cluster plots to cluster time series data based on attributes and select the similarity level at which to classify/plot clusters. Using this clusterer and visualizing exemplars for selected clusters is a powerful scenario discovery and selection approach if time-evolutionary behavior (i.e. the dynamics) is important.
- using a new version of PRIM or Patient Rule Induction Method (Friedman and Fisher 1999) –one that can deal with categorical and continuous uncertainties– with a binary classification function and PRIM box plotting, to identify uncertainty space boxes with high concentrations of runs that perform below/above a particular threshold, and hence, to identify exemplars that represent regions in the multi-dimensional uncertainty space with high concentrations of highly undesirable or desirable outcomes (e.g. catastrophic subspaces) or of outcomes with particular characteristics.

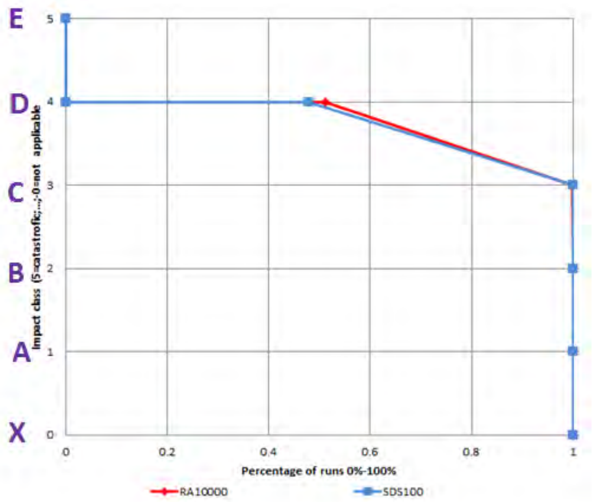
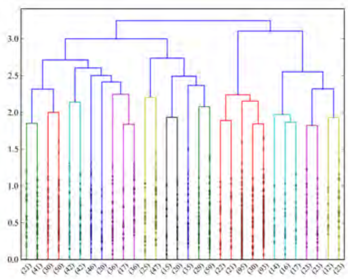
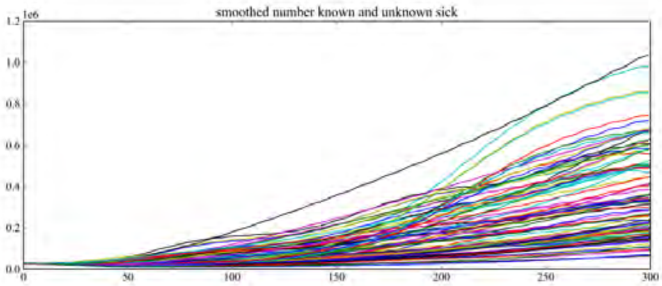


Figure 7: Risk Envelope Diagram of Lyme disease (E=5=catastrophic; D=4=very serious; ...)

The second option, time series clustering, is used here, both for selecting a representative set of exemplars for a computational CA, and for selecting very few exemplars for a traditional CA.



(a) Dendrogram

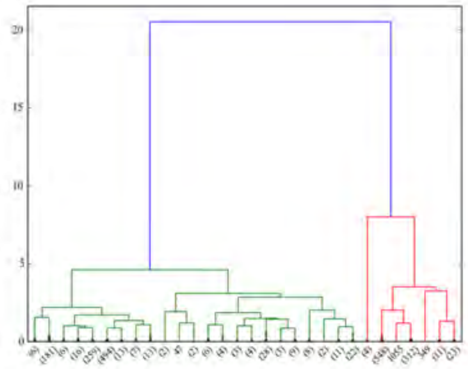


(b) 100 exemplars

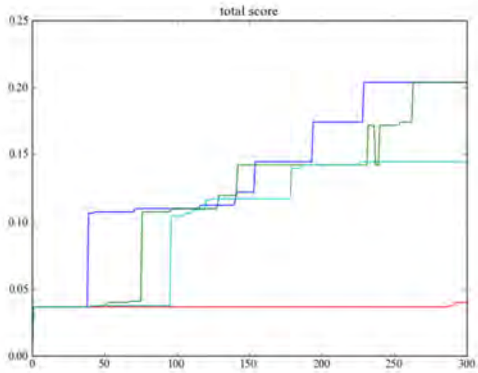
Figure 8: Dendrogram and 100 exemplars

Figure 8(a) shows the resulting dendrogram of the clusterer applied to the 'smoothed number known and unknown sick'. Figure 8(b) plots a set of 100 exemplars selected from the 1000 runs: one automatically selected exemplar for each of the 30 clusters supplemented with 70 hand-picked exemplars from the larger clusters proportional to the cluster size. Comparing the corresponding blue risk envelope in Figure 7 with the original red one shows that this subset is not only representative for the ensemble in terms of types of behaviors, but also in terms of total NRA scores. This subset could thus be used as representative ensemble in a model-based CA under deep uncertainty.

The same techniques could also be used to select one or a much smaller set of scenarios, e.g. for plotting in a traditional risk diagram and/or use in a traditional CA. Forcing the top 4 classes in the dendrogram (see Figure 9(a)) based on a classification on the final NRA score, and selecting only one exemplar per clusters results in the scenarios displayed in Figure 9(b). Cluster 1 represents 995 cases, cluster 2 represents 105 cases, cluster 3 represents 4 cases, and cluster 4 represents 896 cases. The behaviors of these four scenarios on some of the most important key performance indicators are displayed in Figure 10. The first and fourth exemplars would be good representative scenarios for all 'very serious' and 'serious' lyme scenarios in a traditional NRA.



(a) Dendrogram



(b) Exemplar for each of 4 second-level clusters

Figure 9: Dendrogram and exemplars for 4 second-level clusters

3.7 Post-NRA: Capability Analysis under deep uncertainty

The 100 runs subensemble generated in step 6 could then be used as representative set for the entire ensemble in a capability analysis under Deep Uncertainty (see (Pruyt et al. 2012)). The results could then be plotted in a risk envelope diagram in order to assess the (uncertain) risk reduction brought about by one (see Figure 11(a)) or multiple capabilities strategies (see Figure 11(b)), or compare risks and risk reductions over multiple risks (see Figure 11(b)).

4 Conclusions and Future Research

The goal of this paper was first and foremost to illustrate the SD model-based version of the Dutch NRA approach. This paper therefore illustrates the model-based process of the NRA for a particular risk. It involves normal ESDMA followed by plotting of the risk envelopes and scenario discovery to distill representative scenarios. The methods, techniques, and scripts for doing so are available, and could even be used in real time.

The second goal of the paper was to shed light on the risk posed by lyme disease. The future evolution of Lyme disease in the Netherlands is still deeply uncertain. A substantial part of the problems caused by Lyme may remain hidden (i.e. not unambiguously attributable to Lyme disease). Simulation models may therefore be useful to make the invisible and uncertain risk visible.

At first, Lyme was selected because both approaches could be used for it. Along the way, it became clear that the quantitative variant may be more appropriate for Lyme disease: not only is it a slumbering risk, it is also deeply uncertain due to different perspectives on Lyme and due to a lack of knowledge and information.

The medical profession and the Lyme patient association have different perspectives on Lyme disease. Modeling these different perspectives results in very different models about the same issue. Professionals believe that the diagnosis of chronic Lyme disease should be based on specific symptoms, chronic neuroborreliosis and acrodermatitis chronica atrophicans. The Lyme patient association believes that Lyme diagnosis should be based on a much broader definition of symptoms. According to the Lyme patient association, the group of chronic Lyme patients should be much larger than the group would be according to physicians. Physicians are skeptical about broad definitions that do not include proof of infection with Borrelia. This group of patients is nevertheless part of the group treated for Lyme disease in the Netherlands.

Another major controversy relates to Post-Lyme disease syndrome (PLDS) – which refers to people who have chronic complaints after treatment for Lyme disease. According to the medical

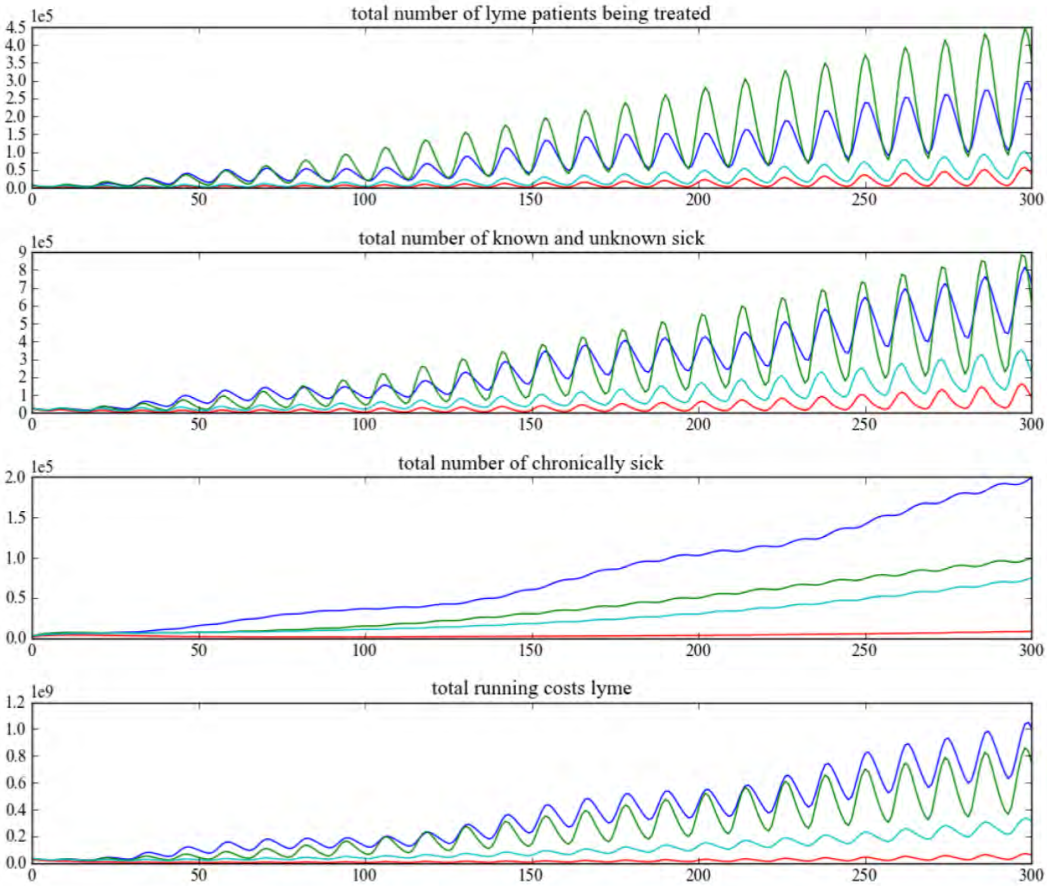
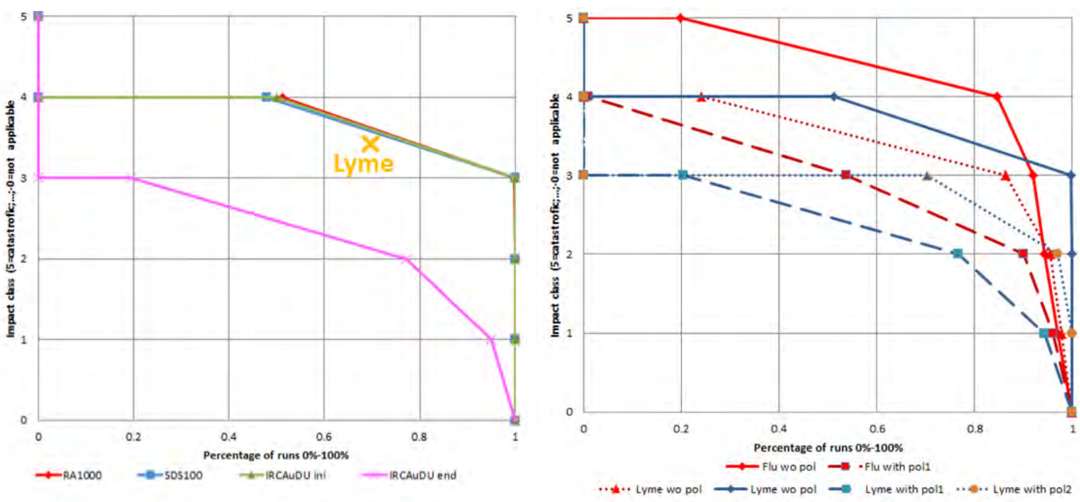


Figure 10: Behaviors of the four representative cases on important key performance indicators



(a) with CA under deep uncertainty

(b) comparing envelopes with flu

Figure 11: Risk Envelopes Diagrams

profession, these chronic illnesses may be treated unnecessarily for Lyme disease, resulting in additional costs and possible complications.

The model presented in section 3 may be problematic for both sides of the Lyme polemic – the discussion about what may or may not be seen as chronic Lyme. Separate models to represent each of the perspectives may be necessary.

Apart from these different perspectives on Lyme and PLDS, most information and data related to Lyme disease in the Netherlands are outdated or incomplete. Using information and data from other countries, eg the USA, may be an option, although it is well known that Lyme in the USA and in the Netherlands are different. Another option may be to treat data and information as uncertain.

After different models representing the different perspectives have been constructed, an ESDMA could be performed over all models to compare the differences and similarities in outputs generated by the difference in perspectives, and to find unifying policies. Different policies for dealing with Lyme disease may also be tested and their robustness compared over the full ensemble of scenarios generated with the three models.

Current and future work will thus extend this single-model ESDMA to a multi-model ESDMA with this NRA model, a model reflecting the perspective of the medical profession, and a model reflecting the perspective of Lyme patients.

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