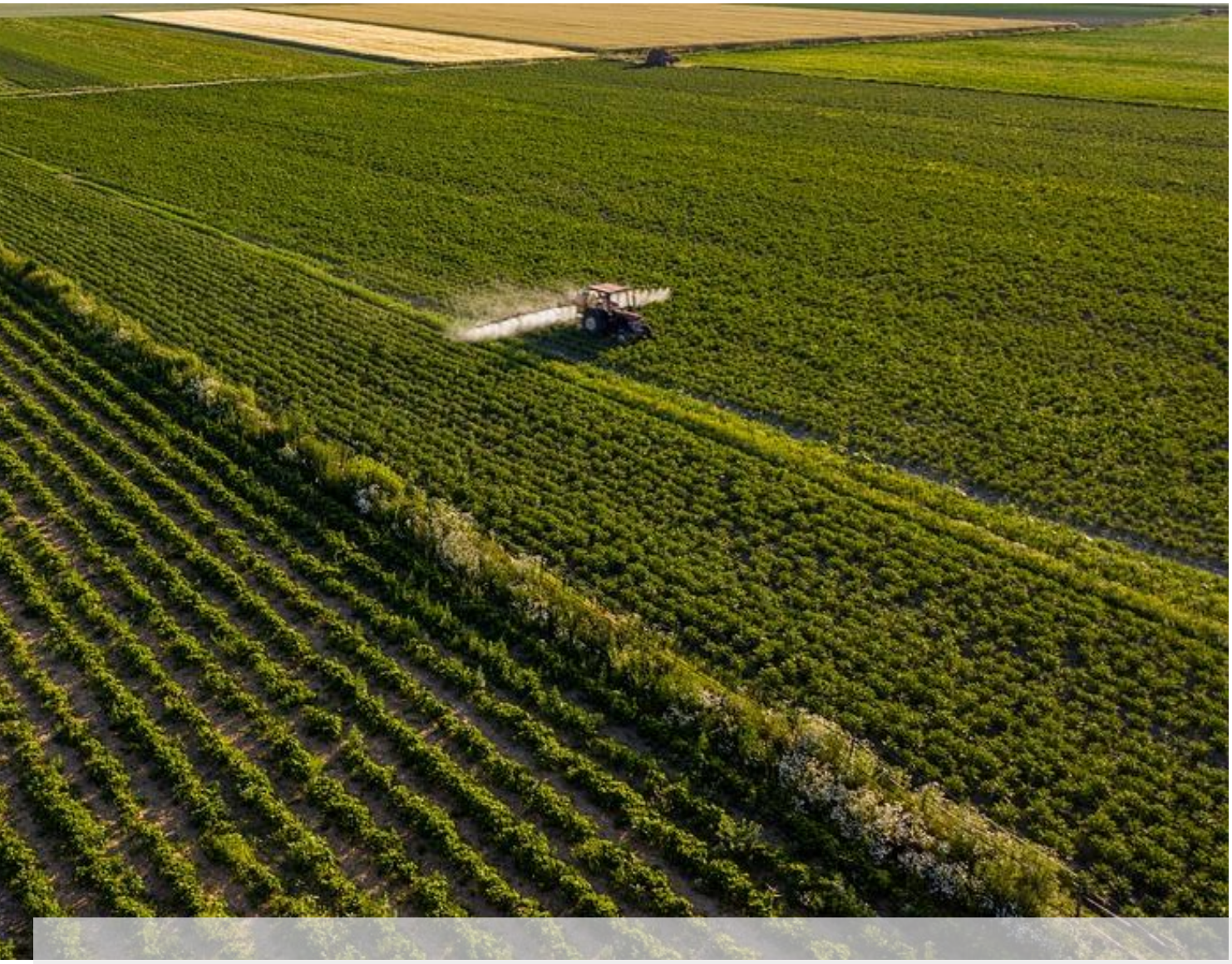


Applying agent-based modelling as a risk analysis tool for enforcement: a case study of the regulation of the Dutch plant protection products chain

Kim van Vliet

MSc Engineering and Policy Analysis

February 2022

TU Delft

This page was intentionally left blank.

Applying agent-based modelling as a risk analysis tool for enforcement: a case study of the regulation of the Dutch plant protection products chain

Master thesis submitted to Delft University of Technology

in partial fulfilment of the requirements for the degree of

MASTER OF SCIENCE

in Engineering and Policy Analysis

Faculty of Technology, Policy and Management

by

Kimberly Melissa van Vliet

Student number: 5185114

To be defended in public on March 7th 2022

Graduation committee

Chairperson and first Supervisor	Dr. H. G. van der Voort, Organization & Governance
Second Supervisor	Prof. dr. M. E. Warnier, Systems Engineering
External Supervisor	Dr. E. E. van der Vaart, Bureau Risicobeoordeling & onderzoek

Foreword

Here it is, the result of six months of work, twenty-five supervisor meetings, hundreds of coffee breaks and ever more personal breakthroughs, small or large. Admittedly, working individually to create this 60+ page document whilst juggling a tumultuous personal life felt like the coming-of-age of me as an academic and a professional. However, as with any heavy task, I could not have completed it alone. I would like to take this opportunity to dedicate a special thanks to all the people who have supported me through this challenging and gratifying time.

The first person to thank is my mom. Throughout my thesis, she has been the safe haven who always welcomed me home to relax, tell my stories and play boardgames after a few long weeks of working on my thesis. Her unwavering warmth and kindness have made the whole endeavour much more bearable. Thank you, mom. It makes me really happy to think I have made you proud.

Secondly, I would like to thank my dear friend Mila. We have really gotten to know each other through this thesis process, first by studying over summertime in “the office” which later culminated in innumerable enlightening coffee breaks. I would like to thank you Mila for showing me how strength can be a vehicle to genuine self-expression and authentic appreciation of others. You have shown me what it’s like to creatively venture out in life and given me all the peptalks I needed to do so myself. Thanks for being a great friend throughout my thesis.

Then there are many other people whom I am grateful for. Alexander, one of the kindest people I know, whom I can always convince to dance with me at parties (yes, this is very important). Francien, whom I admire for her willingness to pursue goals that are societally important yet personally challenging and is always there to help others. Judith, who has steered me through most of the pandemic. Liam, who has helped me explore new dimensions of myself. Gijs, who has been my short vacation in busy times with relaxed evenings and lavish meals. And lastly, Mathijs, who has made me happier than I thought I could be during a thesis period. I am very grateful and excited to explore what life after thesis is like with you.

I would like to thank the thesis circle for being “a group of shared suffering”, although in my opinion, every one of us has had their victories along the way too. Thank you Elvira, Francien, Mila, Ronny, Lotte, Bas and Xander.

Lastly, I would like to thank my first supervisor, Haiko van der Voort, for his enduring support, both content-wise and as a mentor. You definitely struck the right balance between encouraging me to do better and asking me to slow down when necessary. I would also like to thank my external supervisor Elske van der Vaart for her excellent supervision. Even though you were not officially obliged to help me with the contents of my thesis, your feedback throughout the many meetings has been very valuable.

Now it is time to walk the talk and present my thesis. Sisyphus has reached the top. I hope you enjoy reading.

Kim van Vliet
28 February 2022
Delft University of Technology

Executive summary

When it was first introduced, the problem-solving approach offered a new perspective on regulation: instead of procedurally treating every crime case the same, in the problem-solving approach important problems are selected and a thorough analysis is performed on the problem to find creative and effective ways to solve it. Multiple analysis methods have previously been used for risk analysis in the problem-solving approach, amongst which are surveys, (big) data analysis and geospatial mapping. One technique that has not previously been used for problem-solving risk analysis is agent-based modelling. Agent-based modelling is a promising technique for problem-solving risk analysis, as it is able to capture socio-technical systems in terms of agents, their interactions and their context. To investigate the applicability of agent-based modelling to problem-solving risk analysis, the following main research question has been answered:

How can an agent-based model aid a regulatory organisation in performing a PSA-risk analysis through analysing risk concentrations in a complex problem?

To test the suitability of agent-based modelling to problem-solving risk analysis, first a characterization of problem-solving risk analysis was performed to discover what sets this type of risk analysis apart from risk analysis in other regulatory paradigms. The following three unique characteristics were found:

- It is a problem-based process that is undogmatic in its choice of analysis.
- It is aimed at disaggregating risks in as many ways as possible to create tailormade interventions.
- It is located at the heart of the regulatory agency and is performed with the help of analysts and experts alike.

After the characteristics of a problem-solving risk analysis were defined, participatory agent-based modelling was applied to a case study on the regulation of plant protection products in the Netherlands. Six discussion sessions were held with experts from the Dutch Food and Consumer Product Safety Authority, which rendered extensive information on the Dutch plant protection products market. The question that was to be answered by the modelling exercise was:

How are the legal and illegal plant protection products chain interlinked and which link in the chain should be the main regulation target to ensure that as little illegal product as possible reaches the end-user?

The discussion sessions showed that the problem of illegal plant protection products is centred around three main topics: the types of actors in the plant protection products chain, the types of illegal plant protection products and the pathways of acquiring plant protection products. It was also understood why illegal plant protection products in the Netherlands are a complex problem: end-users are driven to buy products that are illegal in the Netherlands due to insufficient approvals of legal products for the Netherlands. Traders are obliged to supply these illegal products or lose their clients to the internet. Furthermore, there is information asymmetry and detection difficulty regarding fake products, which makes it virtually free to buy and sell fake products. Finally, the Dutch Food and Consumer Product Safety Authority does not have the means nor the necessary data to inspect effectively.

The findings from the discussion sessions have been translated to an agent-based model, in which the main dynamic is the updating of trust of the agents (end-users and traders) in the buying methods available to them. The model outcomes that were studied were the percentage of fake and total illegal plant protection products arriving at the end-user. With this model, a Sobol analysis was performed, which shows the impact of various model variables on the model outcomes. Via this analysis, it was found that traders who supply to end-users are a large risk concentration. Other factors that were found to influence the types of plant protection products that reach the end-user are the voluntary compliance levels of end-users and traders, the number of applications of legal products and the traders that sell to other traders. These factors were found to drive the Dutch plant protection products chain through their interaction with the other factors, which implies that the combination of these factors per sector drives system behaviour.

After the Sobol analysis, an optimization was performed to find the most effective policies in terms of reducing the percentage of illegal plant protection products that reach the end-user. The optimization rendered one optimal policy in which local traders and wholesale traders were inspected and the maximum number of inspectors was deployed. This and seven other policies were then tested for robustness. Via robustness testing, it was found that policies in which traders that sell to end-users are inspected were the most robust, both in terms of average performance and worst performance over all scenarios. Also inspecting wholesale traders only marginally improved the robustness of the policies. This is because traders who sell to end-users have a gatekeeper function as to which plant protection products reach the end-user. Additionally, it was found that the number of applications of legal products in the Netherlands were low in every worst-case scenario, which shows that this is a big contextual risk factor.

Via this application of agent-based modelling to the case of plant protection products, preliminary conclusions can be drawn on how agent-based modelling can aid a regulatory agency in performing a problem-solving risk analysis. Agent-based modelling has been shown to be very suitable for exploring a regulatory problem, even when there is scarce knowledge and no data available about this problem. The modelling process was used to offer a first explanation of how the plant protection products chain worked. The experts engaged with the analysis through the discussion sessions, albeit on a qualitative level, which provided an overview of the problem and its complexities. Through experimentation with the model, various risk factors were found that opened possibilities for new types of interventions. It was thus shown that agent-based modelling as a method suits the open explorative type of risk analysis that is required by the problem-solving approach. Future research must be performed to study the suitability of agent-based modelling for problem-solving risk analysis in other types of regulatory problems.

One last important consideration is how to place problem-solving risk analysis and agent-based modelling at the heart of the regulatory organisation. In the current research, the modelling part of agent-based modelling was explicitly left to the analyst by the experts, as they were not acquainted with the method. Furthermore, the experts were very willing to participate in the discussion sessions, but they did not take ownership over the risk analysis process. It can be questioned whether that is because problem-solving is not the dominant regulatory paradigm of the NVWA, which makes it difficult to implement right at the first attempt, or whether problem-solving requires more than putting the experts, the analyst and the resources together. Two recommendations are proposed to position problem-solving risk analysis more closely to the heart of the NVWA: to provide experts that partake in problem-solving risk analysis with a workshop on systems thinking and to iteratively discuss the (conceptual) model with the experts to increase their engagement, their model understanding and the validity of the model.

Contents

List of abbreviations

Abbreviation	Definition
ABM	agent-based model
BuRO	Bureau of Risk-analysis and Research
EUO trader	end-user only trader
KPI	key performance indicator
NOP	“not the original product”
NVWA	Dutch Food and Consumer Product Safety Authority
PPP	plant protection product
PSA	problem-solving approach
TO trader	trader only trader

1. Introduction

Public regulation is indispensable to achieving efficient markets and public goals (Prosser, 2010). Regulation, in the broad definition of "sustained and focused control exercised by a public agency over activities that are valued by a community" (Baldwin et al., 2012, p. 2-3) can be exercised to prevent market failure, to protect human rights, to further social responsibilities and to provide a platform for public participation (Prosser, 2010). Governments have been committed to these tasks for a long time and with the target date of the 2030 Agenda for Sustainable Development fast approaching (Department of Economic and Social Affairs, 2015), organizing regulation such that it fulfils its social function is more important than ever.

Defining what 'good' regulation is, however, is a difficult task, not in the least because what is 'good' is determined by the society in which regulation takes place, which consists of heterogeneous groups of people with different interests (Prosser, 2010). Furthermore, resources directed towards regulation are finite and the number of problems to be solved through regulation are vast (Black & Baldwin, 2010). Baldwin et al. (2012) argue that regulation should be optimized based on five key performance indicators (KPIs):

- does the regulator abide by the law?
- is the regulator held accountable?
- are the procedures fair, accessible and open?
- does the regulator show sufficient expertise?
- is the regulatory regime efficient?

However, after positing these five KPIs, the authors contend that to define a regulator's position on any KPI requires an extensive societal debate on what this KPI entails, which makes it difficult to use these KPIs to define good regulation.

To circumvent defining what makes 'good' regulation, the focus of the debate is often shifted to the regulator's efficiency: the amount of desired outcome achieved per quantity of resources invested (Baldwin et al., 2012; Sparrow, 2000). However, measurement of efficiency comes with its own set of problems: some outcomes, like pollution prevented, are hard to measure. Even if the agency finds a way to measure pollution, it is difficult determine the contribution of the agency to this reduction, due to a possible effect of context variables (Sparrow, 2000, 2016). Neither can the agency know whether the lower detection rates are caused by an actual reduction in pollution crimes committed or whether environmental criminals have obscured their pollution offences better (de Bruijn & Ten Heuvelhof, 2019). Due to these measurement problems and increasing political pressure to show quantified results, many regulatory agencies have reverted to a process-orientation, combined with a focus on regulatory input (e.g. working hours, inspections performed) to determine the efficiency of their organisation (Prosser, 2010). This has shifted away the focus from results achieved towards customers served. Sparrow (2000) argues that in dealing with risks, criminals cannot be served as customers and the focus should be on the reduction of risk, or else regulatory efficiency will be undermined.

The regulatory approach that Sparrow (2000) advanced to oppose this process-oriented, input-focused approach is his problem-solving approach (PSA). The core of the PSA is "…to identify significant risks, problems, or patterns of noncompliance and to design solutions that eliminate or mitigate those problems" (Sparrow, 2000, p. 129). In short, this approach is based on selecting high-risk problems, defining the problem, determining the KPIs, developing interventions, implementation and monitoring and closing the project. The novelty in this approach was that the type of problem to be regulated determines the intervention that is chosen: the focus is on solving the problem and an agency-wide choice of preferred interventions would only hinder finding the fitting solution to the current problem (Sparrow, 2000).

In the problem-solving approach, the role of analysis is redefined. Sparrow (2000) contrasts the analysis performed by most regulatory agencies with a process-orientation with the type of analysis needed for a problem-solving approach. The former is case based: it repeats the same type of analysis for every case of criminal activity, e. g. on one type of aggregation level, on one characterisation of risk or on one type of product. In addition, a large part of its analysis consists of producing reports on the activities performed by the organisation. On the contrary, PSA-analysis requires versatility. Every problem is considered unique and thus requires a unique set of analysis tools. Problems are also disaggregated in many ways, with the goal to provide managers at the regulatory agency information to choose which problems to prioritize. This approach, Sparrow (2000) argues, can help agencies to proactively search out problems instead of reactively following up criminal events.

One condition for a PSA-analysis to be carried out is that a myriad of tools are available to the analyst, to disaggregate the problem in various ways (Sparrow, 2000). Bynum (2001) recommends several tools for PSA-analysis, amongst which are the analysis of pre-existing data sources, surveys and interviews of enforcement officers or victims, discussions by focus groups and spatial mapping of incidents. This type of analysis tools attempts to find patterns through examining past data (Bynum, 2001). More recently, predictive policing has brought new tools to risk analysis. Predictive policing is an enforcement approach in which big data is used to predict relevant crime aspects like victims or locations of crimes. The new tools that predictive policing brings are, amongst others, social network analysis, risk terrain analysis and data mining (Perry et al., 2013; Tayebi & Glässer, 2016). One tool that has to date not been associated to PSA-analysis is agent-based modelling (ABM). An agent-based model, at its core, is "a system of agents and the relationships between them" (Bonabeau, 2002, p.1). This tool can offer disaggregation of a problem in terms of agents and behaviours (Bonabeau, 2002) and it has been applied to a wide range of disciplines, e.g. domestic water management (Galán et al., 2009), burglary (Malleson et al., 2010) and supply chain optimisation (Akanle & Zhang, 2008).

Despite ABM being a promising tool, its usefulness for PSA-analysis has yet to be examined. This research aims to achieve this. To this end, ABM will be used to conduct a PSA-analysis for a case: the domain of plant protection products (PPPs) of the Dutch Food and Consumer Product Safety Authority (NVWA). The domain of plant protection products is looking to broaden its perspective beyond regulation of the end-user to intervening earlier in the PPP-supply chain. The PPP-supply chain is characterized by a complicated European-wide legal structure of PPPs permits and a large market of counterfeit products that do not comply with the legal requirements for PPPs (Streloke, 2018). It is estimated that 14% of all plant protection products in the EU are counterfeit (Wajsman et al., 2017). The permeation of counterfeit pesticides in Europe warrants an in-depth analysis of the problem and how the NVWA can intervene to ensure that no illegal pesticides reach the end-user.

By applying ABM to the plant protection products chain, the current research aims to understand the usefulness of ABM in a PSA-analysis in the context of a regulatory organisation. The case will be used as a means to answer the question: *how can an agent-based model aid a regulatory organisation in performing a PSA-analysis*? It is hoped that successfully applying ABM to a case will pave the way to ABM becoming a standard tool in the regulator's analysis craft shop, thereby increasing the competence of regulators to safeguard public values.

The research proceeds as follows: Section 2 presents a literature review on the role of analysis in various regulatory approaches and it argues for the merits of agent-based modelling for a PSA-analysis. Sub-questions and the corresponding methods are presented in Section 3. A detailed case description is provided in Section 4. Section 5 describes the conceptual model that was created based on the information provided by the domain experts. In Section 6, the conceptual model is formalized into an agent-based model. Section 7 describes the experiments that were performed with the model. Section 8 presents the results of the model experiments, followed by a discussion in Section 9. The conclusion of the research is presented in Section 10.

2. Risk analysis in regulation and the benefits of agent-based modelling

In this section, relevant literature on risk analysis in regulation will be presented. First, the concept of risk in regulation is discussed. Then, the role of risk analysis in the problem-solving approach is considered. This role is then contrasted to the role of risk analysis in other regulation paradigms. After PSA-risk analysis has been defined, the potential contribution of ABM is discussed. Lastly, a reflection is offered on which type of risk analysis paradigms are applicable to the regulatory agency of the case, the NVWA.

2.1 Definition of risk in regulation

The concept of 'risk' is central to public regulation (Haines, 2013). However, defining what constitutes risk shows the elusiveness of the concept. Even the Definition Committee of the Society for Risk Analysis was forced to admit after two years of searching for a definite definition of risk that too many definitions abounded and that it would not be appropriate to select only one (Lowrance, 1976). The technical definition of risk is the possible adverse effect times the probability that this effect manifests, which equates to the formula: risk = hazard x likelihood (Andretta, 2014). Hansson (2005) points out that there are five common definitions of risk, which highlight various aspects of the technical definition. Three are taken up here (Hansson, 2005, p. 7):

> "(1) risk = an unwanted event, which may or may not occur"
> "(2) risk = the probability of an unwanted event, which may or may not occur"
> "(3) risk = the cause of an unwanted event, which may or may not occur"

Especially in the public domain, where not every employee is a risk expert, it should be considered that multiple definitions of risk are used, perhaps simultaneously. For example, in the executive summary of the Integral risk analysis poultry meat chain (NVWA, 2018b), the word 'risk(s)' is used ten times of which four times relating to Hansson's (2005) definition 1, two times to definition 2, two times to definition 3 and another two times to the technical definition of risk as defined by Andretta (2014). This example indicates that 'risk' is a malleable concept and in discussion with experts of the NVWA attention should be paid to which definition(s) of risk they use.

What constitutes a risk is much broader, however, than the focus on a single hazard and its probability. Haines (2013) argues that risk analysis should be placed in a broader perspective that includes "social, political and economic elements" (Haines, 2013, p. 37) of regulation. She distinguishes between three ideal categories of risk: actuarial risk, sociocultural risk and political risk. Actuarial risk relates to technical risk. It is an external risk that can be characterized by a classic risk analysis. Sociocultural risk refers to risks to the collective, events with a moral foundation that could cause societal outrage or discomfort. Political risk is the risk to the regulatory agency of losing its legitimacy. Every public regulator is faced with managing the three types of risk simultaneously, which creates tensions as there are trade-offs in choosing to prioritize one type of risk over the other (Haines, 2013).

The three types of risk can be linked to the goals of the three echelons that are involved in public regulation: inspectors, managers and politics, as defined by de Bruijn & Ten Heuvelhof (2019). Inspectors focus most on actuarial risks: they are involved in reducing the probability of the hazard and they value professionalism. Managers mostly focus on political risk, as they are concerned with establishing the legitimacy of their organisation. Politics' focus is on sociocultural risk: they aim to prevent societal unrest and create an appearance of social stability, for which they have appointed the regulatory agency (de Bruijn & Ten Heuvelhof, 2019). The embodiment of the three different types of

risk by the three echelons in a regulatory agency creates the context for the PSA-risk analysis of the current research since the current research will be situated on the verge of the inspector-management echelon.

The question that remains is how the concept of risk fits in the problem-solving approach. In his two books on the problem-solving approach, Sparrow (2000, 2008) remains rather inconclusive about what a problem is, except for that problems should be at the core of a regulatory agency's operations. Sparrow (2000) refers to solving problems broadly as controlling "risk concentrations, problem areas or patterns of noncompliance" (p. 8). In the chapter on Intelligence and Analysis, he mentions problems and risks in one go: "(…) the new intermediate-level unit of work, variously called *problems, patterns, or risk concentrations*" (p. 261). Thus, to characterize Sparrow's (2000) definition of problems in terms of Hansson's (2005) definitions of risk, a problem is an unwanted event (the risk), the patterns or risk concentrations are the causes of the unwanted event, and the goal of the problem-solving approach is to reduce the occurrence (probability) of the unwanted event. The goal of the PSA-analysis is thus to find the patterns or risk concentrations that underly the problem.

Sparrow (2000) is not concerned with what types of problems (actuarial, sociocultural or political) a regulatory agency has to deal. However, he does argue in his book that regulatory agencies be given the discretion to choose the problems they want to address, openly and with sufficient accountability. By this, he seems to underpin that regulatory agencies should be allowed to focus on actuarial risk. As the NVWA does not currently have this discretion (NVWA, 2019b), all three types of risk will be included in the current research if they appear. It will be reflected on whether the methods that are used in this research are suitable for the types of risks that are proposed.

2.2 The role of risk analysis in the problem-solving approach

Before understanding risk analysis in the problem-solving approach, let us first gain an understanding of what is meant by traditional risk analysis. Traditional risk analysis is mostly concerned with characterizing actuarial risk by estimating risk probabilities and hazards (as of the technical definition by Andretta (2014)), by which regulatory agencies can prioritize actions (Buie, 1996; Hutter, 2006). This corresponds to the first step in the problem-solving approach, which is selecting important problems (Sparrow, 2000). For risk prioritization, risk is thought to be sufficiently defined by following scientific approaches and involvement with experts or other stakeholders is minimal. After risks have been prioritized, the agency determines how to control the risk. This depends on the agency's preferred intervention strategies and is usually focussed on the offender (Eck & Eck, 2012; Hutter, 2006). Thus, after problem selection, the role of analysis in traditional risk analysis is limited.

Analysis plays a central role in the problem-solving approach. The rationale for analysis in this approach is that "the better one understands a risk and the more insightfully one picks it apart, the less brute force will be needed to contain or suppress it" (Sparrow, 2000, p. 256). As every risk is different, Sparrow (2000) argues that risk analysts should be led by the problem and be versatile in their methodology. He contrasts this with traditional risk analysis in regulatory agencies, which he argues are reactive and case-based (Sparrow, 2000). By case-based, he means that enforcement is often based upon high-profile crime cases: a heavy crime is committed and after this, regulatory agencies attempt to find out who committed the offense (Boba, 2003). Furthermore, Sparrow (2000) argues that due to the lack of expert involvement, risk analysis is not at the heart of these agencies who perform traditional risk analysis. As they use one predefined analysis method for every risk, namely finding the offender, these agencies will only effectively be able to handle one type of problem, namely a case that can be solved (Sparrow, 2000).

The idea of problem-led regulation has taken off in the field of policing. In this field, the SARA-approach (short for Scanning, Analysis, Response, Assessment) is commonly used (Boba, 2003). A meta-analysis by Hinkle et al. (2020) has shown that adopting a problem-led approach to policing had on average increased intervention effectiveness by 34%. In the guide *Problem Analysis in Policing* Boba (2003) provides an additional set of guidelines for PSA-risk analysis: the analysis should be an iterative and dynamic process that is focused on finding the patterns underlying to a problem to drive investigations. It should be iterative in that new research questions are generated based previous results of analysis and dynamic in that new methods of analysis should be chosen based on the requirements posed by the new research questions. In addition, it should be a theory-driven process of hypothesis-setting and testing. Lastly, it should be open-ended, inclusive, innovative and creative (Boba, 2003). Thus, compared to traditional risk analysis, PSA-risk analysis demands more creativity from the regulatory agency, which is led by the problem under investigation.

2.3 Risk analysis in other regulatory paradigms

Risk analysis does not pertain only to the problem-solving approach. Other regulatory paradigms also make use of analysis. The role of analysis in three regulatory paradigms will be discussed and contrasted to the role of analysis in the problem-solving approach to understand what constitute the unique characteristics of PSA-risk analysis. The three paradigms include risk-based regulation, responsive regulation and responsive, risk-based regulation.

Risk-based regulation has two common definitions, based on the type of risk that is prioritized. The first is that regulators prioritize the highest actuarial risks: the highest risks to society that are covered by their mandate. The second is that regulators prioritize political risk: the risk that the regulatory agency will not achieve its objectives (Black, 2005). Thus, first the agency determines which activities pose the highest risk to the agency, after which the risk analysis is performed. The goal of this analysis is to make an assessment of the hazards and probabilities underpinning the risk, to be able to allocate inspection resources more effectively. Usually, a ranking of most risky firms is performed based on inherent firm characteristics and compliance records. Thus, after the risk analysis, a number of risk factors pertaining to the regulatees have been identified that help predict whether a firm will violate. By using the available data of a specific firm, the regulator will be able to estimate the risk that this firm will violate. The analysis phase is thus discrete: once the ranking of firms has been created, the analysis is concluded (Baldwin et al., 2012; Black, 2010).

Risk-based regulation and the problem-solving approach have parallels in that they both prioritize ‘risks’ (future projections of unwanted events) and ‘problems’ (unwanted events in the past, present or future) (Baldwin & Black, 2016). However, their approach to analysis is very different. Prosser (2010) argues that “(…) risk-based regulation is essentially a procedural prescription for how the regulator balances different priorities and interests” (p. 10). This is underpinned by the centrality of designing risk-based frameworks: the procedure of prioritizing risks, assessing the risk factors and ranking firms is the foundation of risk-based regulation (Black, 2010). In the problem-solving approach, the goal of the analysis, to find the most important concentrations of risk to provide actionable insight to the regulator, is prioritized over the procedure. This changes the scope of the analysis: risk factors are not explored within one actor group as in risk-based analysis, since the PSA-analysis is more exploratory in nature and will disaggregate the data in new and creative ways pertaining to the problem (Sparrow, 2000). In this, risk-based analysis and PSA-analysis share a common factor: both types of analysis aim to find components underlying the risk, although with a different scope.

The second major regulatory paradigm is responsive regulation. The essence of responsive regulation is that regulatory agencies are not dogmatic in their response to offences. Regulatory agencies should make use of a regulatory pyramid: a predefined, well-communicated description of how they will

escalate their response to an offence when offenders are not willing to cooperate. Responsive regulation promotes fairness and active responsibility of the regulated community, with a focus on the "pluralist, dynamic, deliberative quality (…) of responsiveness" (Braithwaite, 2011, p. 480).

The role of analysis in responsive regulation is minimal. The focus of responsive regulation is not on the selection and disaggregation of risks but on the "direct, interpersonal relationship between regulator and regulated entity" (Ford, 2013, p. 17). When the regulator has a personal history with each regulatee, and when the intention of regulation is to always start with the most educational interventions (Braithwaite, 2011), no risk analysis is warranted: the risk manifests when a regulatee commits an offense and the pyramid provides guidance to the regulator how to react. The existence and communication of the pyramid, in combination with dialogue and an intention to teach is thought to sufficiently reduce the risk of (repeat) offenses (Braithwaite, 2011).

The third regulatory paradigm combines risk-based and responsive regulation under the descriptive name of really responsive risk-based regulation. Really responsive regulation adds responsiveness to the institutional context, the beliefs and attitudes of regulatees and change to responsive regulation (Baldwin & Black, 2008). The combination of the two frameworks places risk-based regulation in a broader context, specifying it as a guiding tool to prioritize resource allocation, to "attune the logics of risk analyses to the complex problems and the dynamics of real-life regulatory scenarios" (Black & Baldwin, 2010, p. 2). For this, three main changes are proposed to the risk analysis of risk-based regulation. Firstly, risk analysis should incorporate the responsiveness of a firm to regulatory interventions, as to balance the amount of resources it will cost to achieve compliance versus the risk that is posed by the regulatee. Secondly, risk analysis should provide guidance on which intervention to perform and include "an analysis of the likely responsiveness of the firm to different stimuli" (Black & Baldwin, 2010, p. 9). Lastly, it should consider the institutional environment and include external factors, the links of the firm hereto and how this affects the firm's riskiness in the risk analysis. For example, the impact of macroeconomic factors on firms' compliance should be considered, if this was found to be relevant. Furthermore, certain contexts may demand the inclusion of qualitative judgement, especially when the regulator is expected to be proactive (Black & Baldwin, 2010). This requires a risk analysis unique to the regulator's context, which sets it apart from the straightforward, more technical procedure of risk analysis in risk-based regulation (Black, 2010; Black & Baldwin, 2010).

Really responsive risk-based regulation has broadened the subject of risk analysis beyond that of risk-based risk analysis (Black & Baldwin, 2010). However, it is still very different from Sparrow's (2000) problem analysis, in that the role of analysis remains primarily to decide upon the allocation of inspection resources. The responsive element does reduce the methodological rigor of risk-based risk analysis, by contending that risk analysis should not be the sole foundation of regulatory intervention-setting, but it should be supplemented by qualitative judgement, a sound constitutional awareness and a broad selection of intervention strategies (Black & Baldwin, 2010). Furthermore, when risk analysis is used to provide guidance on which intervention to perform, it touches PSA-risk analysis in that it searches for the most effective way to reduce the risk. However, as the analysis is performed on a firm-level, no underlying patterns are to be discovered, which is contradictory to the aim of PSA-risk analysis. The main differences between PSA-risk analysis and analysis in the other regulatory paradigms have been summarized in Table 2.1.

Table 2.1: The main differences between traditional risk analysis and PSA-risk analysis.

	PSA-risk analysis	**Traditional risk analysis**	**Risk-based regulation risk analysis**	**Really responsive risk-based regulation risk analysis**
Driver	Problem-based	Case-based	Risk-based	Risk-based
Goal	Find most effective leverage points (risk concentrations) to control a problem	Investigate a case	Assess a risk, rank firms	Assess a risk, assess firms' expected compliance, find a firm-specific suitable intervention strategy
Versatility of analysis methods	Analysis methods are selected based on problem	Analysis methods are predefined	Analysis methods are procedurally predefined	Analysis methods are procedurally predefined, adaptable to the context of the regulator
Means of disaggregation of data	In as many ways as possible to find risk concentrations	In terms of offenders	In terms of its regulated actors	In terms of its regulated actors
Place in organisation	Heart of organisation	Separate department	Separate department	Separate department
Focus	Underlying patterns	Offenders	Risk factors pertaining to actors	Risk factors pertaining to actors, expected compliance, fitting interventions

From the comparison of the role of analysis in the various regulatory paradigms, conclusions can be drawn about the unique features of PSA-risk analysis. The unique features of PSA-risk analysis are:

- It is a problem-based process that is undogmatic in its choice of analysis.
- It is aimed at disaggregating risks in as many ways as possible to create tailormade interventions.
- It is located at the heart of the regulatory agency and is performed with the help of analysts and experts alike.

2.4 The use of agent-based modelling in PSA-risk analysis

In his book, Sparrow (2000) wrote: "Sometimes the most valuable insights relate not simply to the nature of things (incidents, crimes, accidents) but to their relationships to one another, their sequences, structures and cycles" (p. 269). It is just these sequences, structures and styles that an agent-based model attempts to capture. Agent-based modelling moves away from the single firm as the unit of analysis to study a whole system, the agents therein and their relationships (Bonabeau, 2002; Dijkema et al., 2013). Within this system, a wide range of analyses can be performed, as ABMs are flexible and the data collected from the agent-based model is user-defined (Bonabeau, 2002). ABM thus allows for extensive hypothesis-testing, which is a core element of PSA-analysis (Boba, 2003). An agent-based model can thus be a means of explaining how a phenomenon (the risk) emerges (Edmonds et al., 2019). Furthermore, ABM is suitable for an open exploration of the risk, as the problem has to be described accurately and therefore all available knowledge on the topic has to be collected (Nikolic et al., 2013). Even if there is not much quantitative data available, an agent-based model could offer a first explanation of how the relationships in the model cause the observed real-world phenomenon (Edmonds et al., 2019): therefore a problem about which there is a lack of quantitative data, as regulators often face, can still be analysed using agent-based modelling (Bonabeau, 2002). As it is an intuitive method focused on modelling real world phenomena accurately yet descriptively, it can be used to communicate about a problem within the regulatory organisation (Macal, 2016).

Agent-based modelling has been applied to public policy engineering many times (Dechesne et al., 2014). One particularly interesting agent-based model made for the IMF by Chan-Lau (2017) attempts to understand risk in the banking system. This risk is usually calculated using highly aggregated economic models, with one agent representing all micro-level agents. The model's primary agents are the banks, who can borrow or lend money. The model was used to test the stability of the system under different policy variables (capital requirement and reserve-ratio) and to study dynamics of interconnectedness of banks. It was found that "interconnectedness arise mainly from the fact that many banks lend to a single bank rather than several banks borrowing from a single bank" (Chan-Lau, 2017, p. 27).

The objective of Chan-Lau's (2017) model was to create an agent-based model of the banking system and study the risks therein. The use of ABM to this end is a promising first attempt at using ABM for a PSA-risk analysis, but it did not fulfil all the requirements. The requirements that were fulfilled are the focus on a group of agents and the interactions thereof and the multiplicity of the analyses that were carried out. Despite fulfilling these requirements, the ABM was not centred around one problem: risk in the banking system is too broad and perhaps partially for this reason, the risk was not disaggregated via the ABM to actionable risk concentrations. Furthermore, the exercise was primarily scientific in nature: it was not at the heart of the organisation as Sparrow (2000) argues. It was created in isolation and despite the thorough research that was performed prior to building the model (Chan-Lau, 2017), the question remains whether this model will contribute to solving any problems.

To summarize, a problem as defined by Sparrow (2000) can be loosely translated to a risk, which in its technical sense means 'hazard x probability' but has other common meanings. Furthermore, regulators face not only actuarial risk but also sociocultural and political risks. To deal with problems, Sparrow (2000) argues that regulators should prioritize important problems and solve them and to this end, a creative analysis should be performed with the aim of uncovering the underlying patterns or risk concentrations. It was found that the absence of fixed analysis methods and the focus on the function of the analysis (solving problems) instead of the object of analysis (the regulatee) is what sets the PSA-risk analysis apart from risk analysis in other regulatory paradigms. Lastly it was found that ABM is a suitable, yet untried tool for performing PSA-risk analysis.

In this research, an agent-based model will be applied to a case study to investigate the use of ABM in PSA-analysis. This will be done by answering the main research question:

How can an agent-based model aid a regulatory organisation in performing a PSA-risk analysis through analysing risk concentrations in a complex problem?

2.5 Positioning the case: risk analysis at the NVWA

Agent-based modelling as a tool for PSA-risk analysis will be studied within the case of the Dutch plant protection products chain. The Dutch PPPs chain is regulated by the NVWA. The NVWA is a Dutch regulatory organisation that is tasked with regulating seven public values, including food safety, animal health and the environment. For the year 2022, the strategy of the NVWA is to define priorities based on the highest harms to society, political and public concerns and continuity of the organisation. Thus, all three types of risk as defined by Haines (2013) are addressed. For example, within the public value of food safety, the NVWA focuses on the risk of improper treatment of foods (actuarial risk), the risk of improper treatment of animals (actuarial and sociocultural risk) and the risk of navigating a changing political landscape (political risk) (Haines, 2013; NVWA, 2021). By considering other types of risks, the NVWA broadens its definition of what are important problems and therefore deviates from traditional risk analysis, which takes a technical approach to risk (Buie, 1996).

After important risks have been identified, the NVWA aims to take a risk-based approach to dealing with these risks. Currently the NVWA is transitioning from a more reactive, case-based approach to regulation, which was mostly based on random inspections and alerts, towards a risk-based approach which is used to identify high-risk companies in advance. In its inspections, the NVWA strives to treat all offenses within a sector uniformly (NVWA, 2021). This implies that the NVWA generally does not endorse responsive regulation, in which offenses are reacted upon based on the inspection context of the offender (Braithwaite, 2011). Interestingly, the NVWA does pick apart production chains to identify the most high-risk actor groups (NVWA, 2021), which could serve as a basis for PSA-risk analysis. However, chain analysis is the only way in which larger problems are broken down and this analysis is usually not followed up by the creation of a tailormade solution for the problem, which have both been found to be core elements of PSA-risk analysis (Sparrow, 2000). Furthermore, the "official" risk analyses of the NVWA are performed by the Bureau of Risk-analysis and Research (BuRO), which is a separate department of the NVWA (NVWA, 2019a), which shows that risk analysis is not positioned at the heart of the organisation. This is considered necessary, as the advice of BuRO has to be scientific and independent (NVWA, 2021). Risk analysis by the NVWA is thus mostly performed to identify important problems and to understand which (types of) actors pose the greatest risk, to be able to uniformly inspect these high-risk actors.

3. Methods

In this section the sub-questions that the research aims to answer are presented, followed by a rationale for the methods that will be used to answer the sub-questions.

3.1 Sub-questions

To answer the main research question, five sub-questions will be answered:

1. What are the characteristics of a PSA-risk analysis and how do these characteristics compare to risk analysis in other regulatory paradigms?

2. How can expert domain knowledge be used to create an agent-based model?

3. How can an agent-based model be used to find risk concentrations in a complex regulatory problem?

4. How can an agent-based model be used to experiment with possible measures to counteract these risk concentrations?

5. To what extent does the agent-based modelling process fulfil the requirements of a PSA-risk analysis?

3.2 Participatory modelling

Sub-question 1 has been answered by the literature review (see Section 2). Sub-question 2 will be answered by participatory modelling. As the goal of the current research is to study the suitability of ABM to PSA-risk analysis, participatory modelling with the experts of the NVWA is very suitable to build the ABM. This is because, according to Sparrow (2000), the analysis should be at the heart of the organisation and involve different kinds of experts on the problem. Participatory modelling engages the experts of the NVWA in model building (Vennix, 1999). It promotes "purposeful learning process for action that engages the implicit and explicit knowledge of stakeholders to create formalized and shared representations of reality" (Voinov et al., 2018, p. 233). Distilling the implicit and explicit knowledge of the regulator can help to discover the most important patterns underlying the problem and it provides a major source of knowledge (Röckmann et al., 2012). It also provides legitimacy to the modelling exercise by involving experts, as it communicates to the experts that their involvement is important and meaningful (Bynum, 2001). This will make it more likely that the modelling exercise becomes a valued element of the problem-solving procedure. On the contrary, creating a literature-based model at the author's discretion would not embed it within the regulatory organisation and therefore it would not emulate the regulatory PSA, at the risk of proving effective only within the confinements of science. It was thus chosen to perform participatory modelling.

Participatory modelling can be done via direct stakeholder and indirect stakeholder involvement. For this research, indirect stakeholder involvement is chosen, which means that stakeholders are engaged in formulating the problem statement, providing input to and evaluating the model and model use, but not in the construction of the model (Röckmann et al., 2012). This is because the NVWA has finite resources, so domain experts can only participate for a limited number of hours, and because the domain experts have not worked with models before. Thus, they would like to see the implementation of this method before possibly engaging with it (unlike, for example, Cuppen et al. (2020) who created a model with energy infrastructure experts who had already used various modelling techniques).

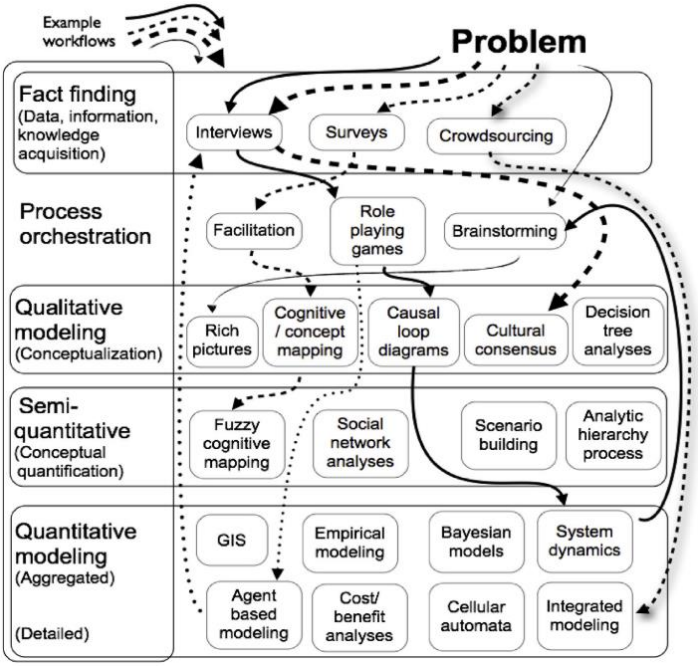


Figure 3.1. Selection of tools for participatory modelling. Adopted from Voinov et al. (2018, p. 235).

There are many participatory modelling tools available. Voinov et al. (2018) have classified a selection of these tools into the five stages of participatory modelling: fact finding, process orchestration, qualitative, semi-quantitative and quantitative modelling (see Figure 3.1). Of these five stages, only process orchestration is inherent to participatory modelling, the other stages may or may not be applied. As can be seen from Figure 3.1, there are many possible combinations of methods. The starting point for choosing a method should be the goal of the modelling exercise. Then, methods should be chosen based on their effectiveness (ability to achieve the goal), efficiency (resources and time required to achieve the goal) and the social value added (promotion of learning and social capital of stakeholders) (Voinov et al., 2018). For this research, three stages will be applied: process orchestration, qualitative modelling and quantitative modelling. Guided discussions amongst the experts of the NVWA will be facilitated using a collaborative tool called MURAL (www.mural.com), which is an online whiteboard platform on which all participants can simultaneously add their input. MURAL is a tool that the NVWA is familiar with. Guided discussions have been chosen because the NVWA is unfamiliar with the method ABM and some guidance is necessary to collect the required kind of information to be able to build a model, e.g. descriptions of agents and actions. The discussion sessions will be used as input for the qualitative modelling: a descriptive summary and analysis of the problem will be drafted by the researcher. This descriptive summary will be approved by the participants and be used to build the model. The model will be created by the researcher and discussed with the participants midway. Finally, results will be discussed with the participants.

3.3 Agent-based modelling

The answering of sub-question 2 will be concluded by the creation of an ABM based on the results that were gathered from the participatory modelling sessions. The ABM will be built in Netlogo (version 6.2.1), because it is applicable to enterprise and organisational behaviour, it has an intuitive interface and facilitates easy model development (Abar et al., 2017). The purpose of the ABM will be to *explain* how a certain problem arises. As the NVWA has indicated that there is not much data available, the model will aim to capture the current dominant narrative on how the problem of illegal plant protection products in the Netherlands works. For this, it is extremely important that the model does not contain any errors that influence the model behaviour (Edmonds et al., 2019). To this end, model

verification will be performed thoroughly by the means of unit testing. A unit test is a piece of code separate from the model, which tests whether one functional piece of code (a "unit") works correctly. There are positive and negative unit tests, i.e. tests of whether the program works as expected and fails when expected (Olan, 2003). Both types of tests will be incorporated.

3.4 The EMA workbench

Sub-questions 3 and 4 will be answered through exploratory modelling in the EMA workbench (v. 2.0). Exploratory modelling is a modelling technique which "aims at exploring the implications for decision making of the various presently irresolvable uncertainties" (Kwakkel, 2017, p. 239). The methods pertaining to exploratory modelling are suitable for PSA-risk analysis, because they are aimed at creating an understanding of how the relationships between the model variables influence model behaviour. Furthermore, the EMA workbench is designed to support a broad range of exploratory modelling analyses and is very flexible. Lastly, it is easy to generate (optimal) regulatory policies within the workbench and test their robustness: the method can thus be used to aid in finding optimal, robust solutions to problems (Kwakkel, 2017).

The EMA workbench will be used to implement two types of analysis: Sobol sensitivity analysis and multi-objective robust decision-making. Sobol sensitivity analysis is performed to find the effect of all variable model parameters on the model outcomes. It is the antithesis of the one-factor-at-the-time analysis that used to be the norm for sensitivity analysis (Saltelli & Annoni, 2010). The Sobol sampling method samples all variables equally over the entire parameter space, so that the first order effect and the higher order effects of the variable can be calculated. The first order effect is the share of the total outcome that is explained by the variation of one variable, all other variables remaining equal. The higher order effects are the share of the total outcome that is explained by the variation of one variable in interaction with the variation of all other variables (Jaxa-Rozen & Kwakkel, 2018; Saltelli & Annoni, 2010). Thus, the influence of one variable on the variation in model outcomes can be calculated, which provides an insight into which model variables comprise the pattern underlying the problem.

Multi-objective robust decision-making makes use of evolutionary algorithms to find optimal policies that score the highest on multiple objectives in one scenario. After this, the effectiveness of these policies over a range of scenarios is determined to find policies that are both optimal and robust. When determining the robustness of a policy, it is important to carefully select the robustness metric(s) that are used to calculate robustness scores (Hamarat et al., 2014). Many metrics are available and the choice of metric should be based on the decision-context, the level of risk-aversion of the decision-maker and whether the decision-maker prefers to maximize performance over minimizing outcome variance. In any case it is better to use multiple metrics, as every metric highlights one aspect of robustness. The two metrics that will be used in this research are mean and variance and the maximin. The mean and variance is chosen because it will most likely be most intuitive to the NVWA and it conveys information about the overall performance of a policy (Mcphail et al., 2018). This metric thus gives an indication of the overall actuarial risk reduction of the policy. The maximin metric is chosen because it is the most risk aversive metric and it conveys information about the worst case scenario that could happen with the implementation of a given policy (Mcphail et al., 2018). This metric thus indicates the possible political risk of not dealing well with a given risk. Combined, these metrics should cover the most import concerns of the NVWA regarding risk of illegal plant protection products in the plant protection chain.

4. Case study: illegal plant protection products in the Netherlands

In this section, the results of the discussion sessions will be presented. First, proceedings of the participatory modelling discussions are described, after which the problem framing of the NVWA is presented. Then the relevant aspects of the problem are described, including the process of acquiring a plant protection product authorization, the relevant actors, the driving processes and the measures of the NVWA. This will be used as the basis for the model conceptualization in Section 5.

4.1 Proceedings of discussions

The discussion sessions were held to answer the following two questions about the plant protection products chain in the Netherlands:

1. How does the NVWA characterize the plant protection products chain in the Netherlands?

2. What makes illegal plant protection products in the Netherlands a complex problem?

The participants of the discussion sessions were experts from the NVWA on regulation of plant protection products in the Netherlands. The group of experts consisted of three senior inspectors and one senior policymaker. Six discussion sessions on the plant protection products chain were held, with two to four of the experts present per session. Furthermore, the conceptualization was discussed with the senior policymaker and the first version of the model was discussed with all four experts. Lastly, the model results were discussed with the experts. The dates and topics of the discussion sessions are presented in Table 4.1.

Table A.1. Details on the discussion sessions with plant protection experts from the NVWA.

Date	Topic	Number of experts
29 September 2021	Problem framing	3
13 October 2021	Problem framing and actor analysis - import	4
21 October 2021	Actor analysis - end user	2
27 October 2021	Actor analysis - traders	4
29 October 2021	Actor analysis - traders and illegal practices	2
4 November 2021	First check conceptualization	1
5 November 2021	Intervention possibilities of NVWA	2
9 December 2021	Presentation first model version	4
1 February 2022	Presentation model results	4

The discussion sessions were held online via Teams and lasted on average 1.5 hours. The discussions were semi-structured (Voinov et al., 2018). After the initial problem framing session, the discussion sessions were structured around the actors in the plant protection products chain and aimed at answering at least the following three questions per actor: what is the main goal of this actor? What behaviours does this actor perform to achieve its goal? How does it interact with other actors and how are the interacting actors influenced by the interaction? The questions were meant to provide a basic structure to the discussion sessions and the facilitator (the researcher) encouraged the experts to discuss other aspects of the plant protection products chain if one arose during the conversation. The facilitator mostly summarized the experts' statements and asked clarifying questions whenever necessary. Written notes were kept by a recordkeeper and by the facilitator. A Mural board was used to engage the experts in the discussion by visually presenting their statements to them and as a third form of note keeping. Experts were asked to write on the Mural board themselves and the facilitator also visualised important information on the board. An example of the Mural board after three discussion sessions can be found in Appendix A.

4.2 Problem framing

The experts described the problem as that they used to mainly inspect the end-user of plant protection products, i.e. farmers and horticulturists. However, as there are over fifty thousand end-users of plant protection products and less than fifteen inspectors, the agency would like to investigate whether inspecting elsewhere in the PPPs chain could be more effective. Effective, in this context, means reducing the use of illegal plant protection products in the Netherlands. Illegal plant protection products come in two main categories: products that are not authorized (in the European Union or in the Netherlands, see Section 4.2) and products that have not been produced according to the mandated production specifications, and are thus counterfeit (see Section 4.2). These illegal PPPs enter the legal PPPs chain. However, how and why this happens exactly, and in what numbers is an information gap that the NVWA is currently attempting to resolve. There is little information available on the pathways through which illegal plant protection products enter the Dutch market, one reason being that especially counterfeit products are hard to detect, as they can be and usually are very similar to the original product. The question that the NVWA would thus like to answer with the model is:

How are the legal and illegal plant protection products chain interlinked and which link in the chain should be the main regulation target to ensure that as little illegal product as possible reaches the end-user?

4.3 Plant protection products authorization in the Netherlands

To understand what makes a plant protection product illegal, the experts indicated that it is important to understand how a product can legally enter the Dutch PPPs-market. First, one must distinguish the active substance and the plant protection product, which is a formulation based on the active substance, for both have a designated approval procedure. An active substance is approved at EU-level: the developer of the substance, usually one of the few big PPP mother authorization holders, provides a dossier with the required information, after which the PPP authorization authority of one of the Member States performs a peer-reviewed evaluation of the substance. After the evaluation, the substance is approved or rejected.

There are three approval procedures through which a PPP can enter the Dutch PPPs-market: via a mother approval, equivalent approval or parallel trade permit (see Figure 4.1). In every case, the College for approval of plant protection products and biocides (Ctgb) evaluates the application before the PPP can be sold in the Netherlands. A mother approval is the first approval of a new plant protection product with a (new) active substance in the EU. It is very costly, as a dossier should be filed for the approval that contains the results of hundreds of toxicological tests. The approval proceeds zonally: per European zone (North, Middle and South) one country is appointed to approve the PPP for that region and after this every Member State in this region individually decides whether the PPP is approved in that country. In the Netherlands, this is done by the Ctgb. In the approval, it is stated exactly where and how the PPP should be produced. Thus, only PPPs that are produced via the mandated production method are legal in the Netherlands.

The second approval procedure is equivalent approval. A producer of PPPs can apply for a permit for a PPP that is chemically equivalent to a PPP that is already approved in the given European zone. This usually happens when the patent on a mother approval expires. Other PPP producers can now buy access to the dossier of the original PPP and thus rather cheaply put a PPP on the market. The uses of the newly approved PPP must be the same or fewer than the original mother approval.

The last approval procedure is the parallel trade permit. The purpose of the parallel trade permit is to allow free trade of PPPs in the EU. This procedure is not about bringing a new PPP on the market and is usually not performed by authorization holders who produce PPPs themselves, but rather by traders. A trader that buys a legal batch of PPPs in another European country can apply for a parallel trade permit for this PPP in the Netherlands, if a chemically identical PPP has already been approved by the Ctgb. To be sold on the Dutch market, the product must be repackaged to contain a label in the Dutch language. It is thought by the experts that most counterfeit PPPs enter the Netherlands under this type of application.

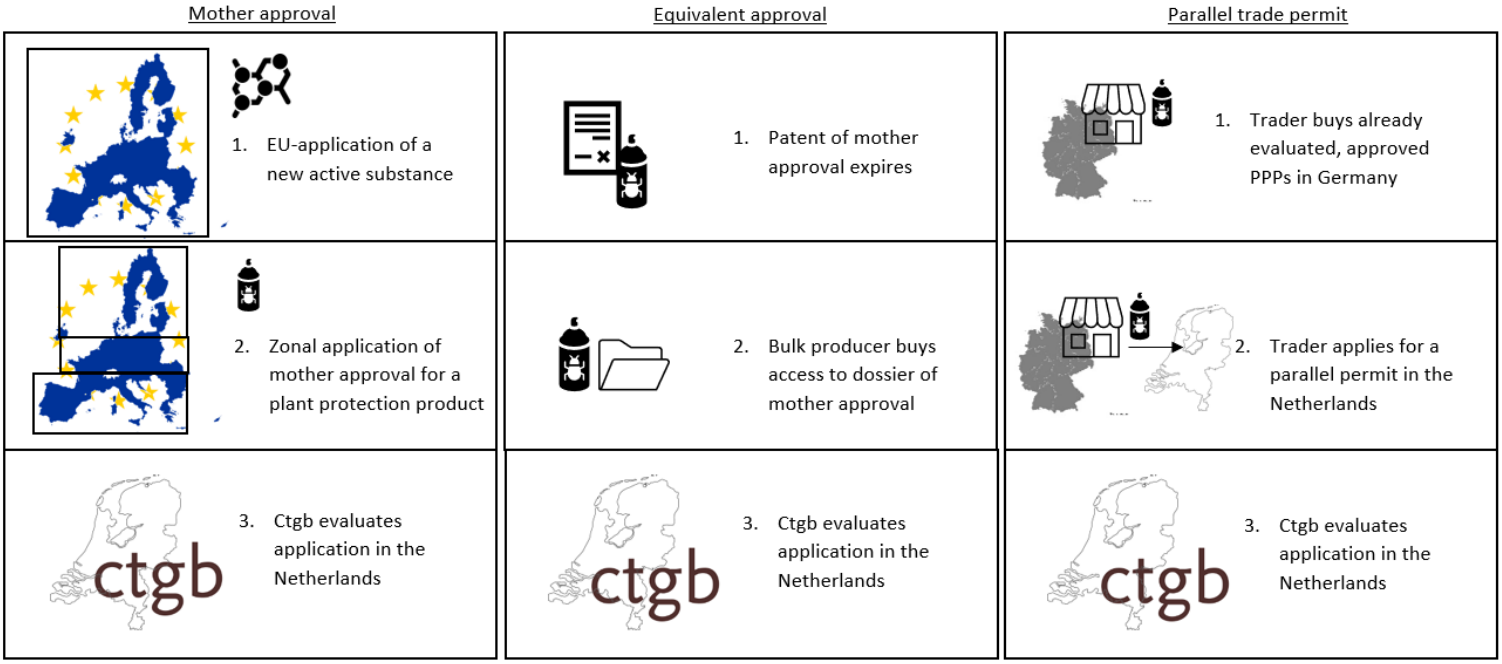


Figure 4.1. Modes of approval of plant protection products in the Netherlands.

As described, PPPs have to be produced according to the mandated production procedure. If they are not, they are not the original product and therefore illegal. The actuarial risk of these products is unknown, as the chemical composition is unknown and therefore no toxicological data on these products is available. The products in this category range from a product that is made at a different factory mostly according to the mandated production procedure to fakes that have no resemblance to the original chemical product (e.g. a soap and water mixture with a fake label). This category of illegal products will further be referred to as 'not the original product' (NOP) products. The detectability of these products depends on how well the original product was imitated chemically and label-wise (e.g. spelling mistakes on the label could reveal the illegal status of the product). Usually, the main component of the original product is also used for the NOP product, thus a full chemical analysis is required to detect that it is a NOP product. This is rarely performed during inspections of end-users and occasionally during inspections of traders.

The other type of illegal product is a product that is illegal in the EU or in the Netherlands. The main reason these products can be found on the Dutch PPPs market is when an original approval expires and is not renewed. If this happens, the PPP is phased out of the Dutch market in three stages: first, the product cannot be bought anymore by traders, then it cannot be sold to end-users anymore and lastly end-users are not allowed to use it anymore. If there is no similar alternative available after this term, traders and end-users might be tempted to keep buying the product from the internet or other countries where the product is still legal. This category also includes products that have never been legal in the EU. The risk of these products is unknown, whilst the risk of products that once were legal

in the EU is known. However, there is a reason that these products are not legal in the Netherlands anymore, e.g. that the product was designed to kill a broad range of pests. Therefore, these products can also pose a risk to the environment. Table 4.2 shows the differences between the two types of illegal products.

Table 4.2. Comparison of products illegal in the EU and NOP products.

	Products illegal in the EU	**NOP products**
Main reason for buying / selling	No (similar) alternative available	High profits for the seller who sells it as a legit product
Basis of illegality	Never approved or expired approval in the whole EU or the Netherlands	Product was not produced in accordance with the mandated production procedure
Detectability of illegality	High: label specifies illegality	Low - high: depends on the chemical formulation and label
Risk	Unknown if never approved, known and low to medium if approval expired	Unknown

4.4 Actors in the PPPs supply chain

The goal of the NVWA for this modelling exercise is to look beyond the end-user as the main inspection target for inspecting on illegal PPPs. Therefore, they were interested in discussing the other actors in the PPPs supply chain. They had previously internally performed an informal assessment of the PPPs chain and its actors, in which they have estimated the risk level of every actor. After some discussion, it was decided to use the actors that were previously identified as medium to high risk as the basis for the participatory modelling discussions. The actors that were discussed are the manufacturer of PPPs, logistics companies, importers, permit holders, traders, advisors and end-users. The findings per actor are summarized below.

Manufacturer

The main goal of the manufacturer according to the experts is to produce and sell as many PPPs as possible to make profit. Manufacturers produce PPPs by commission. Legally, they must make the PPPs as mandated by the approval procedure. However, any company could place an order of PPPs and the manufacturer is unlikely to be aware of the product's application and/or destination, therefore they are likely to be an unaware facilitator of the production of illegal PPPs. As manufacturers are located mostly outside of the Netherlands and Europe, the NVWA cannot regulate this actor.

Logistics company

The logistics company transports PPPs from outside the Netherlands into the Netherlands. The logistics company is usually contracted by the importer. Often, they are unaware of the shipped product, its application or its destination. Furthermore, the NVWA does not have data on what and on which dates logistics companies are shipping and therefore, as an actor, it is an ineffective target for regulation.

Importer

The importer imports the products to the Netherlands, possibly for sale further in Europe. The importer is not a definable actor, as it is a role that can be adopted by multiple actors, e.g. traders or permit holders. It is therefore not possible for the NVWA to regulate the importer as a separate actor.

Permit holder

There are three types of permit holders. The first are the “big ten” that hold most mother approvals. These permit holders develop new products for the European market and thereby determine the range of PPPs that are available in Europe. Their products usually are more expensive than generic products, because this actor needs to redeem the investment costs. This actor wants to make profit by dominating a large share of the European PPPs market, therefore reputation is important to them. To this end, they test their products extensively. Furthermore, they suffer from reputation loss when NOP products are sold under their brand name.

The second type of permit holder is the producer of generic (bulk)PPPs. This actor sells products of the mother permit holder under a different brand name, once the patent expires. Its goal is to make profit. The products this actor makes are often cheaper than the mother approval and of a somewhat lower quality. Reputation is not as important to this actor and the quality of its products is sometimes too low, but they usually do not engage with illegal products according to the experts.

The third type of permit holder is the parallel permit holder. Often, these are traders who are not the owner of the brand for which they apply for a parallel trade permit. They sell PPPs that have been approved in one country to traders in another country. Thus, this type of permit holder is really a trader and shall not be considered as a separate actor.

Trader

A trader has been defined as any actor that sells PPPs who is not a (bulk or mother) permit holder. The main goal of this actor is to make profit. There are two types of traders: traders who sell primarily to end-users (end-user only traders (EUO traders)) and traders who sell primarily to other traders (trader only traders (TO traders)). For EUO traders, customer loyalty is very important. These traders usually have a regional client base, which means these traders are specialized in PPPs for a narrow range of crop types. If they cannot supply a client with a product for their crop and disease, they may go through some lengths to find a suitable replacement product, which could lead to the sale of a product that is illegal in the EU.

TO traders do not depend on customer loyalty as much to make profit, so for them market forces and profit are most important. Their PPPs stock covers a wider range of products to be able to serve a wide variety of EUO traders.

Advisor

An advisor is usually employed by a trader and maintains contacts with end-users (the client). There are also independent advisors that can be hired by end-users. However, the share of independent advisors on total advisors is not very high. The goal of the advisor is to sell the products of its trader and to advise the end-user well. It will always first recommend one of the products of its trader. If there is no such product available, he can order it from another trader. If this is not possible, the advisor can recommend a product that is less effective, or an illegal product that the end-user can order via the internet.

End-user

The main goal of the end-user is to sell as much clean and saleable crops to make a profit. The type of PPP that an end-user buys depends on its type of crop, the disease of the crop, the profit margin of the crop and its contact with its advisors. The end-user represents the demand side of the PPPs market in the Netherlands. If it transpires that the end-user needs a product that is not available via its trader or is not (longer) legal in the EU, they might order a product from the internet, which usually is an illegal product (see Section 4.4).

Figure 4.2 shows a visual classification of the actors based on a rough estimation of their power in the Dutch PPPs chain and their incentive to buy or sell illegal PPPs, i.e. the ease of violation and the relative (monetary) gain of the agent upon violating. The actors have been color-coded according to whether the NVWA can oversee this actor. This figure shows that the trader and the end-user are the only two actors that have power, a high incentive to violate and can be easily regulated.

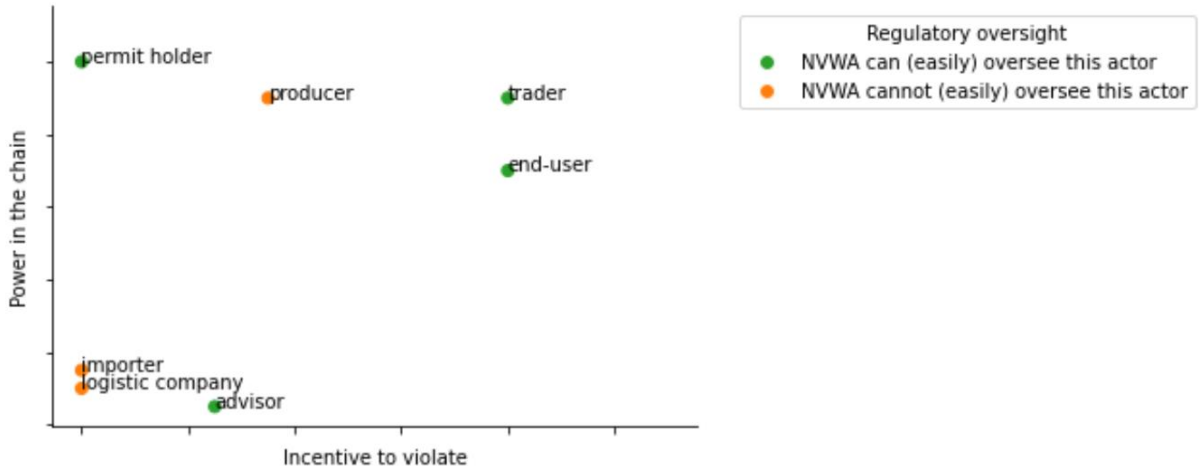


Figure 4.2. Classification of actors in the Dutch PPPs chain.

4.5 Pathways of acquiring PPPs

Figure 3 shows the possible pathways via which a PPP can reach the Dutch end-user as indicated by the experts. The regular pathway by which a legal PPP goes from a manufacturer to an end-user is that the manufacturer produces a PPP for the permit holder via the manufacturing prescriptions in the approval. The permit holder sells the product to a Dutch, CDG-certified trader and the trader sells the product to the end-user. Every trader who sells plant protection products in the Netherlands must have a CDG-certification, which shows the holder has knowledge of proper use of PPPs. A second legal pathway is parallel trade, in which a Dutch CDG-certified trader can apply for a parallel permit to sell a PPP in the Netherlands that has already been approved in another Member State and for which an identical product is already available on the Dutch market. A foreign trader can also apply for a parallel trade permit in the Netherlands and sell this product to a CDG-certified trader. All trade in PPPs that does not proceed via a permit holder and a certified CDG-trader is illegal by definition. These pathways are also shown in Figure 3.

Every actor in Figure 3 can potentially also buy from the internet. Buying from the internet is only allowed if it concerns a PPP that is legal in the Netherlands and that is sold by a CDG-certified trader. When end-users buy from the internet, they can choose from legal products that are offered by Dutch traders, illegal products offered by Dutch traders or illegal products that are offered from outside the Netherlands. End-users are thought to not always be able to discriminate between a legal and an illegal PPP online, especially when the illegal PPPs are sold online by a Dutch trader. Traders are thought to use the internet mostly for buying illegal PPPs from outside the Netherlands, as they trade directly with other traders within the Netherlands.

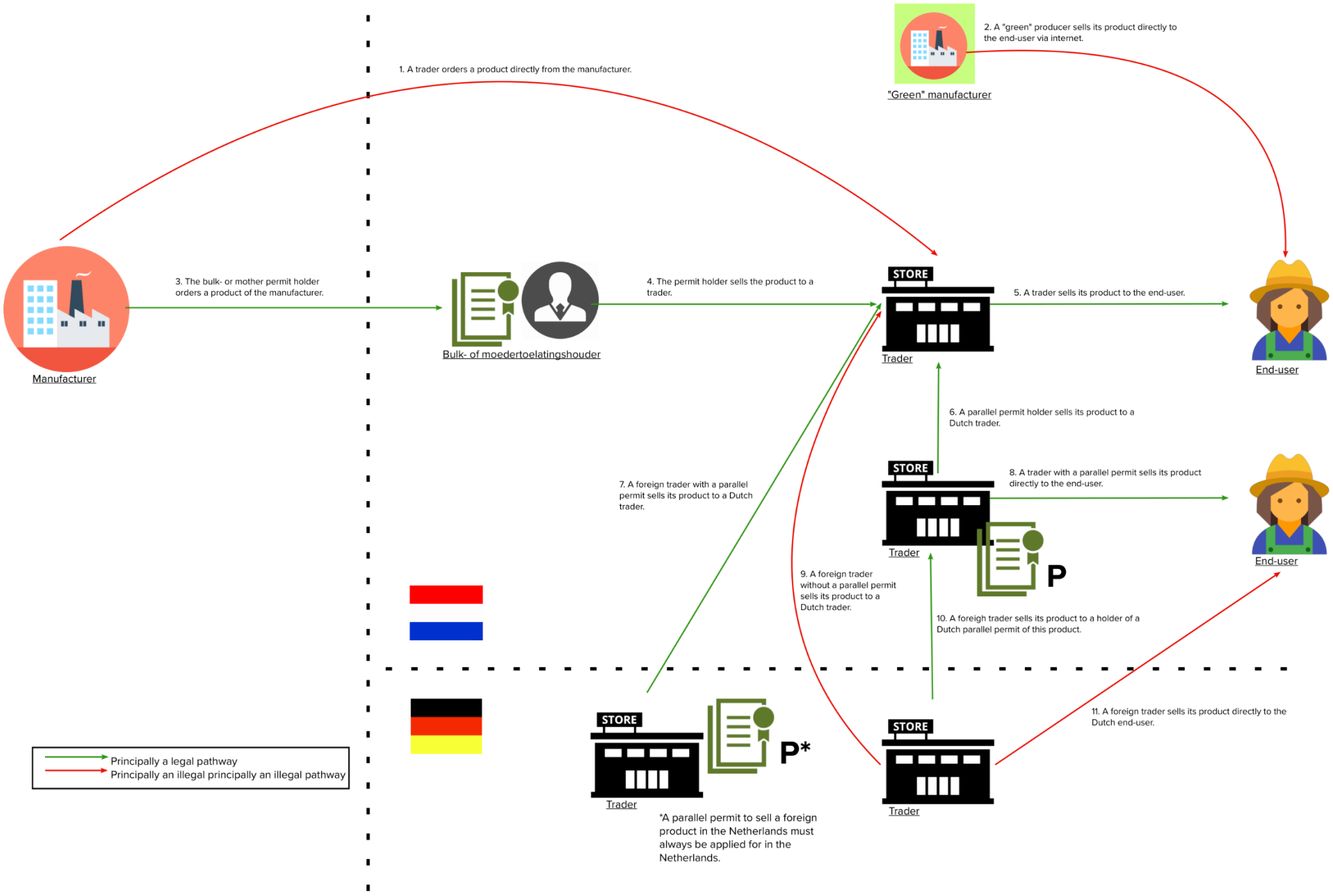


Figure 4.3. Pathways of how a PPP can reach the Dutch end-user.

4.6 The entry of "not the original product" PPPs on the Dutch market

NOP products are hard to detect for two reasons: the label looks like the original product's label and usually the chemical composition is also very similar, thus only a full chemical analysis can reveal that the product is fake. However, at least one actor in the chain must know that the product is a NOP product: the original buyer. The advantage of knowingly buying a NOP product is that the product is bought cheaply and can be sold for up to fifty times the import value. It is therefore lucrative to knowingly buy a batch of NOP products and sell them as real products. For this, there are three pathways, as presented in Figure 4.4.

The first pathway is that a Dutch trader knowingly buys a NOP product, orders it with a Dutch label and sells it directly on the Dutch market. The second pathway is when a foreign trader knowingly orders a NOP product, sells it as a legal product locally and the local foreign trader who buys the product sells the NOP product via a legal pathway to a Dutch trader. The third pathway is when a foreign trader knowingly buys a NOP product and sells it directly on the Dutch market. In all cases, the NOP product enters the market as a legal product the moment it is sold, as the buyer does not know it is a NOP product and assumes its legality. From there on, the product can be resold multiple times under the presumption that it is a legal product. Due to the international character of the PPPs market in Europe, it is hard for the NVWA to track the origin of a PPP, especially because the PPP may have been transported through multiple countries.

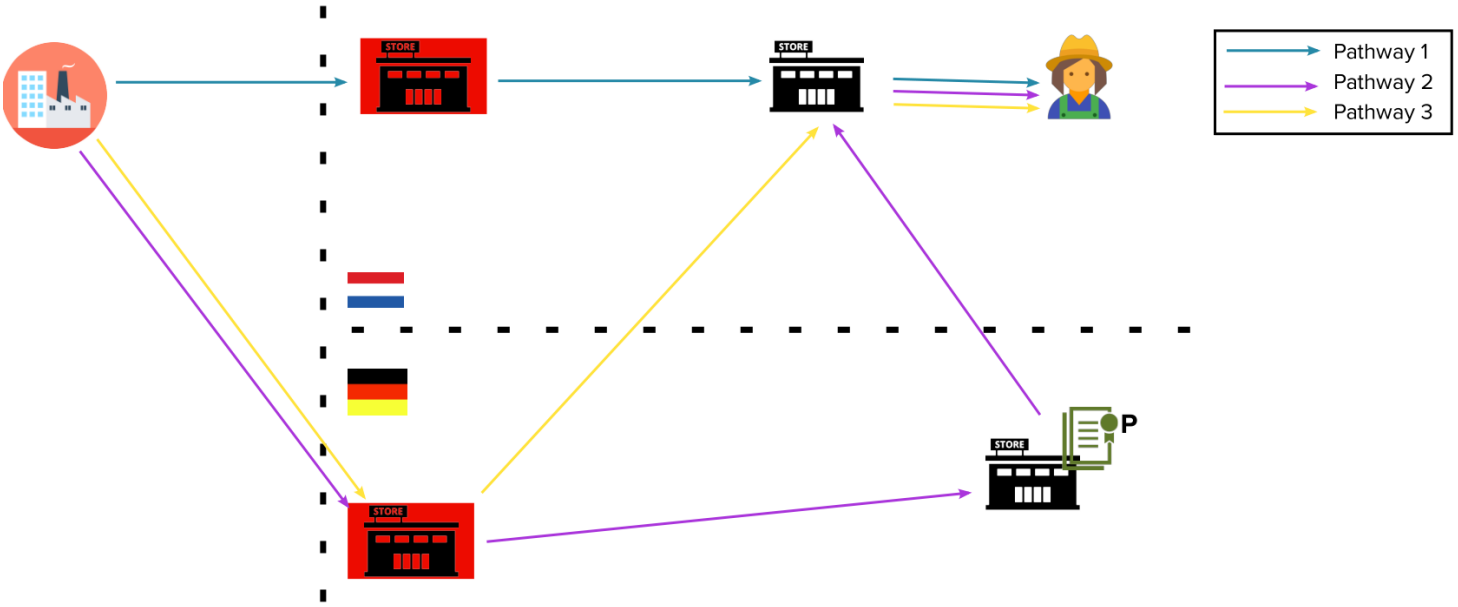


Figure 4.4. Pathways of how "not the original product" PPPs can reach the end-user.

4.7 The regulatory problem

In terms of intervention strategies, the NVWA has three options: administrative checks, chemical analysis of the main component and full chemical profiling. At the moment, inspection mainly takes place at the end-user, whereby chemical analysis of the substances on the end-user's crop is performed. This shows whether an end-user has used a PPP that is not allowed (in the Netherlands or the EU), but not whether the substance was a NOP substance. The PPPs stock of the-end user can also be visually inspected, and the administration in terms of purchasing and sales of PPPs can be inspected. A product that is illegal in the EU is sometimes found in the end user's possession, but due to the limited sampling it is not possible to determine whether and how much NOP products are present at the end-user.

The NVWA can also inspect traders. This entails mostly administrative checks and visual inspection of a selection of PPPs in stock. However, the NVWA only has insight into the CDG-certified traders, who are believed by the experts to adhere to the rules reasonably well. Traders who are not CDG-certified, who thus act illegally, pose the greatest risk and can engage in illegal practices via the internet, from within the Netherlands or from abroad. It is difficult for the NVWA to inspect these traders, because they often operate in secret.

In addition, the internet also perpetuates the problem. The NVWA has little insight into online trade of PPPs. This trade is anonymous, unclear and accessible to everyone. A large part of the PPPs that are available on the internet are offered from abroad, outside the reach of the NVWA. Anyone can offer PPPs on websites such as www.aliexpress.nl and these are available to all traders and end-users. This facilitates illegal trade, according to the experts.

The regulatory problem can thus be summarized as follows:

- The context of the problem is set by the approval procedure of PPPs in the EU. This ensures that only part of all disease-crop combinations is covered by the PPPs that are legally allowed in the Netherlands.
- There is thus a high incentive for end-users to want to use products that are illegal in the EU.
- This motivation is extended to their traders, who want to supply these illegal products to serve their customers and make money.
- There is information asymmetry, a large incentive to violate and detection difficulty regarding NOP products, which makes it virtually free to buy and sell NOP products.
- The NVWA does not have insight into some important areas: import streams of PPPs into the Netherlands, traders that are not CDG-certified and the internet.
- The NVWA has a very low inspection capacity compared to the number of regulatees.

When considering these factors altogether, it is not surprising that the NVWA considers illegal PPPs in the Netherlands an important problem that needs solving.

5. Model conceptualisation

In this section, the findings from the expert discussions in Section 4 will be translated into a conceptualization for an agent-based model. First, the objectives of the model will be stated. Next, the agents and objects in the model will be outlined. Furthermore, the main dynamic driving agent behaviour will be explained. Lastly, the assumptions of the model will be stated.

5.1 Modelling objective and KPIs

The objective of this research is to understand the suitability of the method of agent-based modelling to PSA-risk analysis. For this reason, agent-based modelling will be applied to the case presented in Section 4. The ABM that will be created for the NVWA is entirely based on the expert knowledge that was collected during the discussion sessions (see Section 4) and can be viewed as a synthesis of the current knowledge of the NVWA on the Dutch PPPs chain. Within the context of the NVWA, the modelling objective is to provide a plausible narrative on how the legal and illegal plant protection products chain are interlinked and use this narrative to create a better insight into which regulatory interventions result in the lowest number of illegal PPPs reaching the end-user. Thus, interaction between agents should be plausible in themselves and lead to plausible model behaviour. The main unknown factor is what drives illegal behaviour in the PPPs market. The model will study whether illegal behaviour arises throughout the PPPs chain from individual agent behaviour.

To this end, key performance indicators (KPIs) must be selected and monitored throughout the model run. The KPIs that were advanced by the experts are the total illegal PPPs reaching the end-users and the share of NOP products in the total illegal PPPs. These KPIs will be expressed as percentages of the total PPPs that are bought by the end-users, to be able to compare scenarios in which varying numbers of end-users get diseases on their crops, which would lead to different numbers of PPPs bought per model run.

5.2 Agents

The actors in the system have been described in Section 4.3. Of these actors, two have a high interest, high power and can be regulated by the NVWA: end-users and traders. These agents will be included in the model.

End-users: end-users are defined as any professional user of plant protection products. Their main objective is to keep their crops alive. They have two means of acquiring PPPs: buying them from traders, which is legal if they are CDG-certified and the product that is sold is legal, or buying them from the internet, which can be legal or illegal, depending on whether the seller is a CDG-certified trader and the product that is sold is legal or illegal. End-users are linked to one local trader, whom they can buy their products from locally, because the experts indicated that in reality end-users are usually advised to buy PPPs by an advisor on plant protection products who is employed by a local trader.

Traders: traders are defined as any company who buys and sells PPPs. Their main objective is to make sufficient profit to survive. What constitutes sufficient profit is represented by a user-defined threshold. They have three means of acquiring PPPs: they can buy PPPs from another (CDG-certified) trader, which is legal as long as the PPPs that are sold are legal and the selling trader is CDG-certified. Furthermore, they can buy PPPs from a permit holder, which is always legal. Lastly, they can buy PPPs from the internet, which is always illegal, as PPPs should be acquired from a permit holder or a CDG-certified trader and trading with a CDG-certified trader is thought to usually be performed via direct trade. The client-base of the traders varies, as there are two types of traders in the model: traders who

sell to end-users only and traders who sell to traders only. These traders do not differ in anything other than their client-base.

5.3 Objects

To model the trading of plant protection products, three types of objects will be present in the model:

Inspectors: inspectors are indicators of the locations where inspections take place. They are randomly assigned to an inspection target, after which the inspection procedure is called. Inspectors do not have any interaction with their inspectees nor any own behaviour, nor are their variables updated during an inspection. Therefore, they have been modelled as objects.

Plant protection products: plant protection products represent the products that traders and end-users can buy. The entire range of plant protection products is defined at the beginning, so plant protection products are not altered during the model run. They are created for one crop- and disease-type and they contain information on whether the product is legal, illegal in the EU or a NOP product.

Orders: orders represent the sale and stock of a plant protection product. Orders are created when a sale happens between two agents. They contain a reference to the plant protection product that is in the order and the number of PPPs in this order, as well as the current and previous owners and the method of acquiring the PPP. When the PPP in the order has been used by the end-user, or sold out by the trader, the order will die.

The internet and permit holders will be modelled as a method of acquiring PPPs for the agents. At set-up, plant protection products that are initially only available through the internet will be made into an order with an unlimited number of plant protection products that is only available online. Furthermore, there will be an unlimited number of legal PPPs available via orders that are owned by a virtual permit holder that can be acquired by traders if they choose to acquire their products via the permit holder.

5.4 Agent behaviour

The main agent behaviour consists of buying and selling PPPs. For this, every agent has a selection of buying methods available to them. Every time their crops get a disease (for end-users) or they do not have sufficient stock of a product (for traders), the agent will buy new PPPs. The experts identified that choice of the buying method is driven by the trust of an agent in that the buying method will be suited to achieving its objective (healing the disease of its crops or selling products to make a profit). This approach is known as a social approach to regulation of agent interactions, as the agents themselves regulate the PPPs market by selecting buying methods (Pinyol & Sabater-Mir, 2013). The trust of the agent is based on an aggregation of direct experiences of the agent with buying PPPs that have been identified by the experts. A differentiation has been made between positive and negative experiences, that respectively in- or decrease trust. The trust is updated every timestep and is calculated as:

$$(1)\ Trust(a,i) = Max\ (\ 0.0001, Min\ (\ 100,\ \ Trust(a,i - 1) * \sum TM(i)\ )$$

Where:
Trust(a,i): Trust in buying method a at timestep i
TM(i): the percentage trust modification in the given timestep

Thus, every timestep, the trust of the agent in one of its buying methods is changed according to the experiences that the agent has had with the method. The trust in the method cannot reach 0, nor can it be higher than 100.

The negative experiences an agent can have with a method are:

For both types of agents:
- the product did not arrive via this method
- the regulator found an illegal PPP that was bought via this method
- the product I ordered via this method appeared to be a NOP product

End-user-specific
- the plant protection product ordered via this method does not cure the disease of my crop
- the method has no product available for my crop-disease combination

Trader-specific
- the method has no product available for my stock request
- via this method I could not make sufficient profit

The positive experiences an agent can have with a method are:

For both types of agents:
- the product I ordered via this method passed an inspection without being caught as illegal

End-user-specific
- the product I ordered via this method cured the disease on my crop

Trader-specific
- a whole order I acquired via this method was sold without problems

The dilemma for traders in the model is thus that they must make sufficient profit and therefore need to serve their customers (end-users and other traders) well. However, especially when not all crop-disease combinations are covered by legal products, serving their customers well might mean buying some products illegally from the internet, or else the end-users might start using the internet themselves, which would cost the trader profit and might make them lose trust in their legal buying methods. However, when customers get inspected and fined for a product they bought from a trader, their trust in this buying method will decrease. Therefore, selling illegal products to end-users is also not a reliable strategy. For customers, the dilemma is between acquiring their products via a trader and not always having a suitable product available to them, or buying via the internet, which is illegal and risky in terms of being inspected and does not provide a guarantee that the product will work. In the model, these considerations will be played out and the dynamics can be observed. Figure 5.1 provides an overview of the mechanisms guiding the model behaviour.

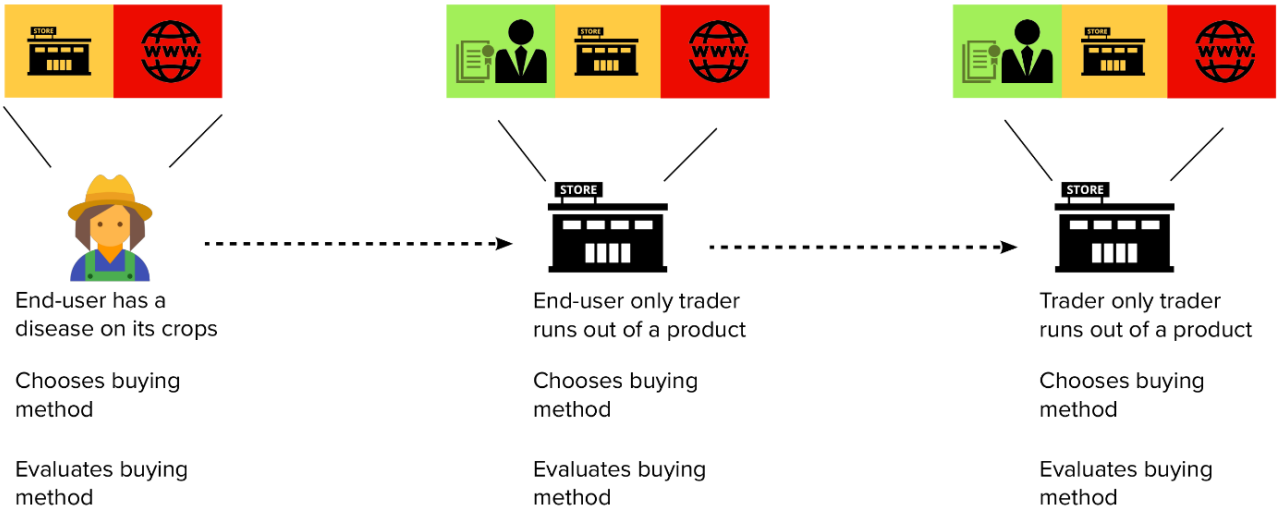


Figure 5.1. Overview of the process underlying the main dynamic in the model.

To regulate the agents' behaviour, the NVWA can perform inspections. Upon inspection, the inspectors will sample a number of PPPs that are owned by the inspectee. If they find an illegal product (either illegal in the EU or a NOP product), they will "fine" the inspectee (although money is not explicitly included in the model) by which the inspectee will lose trust in the buying method via which it acquired the PPP. As inspection levers in the model, the NVWA can choose where to send their inspectors: to end-users, EUO traders and/or TO traders. Furthermore, the NVWA can determine how often they want to perform chemical profiling of PPPs and how many PPPs they want to inspect when visiting the end-user or trader.

5.5 Assumptions and simplifications

The model is built on the knowledge of the experts of how the Dutch PPPs chain works. However, the experts have indicated multiple times that their knowledge on illegal processes in the PPPs chain is limited and therefore the case description that was provided in Section 4 can be viewed as containing the main assumptions of the model. However, not all information provided by the experts was used in the model. The main simplifications are:

- the PPPs that are approved in the Netherlands do not change during the model run.
- the diseases are uniformly spread per crop type and throughout the simulation. No seasonal effects have been included.
- there are no crop sectors in the model. End-user behaviour is thought to vary per crop type (e.g. more expensive crop types can buy more expensive legal products).
- prior experience with PPPs of the end-user has not been modelled. This is thought to play a role in the type of PPP an end-user chooses from the internet or demands from its trader.
- CDG-certification of traders has not been modelled.
- inspections are random and not based on risk analyses or prior experience.
- agents do not update their perceived chance of being inspected after an inspection.
- the cost of interventions has not been included in the model. Interventions such as inspections or chemical profiling are free.

6. Model formalization

In this section, the conceptualization presented in Section 5 will be converted to an agent-based model. First, a model narrative is presented, after which the model narrative is formalized in a business process diagram. Next, model implementation details will be provided. Lastly, the model verification process will be described.

The code of the model and the data analysis can be found on:
https://github.com/KimvVliet/PlantProtectionProductsNVWA.

6.1 Model narrative

A model narrative informally describes how the generative model behaviour is created through individual agent behaviour: it describes what agents do and when and with whom (Nikolic et al., 2013). A model narrative describes what happens in one timestep, a tick. In the model, every timestep represents one month. The time unit month has been chosen because it represents one cycle in which end-users can get a disease on their crops and cure the disease. Every month, end-users wake up and might find that their crop has a disease. When there is a disease on their crop, they will decide upon a buying strategy for acquiring a suitable plant protection product. If they are a compliant end-user, they will buy from their local trader. However, some end-users might deviate from the law. These end-users weigh the trust they have in buying from the internet against their trust in their local trader and they consider their neighbours' opinions on the buying methods.

If an end-user chooses to buy from their local trader, the local trader will search their stock for a PPP that is suitable to the crop and disease of the end-user and offer it. The end-user will buy the product unless they can see the product is a NOP product, in which case they will reject the product and lose some of their trust in their local trader. If no suitable product is available, the trader will offer a PPP that is suitable for the disease of the crop of the end-user, but not for their crop type. This makes the PPP less effective. When the trader is able to offer a product, they will get paid. A new order is created that is owned by the end-user. If the trader cannot offer any product, the end-user will decrease their trust in the trader.

If an end-user opts for buying from the internet, they will choose an online product for their crop-disease combination randomly. If the product is illegal, it might be intercepted at the Dutch border. In this case, no order is created and the trust of the end-user in the internet is decreased. If the product does reach the end-user, an order is created that is owned by the end-user. If the end-user bought an online product that is offered online by a trader, the trader will get paid. If there is no suitable product, the end-user will decrease their trust in the internet.

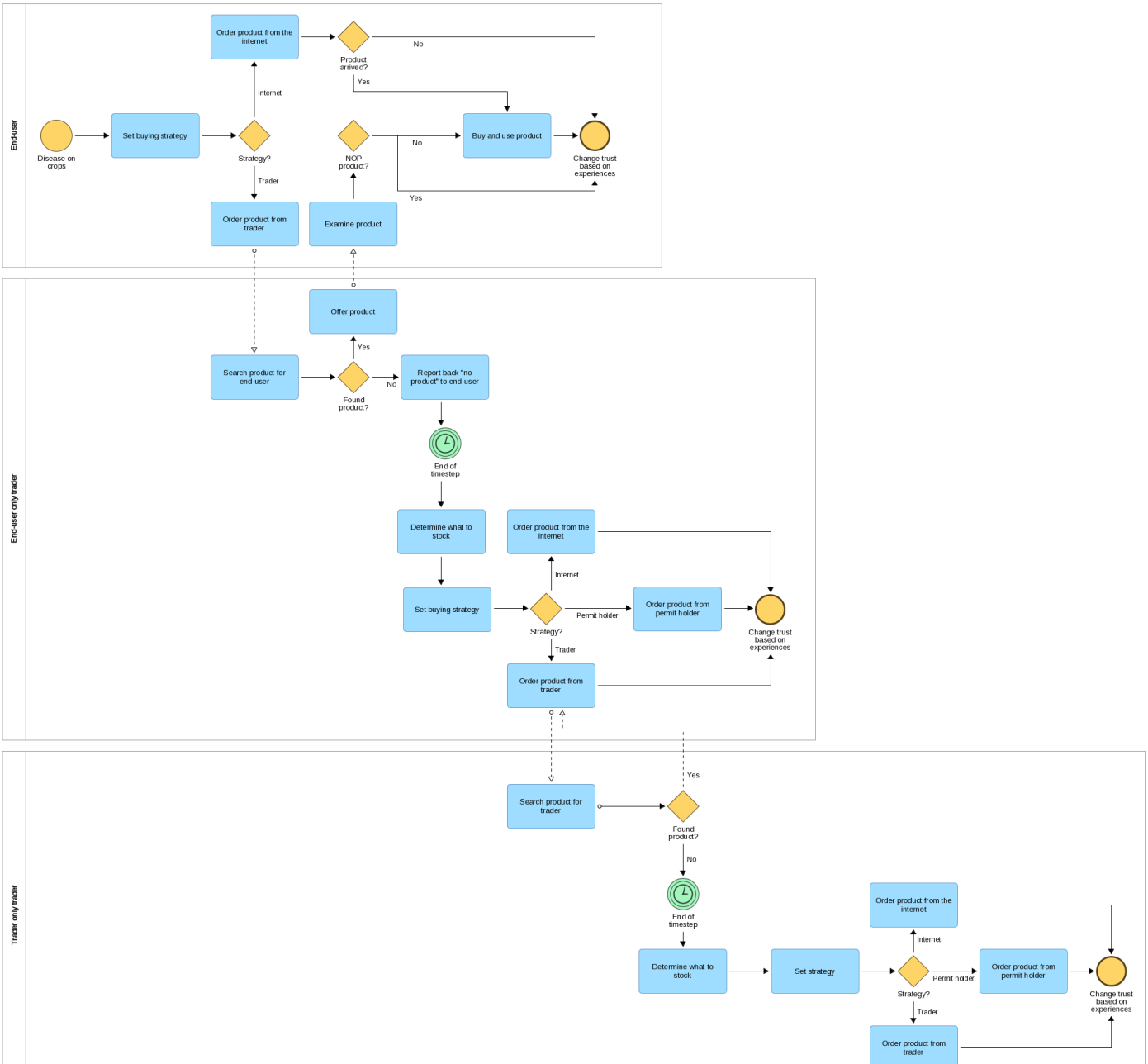
Once the end-user has acquired a PPP, they will use it. If the PPP cures the disease, the trust of the end-user in the buying method increases. If the PPP does not cure the disease, the end-user will decrease their trust in the buying method by a moderate amount if their crop is still alive. If the crop has died, the end-user will decrease their trust in the buying method by a large amount.

If a trader cannot offer a product to a buyer (end-user or trader), they will order new products. First, traders set their stocking strategy. For this, they can choose from buying from the permit holder, another trader or from the internet. For the internet, they will weigh the risk against the potential profit. If this is favourable and they trust in the internet as a buying method, they will buy from the internet. If not, they will choose to buy from the permit holder or from another trader, depending on which buying method they trust most. After choosing a buying method, they will take stock of which products they need to buy.

Next, the trader will attempt to buy the requested products. For every buying method, the trust in the method will be decreased if the method does not have a requested product available. When buying from the internet, there is a chance that the PPP will be intercepted and does not reach the trader. This decreases the trust of the trader in this buying method by a moderate amount. If buying from another trader, the trader can access all PPPs that are owned by the traders they are linked to. The trader will buy suitable products unless they can see the product is a NOP product, in which case they will reject the product and lose some of their trust in buying from other traders.

Lastly, inspectors move to an inspection target randomly. At the target, they will sample a number of PPPs and check if the product is legal. If a PPP is inspected but not caught, this will slightly increase the trust of the inspectee in the method via which they acquired the PPP. If a PPP is found to be illegal (NOP or illegal in the EU), the inspectee will be fined, which results in a large decrease in the trust in the buying method via which the inspectee acquired the PPP.

To summarize, this section presented a model narrative that shows the main processes via which actor acquire PPPs in the model. The model is intended to be a translation of the expert knowledge to an ABM and the model narrative has presented a high-level overview of the processes that will occur in the model. A formal business process model of the model narrative is shown in Figure 6.1. The business process model is created according to BPMN version 2.0.2 (see Object Management Group (2013)). An enlarged version of the individual actor pools is shown in Appendix B.



6.2 Model implementation

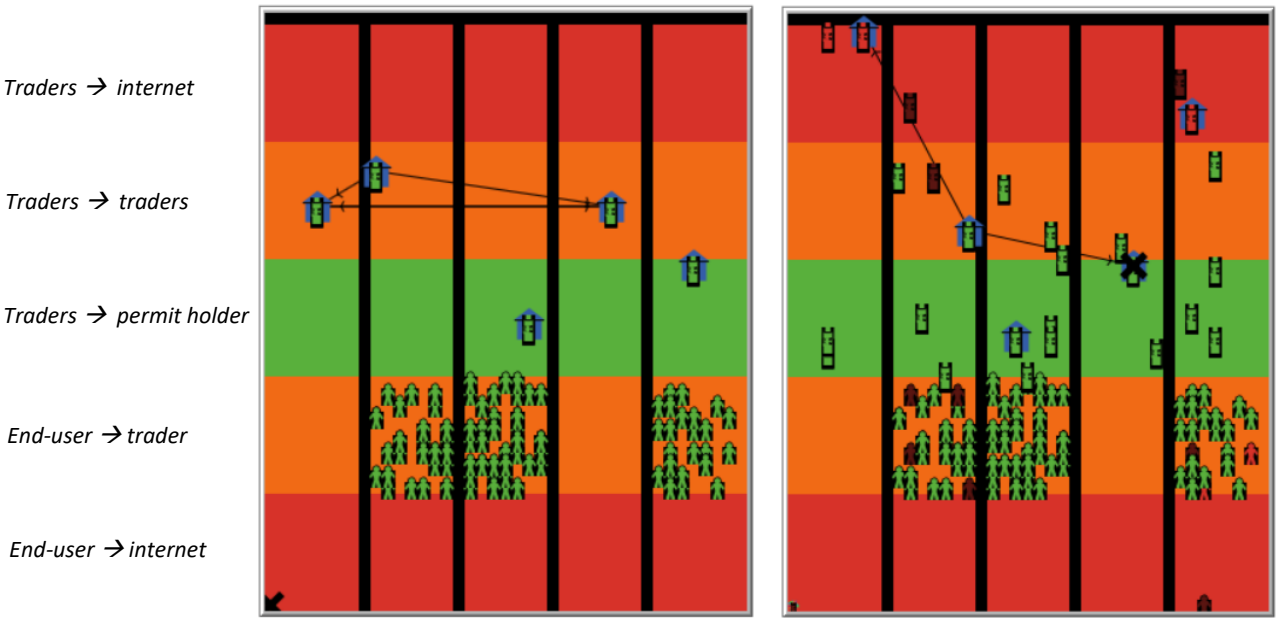
To implement the model, the model narrative has been translated to code. This includes parametrization of the most important model variables. The model parameters that can be varied by the user are divided over five types of parameters: model settings, setup variables - context, setup variables - NVWA, run variables - context and run variables - NVWA. The parameters and their ranges have been described in Table 6.1.

Table 6.1. Model parametrisation.

Model parameter	**Range**	**Description**
Model settings		
Fixed-seed?	True / False	Repeat the run with the seed number from the previous run.
Random_seed_value	-∞ - ∞	User-specified random seed.
Progression_visualisation?	True / False	Turn on the visualisation of creation of PPPs and choice of buying methods.
Fixed_trust_period	0 - 60	The number of ticks traders and end-users can trade without modifications in their trust in buying methods.
Setup variables - context		
Nr_of_types_of_crops	1 - 10	The number of different types of crop an end-user can get at the start of the simulation. Every end-user gets assigned one crop type.
Nr_of_types_of_diseases	1 - 5	The number of different types of diseases the crop of an end-user can get.
Nr_of_end_users	10 - 500	The number of end-users in the simulation.
%_always_comply_end_users	0 - 100	The percentage of end-users that always comply with the rules.
Nr_of_traders	0 - 100	The number of traders in the simulation.
%_always_comply_traders	0 - 100	The percentage of traders that always comply with the rules.
%_traders_end_user_only	10 - 100	The share of traders that sell to end-users only. The other traders sell to traders only.
%_coverage_of_disease_crop _combinations_legal_products	0 - 100	The percentage of total crop-disease combinations that are covered by legal products.
Setup variables - NVWA		
Nr_of_inspectors	0 - 10	The number of inspectors in the simulation.
Inspect_end_users?	True / False	Indicates whether end-users will be inspected.
Inspect_end_user_only_traders	True / False	Indicates whether EUO traders will be inspected.
Inspect_trader_only_traders	True / False	Indicates whether TO traders will be inspected.
Run variables - context		
Minimum_profit	0 - 5000	The minimum profit that a trader needs to make every twelve ticks.
%_avg_change_to_get_disease	0 - 100	The average chance that an end-user gets a disease every tick.
Inspection_chance_NL_border	0 - 100	The chance that a package is inspected when sent via the internet.
Run variables - NVWA		
Fine-to-profit ratio	0 - 2	Indicates how much higher the fine is compared to the potential profit from buying and selling illegal PPPs.
%_profiling_used	0 - 100	The percentage of times chemical profiling is used to sample a PPP upon inspection.
nr_of_PPPs_inspected_upon _visit_trader	1 - 50	The number of PPPs sampled upon inspection of a trader.
nr_of_PPPs_inspected_upon_ visit_end_user	1 - 5	The number of PPPs sampled upon inspection of an end-user.

With the parametrization, the model can be run. At set-up, plots of land are created with different types of crops. Then, end-users and traders are placed randomly on the map. End-users get assigned the crop of the patch they are on, which creates a regional prevalence of certain types of crops. A user-specified percentage of traders is assigned to serve end-users only, after which end-users are connected to the EUO trader closest to them. Thus, one EUO trader mostly serves end-users with the same type of crop. Next, PPPs are created. First, mother approvals are created randomly for the user-specified percentage of disease-crop combinations. Next, cheaper and slightly less effective bulk products are created for a share of the mother approvals. Then, PPPs that are illegal in the EU are created. These are very effective original products, but illegal in the EU. Lastly, NOP products are created. These are based on a mother or bulk PPP, but less effective. Furthermore, they are not an original product and get a random similarity to the original product. After the PPPs have been created, traders get assigned a range of legal PPPs as initial stock. The offer by the virtual permit holder is created by creating orders with mother and bulk products that contain an infinite number of legal PPPs. Lastly, the online offer is set up by creating orders that contain an infinite number of illegal PPPs. Furthermore, a random number of traders get assigned to sell their PPPs online. The orders of these traders become available online.

When the progression visualisation is switched on by the user, after setup the traders are placed in their respective column. The end-users connected to an EUO trader appear in the same column below their local trader, see Figure 6.2(a). The row colours indicate the buying method that was chosen by the agent. The top three rows indicate the buying methods of the traders and the bottom two rows those of the end-users. Agents move to the row that corresponds to their current buying method. Black lines are drawn between a trader who buys from a TO trader. When a trader buys a PPP, the PPP is created at the location of the trader and it is coloured according to its legal status. End-users change colour according to the legal status of the product they buy. For example, in Figure 6.2(b) the trader in the rightmost column has bought three legal PPPs from a permit holder, one legal PPP from another trader and two illegal PPPs from the internet. Of its clients (end-users), one has bought an illegal PPP from the internet and all others have bought PPPs from the trader, of which three bought an illegal product and all others bought a legal product.



(a) Tick 0. *(b) Tick 33.*

Figure 6.2. Example of model interface at tick 0 and tick 33.

To summarize, in this section the model parameters that can be varied by the model user have been presented. These will later be used to experiment with the model and create insights for the NVWA (see Section 7). Furthermore, the setup of the model has been described and the model visualisation has been explained. Together with the model narrative (see Section 6.1), this should allow the user to have a global understanding of how the model works.

6.3 Model verification

Model verification ensures that model outcomes are based on a model that is coded as intended and are not caused by errors in the code (Nikolic et al., 2013). Four types of tests have been performed: unit testing, recording agent behaviour, interaction testing and multi-agent testing. A summary of each type of testing will be described below. For details on what was verified, see Appendix C.

Unit testing has been performed for every individual function in the setup and model run. Positive and negative unit testing have been performed for each function. The model has passed all unit tests, which indicates that every individual function performs according to its objectives.

Agent behaviour has been recorded by following the state variables of individual agents. Via this method, it has been confirmed that basic agent behaviour happens correctly. Amongst other things the acquiring and curing of crop diseases of end-users, the registering of client requests and the trust modifications have been checked. In the final model version, no errors in individual agent behaviour have been found by examination of the state variables.

Interaction testing has been performed with a minimal model of one end-user, one EUO trader and one TO trader. Various dynamics have been observed, especially that the number of legal PPPs sold to the end-user varies largely per model run: in some cases, when the legal products mostly cover the needs of the end-user or when the EUO trader is not willing to violate, end-users almost only acquire legal PPPs. However, if the EUO trader starts buying from the internet, its end-users can only acquire illegal PPPs. These dynamics were all plausible given the model settings. Furthermore, through interaction testing it was found amongst other things that traders only buy PPPs when they have no more stock of a product and that end-users can only buy illegal products from their trader if an illegal product has previously been acquired by this trader. No coding errors were found through interaction testing in the final model version.

Multi-agent testing has been performed with 500 end-users and 20 traders. Via multi-agent testing, sanity checks were performed with a fixed seed to check whether the model behaviour changed as expected when different user-defined variables were changed. For example, it was tested whether less illegal PPPs reached the end-user if the coverage of crop-disease combinations is higher, or when there are more inspectors. The sanity checks were all passed for the final model.

To summarize, the model has gone through the verification phase, in which errors in the code have been searched for and corrected. This means that the results from the model are most likely not caused by wrong coding, but by the dynamics that have been included in the model (see Section 6.1 and 6.2).

7. Experimental Design

In this section, it is described how the implemented model as detailed in Section 6 will be used to perform the PSA-risk analysis. The variability of the model is discussed, after which the experimental setup is introduced.

7.1 Variability testing

The model has many parameters. To not have to test every parameter for every experiment, for all experiments some parameters that are thought to have a low impact have been set throughout all model runs. They can be found in Table 7.1. The run length for all experiments has been set at 396 ticks. This equals 36 ticks for the fixed trust period, in which trust of the agents does not change, and an additional 360 ticks, which equals 30 years. This time period has been chosen because it is a relevant time window for the NVWA and it can be assumed that context variables like climate change and PPP-laws are stable within this timeframe.

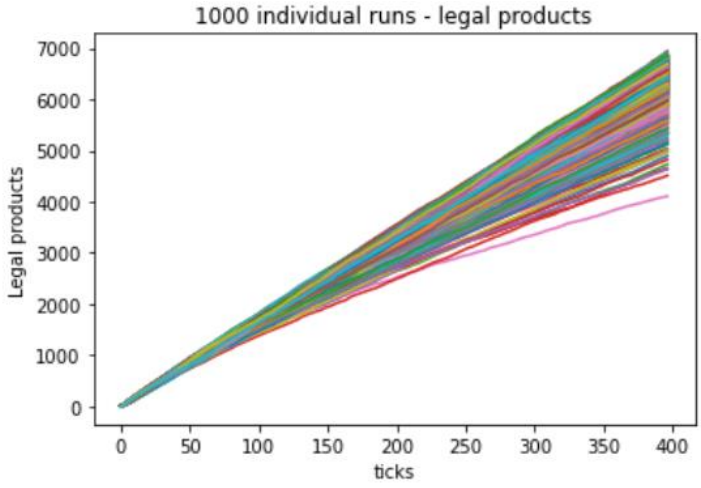
Table 7.1. Values of model parameters that have been set throughout all experiments.

Model parameter	**Value**
Progression_visualisation?	False
Fixed-seed?	False
Fixed_trust_period	36
Nr_of_types_of_crops	5
Nr_of_types_of_diseases	2
Nr_of_end_users	300
Nr_of_traders	15

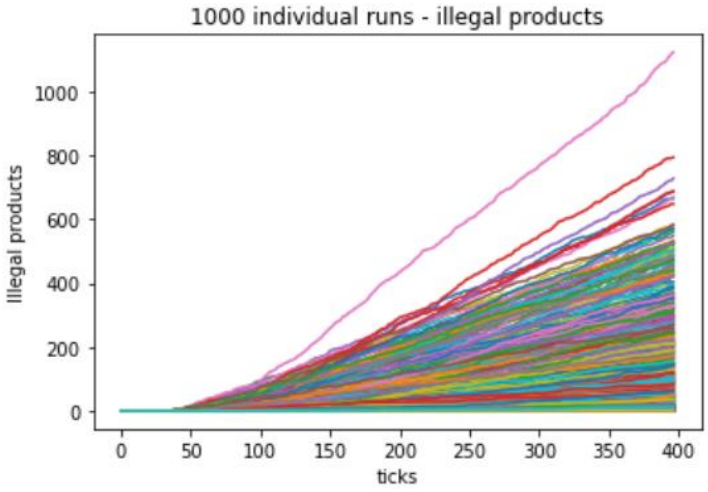
Agent-based models are usually stochastic (Nardini et al., 2021). To ensure that results from experimentation are not a mere fluke caused by the inherent randomness of the model, it is important to get an idea of the variability of the model and the minimum number of model replications that are required to approximate the average outcome value. To this end, the model has been run 1000 times over a scenario without inspections and with plausible values for the other parameters (for parameter values, see Appendix D). The outcomes of the variability testing are shown in Figure 7.1.

Figure 7.1 shows that the model is highly variable. Comparing Figure 7.1(a) and 7.1(b) shows that the model outcomes vary highly for both legal and illegal products. This can be explained by the many stochastic elements in the model, amongst which are the share of end-users with different crop types, whether legal products are available for the crop types of the end-users, whether a disease is cured by a PPP and whether a NOP product is discovered by the buyer. Figure 7.1(c) shows the average and standard deviation of the NOP products that have arrived at the end-user over 1000 model runs. This again shows that one single model run cannot be used to conclude anything about the effects of a set of parameter settings on the KPIs. Thus, multiple runs must be performed to approximate the average outcome value. Figure 7.1(d) shows the average outcome values averaged over various numbers of runs. From this figure, it can be concluded that the minimum number of runs that must be performed and averaged over to get a representative outcome is 50 runs. With 50 runs, the shape of the outcome curve approximates that of the average of 1000 runs. The number of NOP products that arrive at the end-user averaged over 50 runs is lower than that of the average of 1000 runs. However, as this is an explanatory model that is used to perform a risk analysis with and the model is highly stochastic, the exact number of PPPs is not an outcome of interest and approximation of the outcome curve is the important factor. Furthermore, repeating the model at least 500 times for every experiment, as

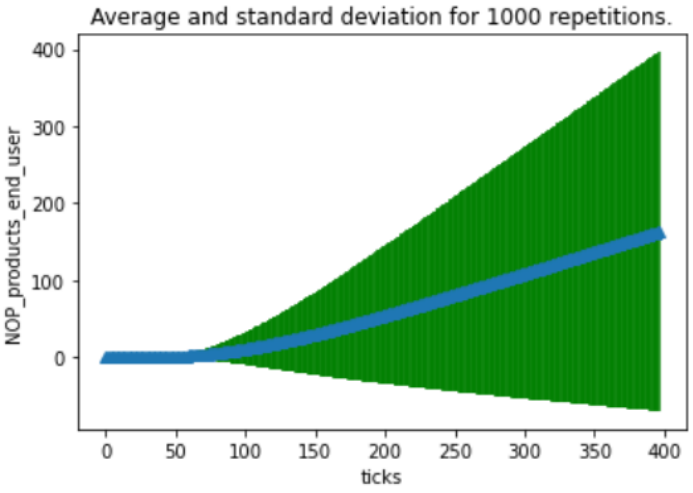
suggested by Figure 7.1(d) would be too computationally expensive. Therefore, the number of model repetitions for every experiment have been set at 50.



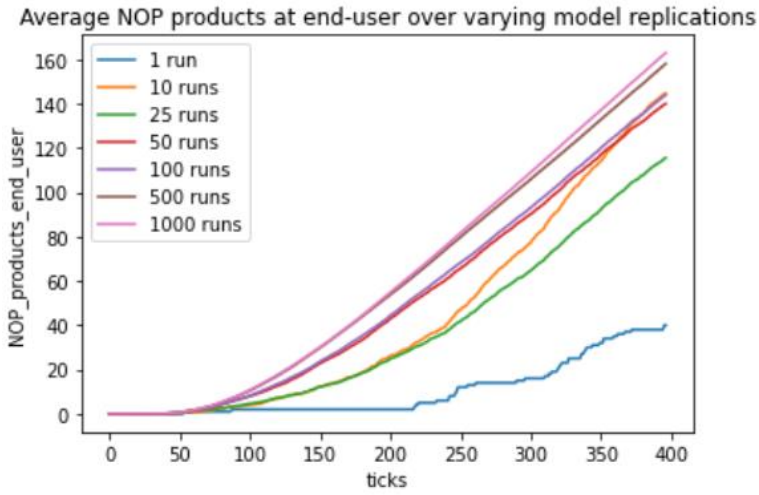
(a) 1000 individual model runs - legal products



(b) 1000 individual model runs - illegal products



(c) Average and st.dev. - 1000 runs - NOP products



(d) Average NOP products - varying model replications

Figure 7.1. Variability testing.

7.2 Sobol experimental setup

To understand the effect of the model parameters on model behaviour, a Sobol analysis is performed. For the Sobol analysis to be feasible in terms of number of runs, an additional four parameters have been set constant. The average chance to get a disease has been set at 5%, as this variable mostly determines how often end-users get a disease on their crops but it does not alter model behaviour. Furthermore, the number of PPPs inspected upon inspection of an end-user has been set at 3, as the end-user is expected to own only one or two PPPs at a given time step. To be able to test the effect of different inspection interventions on model outcomes, at least one inspection target group (end-users, EUO traders or TO traders) must be selected or else the model will give an error. As the NVWA has always inspected end-users and will continue this practice in the future, the inspect end-users variable has been set to True. Lastly, the fine-to-profit ratio has been set to 1, as with 315 agents in the simulation and up to 10 inspectors, the fine-to-profit ratio would have to be set at 30 to have any impact in the model. The Sobol parameter settings have been summarized in Table 7.2. All other model variables will be sampled during the Sobol analysis. As prescribed by a Sobol analysis, the number of

parameters * 2 + 2 combinations of parameters will be sampled. Thus, 24 combinations will be sampled. 100 Scenarios will be run per combination of parameters.

Table 7.2. Sobol parameter settings

Model parameter	**Value**
%_avg_chance_to_get_disease	5
nr_of_PPPs_inspected_upon_visit_end_user	3
inspect_end_users?	True
Fine-to-profit_ratio	1

7.3 Optimization and robustness testing experimental setup

For the optimization, an optimal policy will be found that minimizes the two KPIs: the percentage of NOP products and the percentage of total illegal products that reach the end user. The policy variables of the NVWA are the number of inspectors, whether to inspect EUO traders and/or TO traders, the number of PPPs inspected upon inspection of a trader and the percentage of all PPPs which are sampled using chemical profiling. The constant parameters are set according to Table 7.1 and Table 7.2. For the optimization, a moderate base case scenario is chosen that is shown in Table 7.3. The number of function evaluations, which indicates how often the evolutionary algorithm iteratively searches for the optimal solution, is set at 10000. The epsilon values, which determine the coarseness of the solution grid, are 0.5 for both KPIs (Maier et al., 2019). Convergence will be checked by epsilon progress and hypervolume. Epsilon progress is a measure of the new solutions found in the epsilon grid. Hypervolume is a measure of how much of the outcome space to be minimized is covered by the solutions that are found. For this, the likely solution space must be defined (Liefooghe et al., 2018). The expected range for the percentage NOP products that reach the end-user has been set at 20%. For the total percentage illegal products the expected range has been set at 30%.

Table 7.3. Optimization scenario

Model parameter	**Value**
%_always_comply_end_users	70
%_always_comply_traders	50
%_traders_end_user_only	70
%_coverage_of_disease_crop_combinations_legal_products	70
Minimum_profit	3000
Inspection_chance_NL_border	10

The policies that are rendered by the optimization will be tested for robustness. As discussed in Section 3.4, robustness will be calculated via two metrics: mean and variance and the maximin. Every policy will be subjected to 200 scenarios.

8. Results

In this section, the results from the experiments as outlined in Section 7 will be described. First the results from the Sobol analysis are presented. Thereafter, the results from the optimization are shown and finally the robustness scores of the policies will be described.

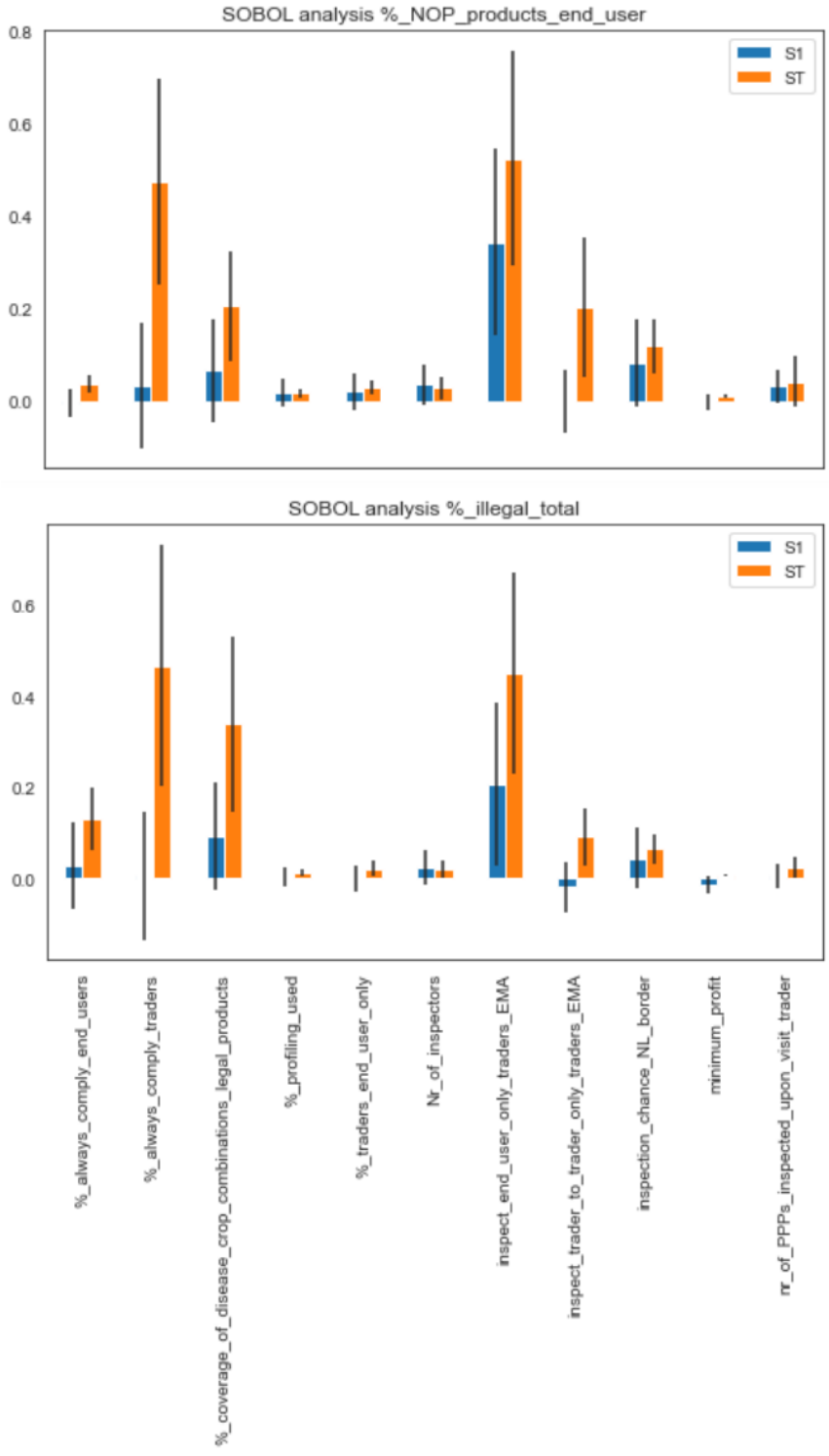
8.1 Results Sobol

The results from the Sobol analysis can be found in Figure 8.1. The tables with numerical values can be found in Appendix E and a description of the meaning of the model variables can be found in Table 6.1. Figure 8.1(a) shows that only one variable has a significant first order effect on the percentage of NOP products arriving at the end-user, namely the policy decision to inspect EUO traders, which explains 30% of the total variance in this KPI. Furthermore, it shows large interaction effects between the percentage of traders which always comply, the coverage of crop-disease combinations by legal products, the policy decision to inspect EUO traders and TO traders and the inspection chance at the Dutch border. It is apparent from Figure 8.1(a) that model behaviour is largely driven by the interaction effects from these variables. The largest share of model behaviour is driven by the interaction effects of the policy decision to inspect EUO traders (53%) and the percentage of traders which always comply (49%). The effect of the six other variables is negligible.

When comparing Figure 8.1(a) with Figure 8.1(b), which shows the Sobol outcomes for the total percentage of illegal products that reach the end-user, it is apparent that the parameters which drive the KPIs are similar for both KPIs. The main difference is that for the total percentage of illegal products the percentage of end-users that always complies has a significant interaction effect (13%). Furthermore, the amount of variance that is explained by the variables differs by a small amount between the two KPIs. These differences have been summarized in Table 8.1.

Table 8.1. Differences in Sobol total order effects for two KPIs.

Parameter	**Total order effect - NOP products (%)**	**Total order effect - total percentage illegal products (%)**
%_always_comply_end_users	4	13
%_always_comply_traders	49	47
%_coverage_of_disease_crop _combinations_legal_products	17	34
Inspect_end_user_only_traders?	53	45
Inspect_trader_to_trader_only_traders?	19	9
Inspection_chance__NL_border	12	6



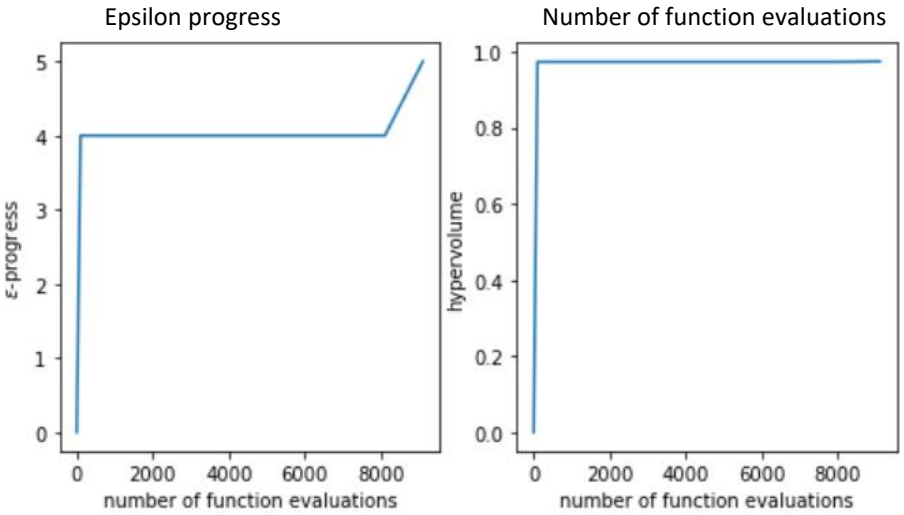
(a) Sobol analysis of the percentage of NOP products at the end-user.

(b) Sobol analysis of the percentage of total illegal products at the end-user.

Figure 8.1. Results from the Sobol analysis.

8.2 Results optimization

Figure 8.2 shows the convergence metrics of the optimization. What can be seen in Figure 8.2(a) is that the epsilon progress seems to converge nearly at the start of the optimization, yet near the end a new optimal policy was found. This new optimal policy was most likely found within the same epsilon square, as the hypervolume converged at the beginning of the optimization and did not increase further during the optimization process (see Figure 8.2(b)).



(a) Convergence: epsilon progress (b) Convergence: number of function evaluations

Figure 8.2. Convergence metrics.

The number of optimal policies that were found is 1. Averaged over 50 runs, the percentage NOP products arriving at the end-user under this policy was 0.09% and the percentage of total illegal products was 0.65%. The policy is presented in Table 8.2. All inspection variables of the optimal policy are high: the maximum number of inspectors is employed, inspections at all locations take place and 40 out of a maximum of 50 samples are taken at every inspection. Contrarily, the percentage of profiling used in the optimal policy is low, 4 out of a maximum of 100.

Table 8.2. Policy parameter settings of the optimal policy value.

Policy parameter	**Optimal policy value**
Nr_of_PPPs_inspected_upon_visit_trader	38
Inspect_end_user_only_traders?	True
Inspect_trader_to_trader_only_traders?	True
Nr_of_inspectors	10
%_profiling_used	4

As testing only one policy for robustness will not render an overview of the trade-offs in robustness regarding various inspection strategies, seven other inspection strategies will be tested for robustness. These policies have been included in Table 8.3.

Table 8.3. Policy parameter settings of the original optimal policy plus seven other policies.

Policy number	Nr_of_PPPs_inspected_upon_visit_trader	Inspect_end_user_only_traders?	Inspect_trader_to_trader_only_traders?	Nr_of_inspectors	%_profiling_used
0 (optimal)	38	True	True	10	4
1	38	True	False	10	4
2	38	False	True	10	4
3	38	False	False	10	4
4	38	True	True	1	4
5	38	True	False	1	4
6	38	False	True	1	4
7	38	False	False	1	4

8.3 Results robustness

The mean and standard deviation of the model outcomes for the different policies have been plotted in Figure 8.3. Figure 8.3 shows that inspecting EUO traders has a large effect on the KPIs: all policies that include inspection of EUO traders result in an average percentage of total illegal products reaching the end-user of below 5%. Furthermore, these policies appear to be robust: the standard deviation of KPIs under these policies is low (below 5.5%). Inspecting EUO traders in combination with TO traders appears to have no additional effect on the number of illegal PPPs reaching the end-user. Furthermore, inspecting EUO traders compared to not inspecting any traders on average has a positive effect on the percentage of illegal products that reach the end-user. For the total illegal products, the difference between inspecting no traders and trader-only traders is 6.5% with 10 inspectors and 7.0% with only 1 inspector. However, the standard deviation of both policies is sizeable (15% and 18% with 10 inspectors and 14% and 18% with 1 inspector). This indicates a low robustness of these policies. Lastly, Figure 8.3 shows that the difference between inspecting with 1 inspector (policy 4 - 7) versus 10 inspectors (policy 0 - 3) is small: the average KPI value of the policies over the different scenarios is similar for both policy settings.

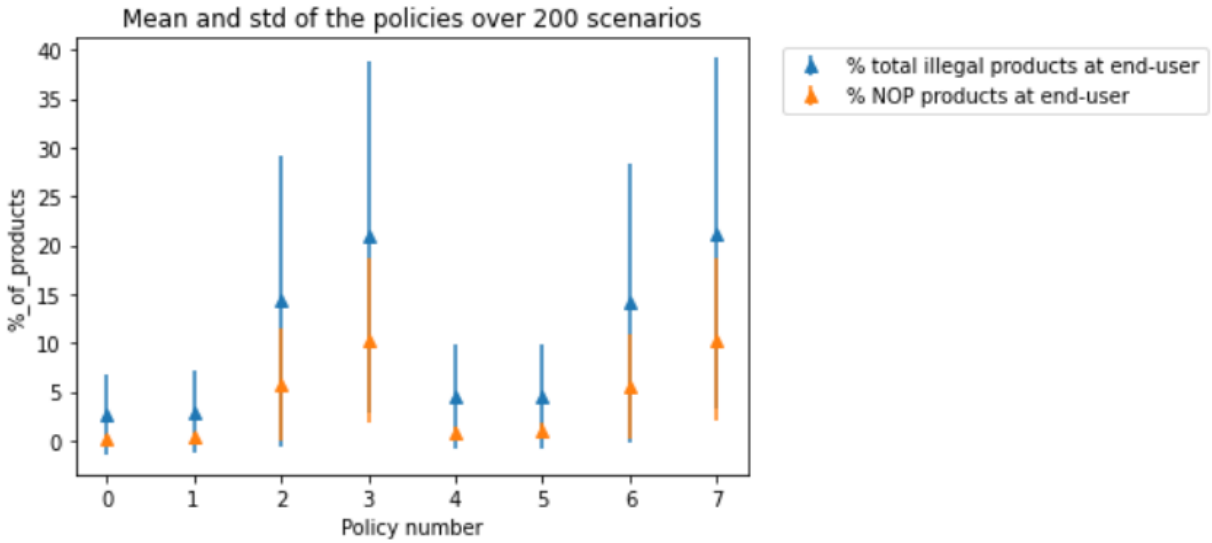


Figure 8.3. Robustness - mean and standard deviation of the policies over 200 scenarios.

Table 8.4 contains the scenario per policy with the highest percentage of NOP products arriving at the end-user. The maximin values of the policies follow the same pattern as was seen in Figure 8.3. The policies in which EUO traders are inspected perform best, whether the policy contains 1 or 10 inspectors (2% and 4% NOP products respectively). The policies which inspect TO traders have the next lowest maximin value: 23% with 10 inspectors and 20% with 1 inspector. Lastly the policies which only inspect end-users have the highest maximin values: 37%.

Two observations can be made about the scenarios in which the policies perform the worst. Firstly, the percentage of crop-disease combinations that is covered by the legal products is generally low: between 15 and 48%. Secondly, it is not simply a combination of the lowest compliance rates at both types of agents that makes the worst-case scenario: only policy 0 performs worst in a scenario with a low compliance amongst end-users (2%) and traders (6%). Policy 3 and 7, in which traders are not inspected, perform worst when end-users are very compliant (100%) and traders are maximally incompliant (1%). Policies 2, 5 and 6, in which one type of trader is inspected, perform worst when end-users are moderately compliant (49%, 53% and 53%, respectively) and traders are not very compliant (7%, 31% and 31% respectively) and the inspection chance at the Dutch border is low (5%, 12% and 12% respectively). Policy 1 and 4 show yet other combinations of compliance.

Table 8.4. Maximin scenarios for the highest percentage of NOP products reaching the end-user.

Policy	Max pct NOP products	Inspection_chance_ NL_border	%_always_comply_ end_users	%_always_ comply_traders	%_traders_ end_user_only	Pct_ coverage
0	2	41	2	6	22	16
1	2	18	4	53	43	15
2	23	5	49	7	43	48
3	37	27	100	1	53	19
4	4	24	33	11	82	19
5	4	12	53	31	72	20
6	20	12	53	31	72	20
7	37	27	100	1	53	19

The maximin scenarios of the percentage total illegal products show similar patterns as those of the percentage NOP products, as shown in Table 8.5. However, the scenarios in which these maximum values are generated differ from the scenarios of the percentage NOP products. The primary similarity is that the percentage of the crop-disease combinations that are covered by the available legal products again is low in all worst-case scenarios. However, the average compliance of the end-users generally is much lower (it varies between 1% and 33%, instead of 2% and 100%). Furthermore, there are no worst-case scenarios in which end-users comply 100%, yet in the worst case of policy 0 traders comply 98% and end-users 16%, with a low inspection chance at the Dutch border and a very low coverage of crop-disease combinations (12%). In all other worst-case scenarios, both end-users and traders do not have a high compliance.

Table 8.5. Maximin scenarios for the highest percentage of illegal products reaching the end-user.

Policy	Max pct illegal products	Inspection_chance_ NL_border	%_always_comply_ end_users	%_always_ comply_traders	%_traders_ end_user_only	Pct_ coverage
0	19	7	16	98	84	12
1	18	18	4	53	43	15
2	65	6	1	28	47	17
3	70	41	2	6	22	16
4	23	24	33	11	82	19
5	26	24	33	11	82	19
6	60	6	1	28	47	16
7	71	41	2	6	22	16

9. Discussion

In this section, a synthesis will be made of the aspects of this thesis that are relevant for PSA-risk analysis. First, the implications of the results in Section 8 will be discussed. Next, the model limitations will be discussed. Then, a reflection will be provided on the process of building an ABM through participatory modelling within a regulatory organisation. Lastly, a reflection will be given on the applicability of ABM to PSA-risk analysis.

9.1 Implications of the results for the NVWA

From the results in Section 8, implications can be drawn for the problem of illegal plant protection products in the Dutch plant protection products chain. Firstly, two risk concentrations have emerged. The first is that EUO traders play a leading role in the number of illegal PPPs arriving at the end-user. This is because end-users only have two buying methods to choose from: the internet and EUO traders. The internet offers mostly illegal PPPs (partly dependent on the online offer of the traders in the simulation). When EUO traders mostly buy illegal PPPs to sell to their clients, end-users can mostly only buy illegal PPPs from both of their buying methods, and since they do not want their crops to die, they are "forced" to buy an illegal product. The second risk concentration is TO traders. However, the risk of TO traders is dependent on whether EUO traders are willing to buy from TO traders, as EUO traders ultimately are the gatekeepers to the PPPs reaching end-users. Thus, if EUO traders are inspected and illegal PPPs are found and their trust in buying PPPs from TO traders decreases, the effect of the behaviour of TO traders on the total PPPs bought and sold decreases. Furthermore, TO traders are one in three ways from which EUO traders can acquire their PPPs. It is a buying method that does not offer "unique" PPPs (only PPPs that can either be bought from a permit holder or from the internet) and it has a downside of making less profit because the selling trader takes a margin of the final sale price of the product. Therefore, EUO traders will most likely never only buy from TO traders and the risk of this actor is moderate.

Two factors that contribute to the risk posed by traders are the percentage of disease-crop combinations covered by legal products and the compliance of the actors in the PPPs chain. The results show that with a low coverage, end-users will look for effective products on the internet. As their trust in this buying method grows, soon they will buy all their products from the internet. Furthermore, the level of overall compliance of the actor groups also determines how many illegal PPPs reach the end-user: generally, high compliance of traders will drive end-users to buy their products from the internet if they cannot get a suitable legal product. However, low compliance of traders will create the aforementioned situation in which end-users are caught between buying illegal products from the internet or buying illegal products from their local trader.

A few other observations can be made based on the model results. Firstly, the fine-to-profit ratio has to be very high, much higher still than the maximum of 2 in the model, to deter traders from buying illegal products. However, currently actors do not update their inspection chances in the model, so they observe a low inspection chance throughout the model run. Perhaps updating inspection chances might change this dynamic. Secondly, the inspection chance at the Dutch border does not have a large effect on the number of illegal PPPs reaching the end-users, as long as there is no sanction for the buyers when an illegal product is found. Currently, the trust in buying from the internet decreases when a package does not arrive. However, this is not sufficient to deter agents from buying from the internet. Lastly, the number of inspectors does not need to be very high: the effect of inspecting EUO traders is similar when inspecting with 10 inspectors or with only 1 inspector. Therefore, inspecting smartly instead of with a large number of inspectors appears to be most effective.

The guidelines for the NVWA that can be drawn from the model results are:

- Inspecting EUO traders appears to be an effective and robust strategy to reduce the number of illegal PPPs that reach the end-user, as EUO traders are the gatekeepers of which products reach the end-user.
- Monitoring voluntary compliance is important, as voluntary compliance has a very large effect on the problematic behaviour.
- Increasing voluntary compliance in one actor group will most likely only be effective if voluntary compliance in the other actor groups is also moderate to high.
- Voluntary compliance can only be high when the coverage of legal products is high and end-users do not have to resort to illegal products as a last resort. Increasing voluntary compliance of traders when the coverage of legal products is low will most likely not be very effective, as this will drive end-users to the internet.
- The inspection chance at the Dutch border does not seem to have a large effect on the number of illegal PPPs that reach the end-user, as long as the buyer of the product is not sanctioned.

These guidelines mostly but not entirely match the current practices of the NVWA. In recent years, the NVWA has aimed to adopt a chain-perspective on regulation (BuRO, 2019; NVWA, 2020). This means that multiple production chains that are regulated by the NVWA have already been mapped (see, for example NVWA (2019a)). The current research suggests that adopting a chain-perspective and evaluating the risk of different types of actors in the chain can be a very useful way to increase the effectiveness of regulation. The inspection efforts of the NVWA in the Dutch PPPs chain, however, have mostly remained targeted at the end-user. In 2018, 535 inspections were carried out at the end-user, whilst 181 inspections were carried out at the other actors in the Dutch PPPs chain (import, traders and permit holders) (NVWA, 2018a). This research suggests that at current inspection capacity, targeting individual end-users is not a very effective strategy to reduce the number of illegal PPPs arriving at the end-user and that inspection efforts could better be concentrated at the EUO traders who have a gatekeeper function as to which PPPs reach the end-user. Furthermore, the NVWA already aims to increase voluntary compliance in end-users. The NVWA advises end-users with crops that are uncommon in the Netherlands and for which thus few PPPs are available on how to control the disease on their crops and helps them to get permits for new PPPs. This is done to ensure that end-users with uncommon crops do not revert to illegal PPPs and thus to increase voluntary compliance. Increasing voluntary compliance in the other actors is not mentioned as a priority for the NVWA, however (NVWA, 2018a). The current research indicates that increasing voluntary compliance in the end-user might be problematic when EUO traders are inclined to buy and sell illegal PPPs. It is therefore suggested that EUO trader and end-user voluntary compliance should be targeted simultaneously.

9.2 Model limitations and validation

Every model comes with limitations (Nikolic et al., 2013). The major limitation of the current model is that it is not based on scientific theories or data, because the model represents a reflection of the implicit and explicit knowledge of the domain experts. It is thus mostly assumption-based, namely the assumptions of the domain experts on how the Dutch PPPs market functions. It should be noted that the dominant narrative of the experts resembled that of the homo economicus, the rational agent who acts primarily out of self-interest and always aims to maximize its utility. However, this is only one paradigm through which to view the motivations of agents in the model. Other theories have put more emphasis on “irrational” behaviours like acting upon social motivations, overconfidence or loss aversion (McMahon, 2015). Similarly, the trust mechanism that is implemented in the model is currently rather minimal, as it only considers the direct experiences of the agents. Other trust mechanisms also contain direct observation of other agents’ actions and differentiate between

different types of cognitive dimensions (e.g. values or knowledge of the agent) (Pinyol & Sabater-Mir, 2013).Thus, considering that the model represents the views of the experts and only one paradigm of agent behaviour, the model explains one narrative of the dynamics of how illegal PPPs reach the Dutch end-user. The model can thus not be viewed as providing any definitive truths as to how inspections should be carried out. Instead, it can be used as a device for thinking about the problem, to spur discussion and to generate new research questions (Freebairn et al., 2018). Furthermore, it has provided some first insights into the greatest risk concentrations in the Dutch PPPs market and into which factors might not be of much interest to the NVWA.

Another limitation of the model is that it has not been thoroughly validated. Model validation is performed to understand whether the model is fit for its purpose (Nikolic et al., 2013). Louie & Carley (2008) indicate that an agent-based model should be validated threefold by reviewing the conceptual validity, data validity and operational validity of the model. Conceptual validity refers to whether the theories and concepts included in the conceptual model fit the modelling purpose (Louie & Carley, 2008). In this research, a written version of the conceptual model has been reviewed by the domain experts who partook in the discussion sessions. The experts indicated that at first sight, the conceptual model looked good to them. However, no in-depth discussions of the conceptual model were held, due to time constraints. To ensure conceptual validity, it is recommended that the conceptual model is discussed with the domain experts in an iterative manner, in which the researcher reports back the conceptual results from the last discussion session at the start of the new discussion session. This will ensure that the model concepts align with the information provided by the experts. However, this is not sufficient to assess conceptual validity, as the conceptual model still only reflects the views of the experts who engaged in the discussion sessions (Nikolic et al., 2013). How to properly validate the conceptual model will be revisited shortly.

The other two types of validity that should be reviewed are data validity and operational validity. Data validity means checking whether the data have been used appropriately regarding the purpose of the model, i.e. checking what data have been used and how (Louie & Carley, 2008). The current model is not based on real-world data, as no relevant data sources were available, e.g. records of cases of illegal plant protection product sales. Operational validity means checking whether the model outcomes match the system under study (Louie & Carley, 2008). However, there is no observed real-world data available on the model outcomes, other than the estimate that 14% of all plant protection products in the EU are counterfeit (Wajsman et al., 2017). There are no data available about the percentage in the Netherlands. The average percentage of illegal plant protection products that reach the end-user for the eight different policies are in the range of 2% - 21%, which is a plausible range compared to the estimated 14% of Wajsman et al. (2017). When discussing the model outcomes with the experts of the NVWA, they recognized the gatekeeper function of the EUO traders and commented that veterinarians have the same function in regards to antibiotics in poultry (NVWA, 2012). This dynamic in the model thus seems valid. Despite these two minor points of operational validity, the model cannot be expected to quantitively reflect the real-world system, as it is not based on input-data. Even a qualitative reflection cannot be expected, however, as the creation of this model is the first time that an attempt was made to make the dynamics within the Dutch PPPs market explicit. There are thus no real-world dynamics that the model is supposed to match to.

In the face of the lack of data on the real-world system, the question that arises whether the model should be reviewed on data and operational validity. Louie & Carley (2008) argue that the validation of a model should be based on its purpose, and that models of which the data and operation have not been validated “are of particular use when the theory connecting agent-level behaviour to system-wide, emergent behaviour is not well-understood” (p. 254). This is in line with Axtell & Epstein's (1994)

classification of four levels of model analysis, in which the lowest level is the “caricature of reality” (p. 29), in which the model is shown to graphically match the system of interest. The authors merit these models as powerful tools to advance fields in which the relations between micro-level structures and macro-level behaviour are unknown. A model that is not based on data and that cannot be operationally validated such as the current model can thus still offer value in terms of increasing the system understanding. This aligns with the purpose of the model of offering a first explanation of how the relationships in the model cause the observed real-world phenomenon of illegal plant protection products entering the Dutch PPPs market (Edmonds et al., 2019).

For the current model, expert validation is proposed to fulfil two functions: increasing conceptual validity and maturing the (conceptual) model. Expert validation is a validation technique in which experts that have not previously worked with the model are asked to review the model and its assumptions. These experts have to be different from the original experts who provided the model input (Nikolic et al., 2013). For the current model, a mix of additional domain experts and stakeholders that are represented in the model is recommended. First the model can be discussed with each stakeholder group individually and after this a discussion amongst all experts and stakeholders can be facilitated. It is important to make the assumptions and individual agent behaviour in the model explicit during these discussions, so that the experts can discuss the conceptual model beyond what they can see from the user-interface (Nikolic et al., 2013). This will help to check the assumptions made by the experts in the original discussion sessions. It is very likely that through expert validation, new and conflicting insights will arise about the Dutch PPPs market, as the current model offers only a first explanation of how the Dutch PPPs market works based on the perceptions of the experts of the NVWA. In other words, it is likely to be partially invalid. Thus, the expert validation will help to mature the (conceptual) model and the understanding of the Dutch PPPs market of the NVWA.

Expert validation will render a more conceptually valid caricature model. However, if the model is to be used for other purposes than a thinking device, i.e. when the purpose of the model changes from explanation to prediction (Edmonds et al., 2019), changes need to be made to the model. First and foremostly, the model and especially the model relations need to be quantified. Data would be needed on how much trust in- or decreases upon various experiences with buying methods, on the level of voluntary compliance in different actor types, on the effectiveness of different PPPs and on the similarity to the original product of NOP products. Also, data validation must be performed after the model is finished, through a second data collector who examines the biases that are present in the way the data was collected and used in the model (Louie & Carley, 2008). Secondly, empirical data must be collected on the system under study to understand whether the outcomes of the quantified model match the real-world outcomes. This data is necessary to improve the understanding of the NVWA of the Dutch PPPs market and to be able to validate the operation of the model (Louie & Carley, 2008). Lastly, a few system components that might alter model dynamics are currently missing from the model. These include that agents dynamically calculate their perceived inspection chance, agents dynamically change their willingness to comply based on inspections and implementation of dynamic adaptation of the range of legal products available in the model to simulate expiration and application of permits. These changes would make the model more responsive to different regulatory strategies and would provide more information on their effectiveness.

9.3 Reflection on the modelling process

Some observations can be made about the participatory modelling process. Firstly, the discussion sessions went well. Sufficient information was generated to serve as the basis of the conceptual model. The experts engaged in the discussion and were willing to disagree or indicate when they were uncertain about the accuracy of a statement. However, after the initial six discussion sessions, there

was a decrease in interest in the modelling endeavour. The experts have indicated that they did not understand agent-based modelling, as this was the first time they were introduced to this modelling technique and that they were curious to see the end result. This resulted in a paucity of feedback on the model details by the experts. Also, because of the lack of engagement with the model in the model building stage and because the experts were also unfamiliar with the EMA workbench, the model experiments were designed by the researcher. It is to be questioned whether this has increased the legitimacy of the model to the experts. However, by not overburdening the experts with meetings, the willingness of the experts to participate in future model-building projects has been preserved, which may ultimately benefit the application of agent-based modelling within the NVWA.

Furthermore, there are still questions of how the current research will be embedded within the organisation, as the researcher will not be present to supervise this process and the domain experts of the NVWA still have no knowledge of agent-based modelling. More attention could have been paid to familiarizing the domain experts with the method to embed the ABM within the NVWA. However, Nikolic et al. (2013) argue that the goal of participatory modelling is not to make the stakeholders experts on the ABM. "A model is usually too complex to just hand over to non-modelling stakeholders. Instead of just delivering "the model" as a final product to the stakeholder, modellers need to realise that the actual product is the insight into the stakeholders problem" (Nikolic et al., 2013, p. 132). Thus, the focus of the interactions with stakeholders should be on presenting the results clearly and engaging the experts in discussions on the results and this should be sufficient to create value for the experts via the modelling process. After the presentation of the final results, the experts indicated that the modelling process was useful to them and that the model could be used as a discussion model. They also discussed future steps to incorporate the model in their work more. This is a positive indication that the modelling results have led to insight into the problem. However, it would have been interesting to monitor the experience of the experts with the process more formally, for example via a survey at the beginning, halfway and at the end of the research.

9.4 Agent-based modelling in PSA-risk analysis

The question that remains is whether ABM as a tool is suitable to PSA-risk analysis. For this, the three main characteristics of PSA-risk analysis that were found in Section 2 will be revisited and a reflection will be offered to which extent the current ABM exercise corresponds to the characteristics.

The first characteristic is that *PSA-risk analysis is a problem-based process that is undogmatic in its choice of analysis methods*. The ABM was created to analyse the problem that was proposed by the domain experts, namely the interaction between the legal and illegal PPPs chain. The ABM was used to synthesize the current knowledge of the experts into one plausible explanation of how illegal PPPs reach the end-user and to perform an analysis of which agents and which factors influence the KPIs. The ABM was thus centred around a problem and also led by this problem. The types of risks the problem represented were actuarial, sociocultural and political risk, as the experts have indicated that the environmental impact of illegal PPPs is unknown but most likely very high (actuarial risk), the use of illegal PPPs can be provoking to local residents (sociocultural risk) and that the NVWA has the public function to stop end-users from using illegal PPPs (political risk) (Haines, 2013). The current research thus shows that ABM can be applied to problems that represent all different types of risks, as long as the risks can be represented by a clearly defined KPI, i.e. illegal plant protection products reaching the end-user.

Due to the nature of this research, in which the use of ABM for PSA-risk analysis is studied, the analysis method had been chosen already. However, a case study was selected for which an ABM seemed appropriate, so the analysis method did fit the problem. However, as Sparrow (2000) also indicates, it is unwise to use a hammer on a screw and caution should be exercised not to think of ABM as a holy

grail for PSA-risk analysis. ABM should only be considered as an analysis method when the problem exists within a system of interacting agents and in which the problem behaviour emerges as a result of these interactions (Bonabeau, 2002). Furthermore, the time invested in the modelling exercise should roughly equal the expected value of the insights to be generated. In other words, it is only beneficial to build an ABM when the problem is sufficiently complex and the complexity needs to be understood further.

The second characteristic is that *PSA-risk analysis is aimed at disaggregating risks in as many ways as possible to create tailormade interventions*. The current ABM has been used to disaggregate the problem in terms of the different actors involved in the problem, their main characteristics and context factors. It has thus been used to disaggregate the problem of illegal PPPs in multiple ways through which risk concentrations were found. With this ABM, even more ways of disaggregating the problem were thinkable, for example by analysing individual actor behaviour or an analysis focused on the different buying methods themselves. Furthermore, by being forced to explicitly describe the system under study, the experts naturally mentioned various forms of disaggregation that were relevant to the problem (actors, types of PPPs, pathways of acquiring PPPs). ABM thus invites to think in terms of important risk concentrations.

Through the experimentation with the ABM, the highest risk concentration was found to exist amongst the EUO traders. Furthermore, a specific context was found in which the risk was the highest, when there was a low coverage of legal products of possible crop-disease combinations. In addition, various factors were found to *not* pose a high risk: the structure of the chain in terms of end-users per trader and number of PPPs that are inspected per visit appeared to not largely influence the KPIs. These results are good first indicators of where the risk concentrations might lie in the Dutch PPPs chain and can be used as a basis to create tailormade interventions for the problem of illegal plant protection products in the Netherlands. The results did not render tailormade interventions directly, because a large portion of the modelling process was devoted to creating a first explanation of how illegal PPPs reach the end-user and therefore, the model is of too high level to directly inform the NVWA on an intervention strategy. Agent-based models that are created to study societal problems usually only seek to inform policymakers and not to directly propose a solution (see for example Hayes et al. (2012) or Paredes-Frigolett et al. (2015)) (Dechesne et al., 2014). Therefore, in the context of PSA-risk analysis, ABM can be viewed as a thinking device that helps in pointing regulators to effective intervention strategies.

The final characteristic is that *PSA-risk analysis is located at the heart of the regulatory agency and is performed with the help of analysts and experts alike*. The current ABM has not yet been embedded at the heart of the organisation. By performing participatory modelling, expert knowledge was used as the basis of the model conceptualisation, which ensured that the model was relevant to NVWA practices. However, due to the unfamiliarity of the experts with the method, it can be questioned whether the analysis is at the heart of the organisation. ABM does have the potential to be central to the regulatory organisation, as constructing an ABM with experts shows the experts their input is valued (Röckmann et al., 2012). However, it is important that more focus lies on communicating the results of the model back to the domain experts (Nikolic et al., 2013). Furthermore, the legitimacy of the analysis could have been increased had the researcher not been an external analyst. Boba (2003, p. 31) argues that to increase the legitimacy of PSA-risk analysis "the problem-analysis function must be spoken of with respect and an emphasis on legitimacy and (…) placed in a prominent position in the department". Van der Voort (2018) proposes three ways in which (PSA-) risk analysis could be more embedded within the organisation: through internalizing the needs of the regulatory organisation within the data scientist, through institutionalising an analysis department that houses both analysts

and staff of the regulatory agency or through mere exposure therapy of experts and analysts working on risk analysis projects together. None of these three options could have realistically been achieved within the scope of this research. Embedding agent-based modelling as a PSA-risk analysis method at the heart of the NVWA will most likely take time and not achieving this within this current research does not indicate anything conclusive on the ability of ABM to be at the heart of the regulatory organisation.

This research shows that ABM is a suitable method for PSA-risk analysis, if it can be embedded at the heart of the organisation. However, PSA-risk analysis may not be as straightforward as it has been presented thus far. Sparrow (2000) presents risk analysis as an exercise that, once it is placed at the heart of the regulatory organisation and supported by qualified analysts, will naturally present regulatory solutions to the problems under study. He writes: "The information craft shop (…) would be staffed by analysts skilled in a range of analytical disciplines, adept at drawing raw materials (data) from a range of sources, skilled at selecting the right analytical techniques for the job, and capable of producing made-to-order information products that support decisionmakers" (p. 270). In this, he envisions that experts and analysts work together to perform the analysis. Other than highlighting that analysis should be focused on creatively disaggregating risks, be available to the whole organisation and requires new data sources and investments, no guidelines are provided on how the analysis should practically be carried out in terms of combining skilled analysts with expertise from the organisation. Boba (2003) points out that the analyst should have communication skills to navigate their position between the, sometimes apprehensive, inspectors and the management of the regulatory organisation. Furthermore, besides analytical skills, the analyst needs facilitation skills and marketing skills to extract experience-based knowledge from experts and to sell the problem-solving analysis to the inspectors (Boba, 2003). Implementing a PSA-risk analysis thus is not a straightforward task.

In the current research, two lessons have been learnt about the implementation of PSA-risk analysis within a regulatory organisation that usually performs its risk analysis via standard methods in a separate department (NVWA, 2021). Firstly, the analysis process was still very much driven by the analyst. The analyst chose the methods, facilitated the data collection process and took ownership of the end result. The experts of the NVWA were somewhat tentative in the process and they indicated that this was partially caused by the unfamiliarity with ABM as a method. Implementing PSA-risk analysis thus requires more effort than providing an analyst to the service of the experts: the experts also have to be trained in the mindset of problem solving and be able to take responsibility and active interest in the problem-solving process. This may not come natural to experts who are used to looking at cases individually and who are not used to taking a systems perspective (Boba, 2003). Another way of improving the ownership of the experts over the PSA-risk analysis process is increasing familiarity with problem-solving (Boba, 2003; Sparrow, 2000; van der Voort, 2018). However, this process takes time and as projects, especially early ones, may not always render results, exposing experts to problem-solving risk analysis is not guarantee that experts will take ownership of the process.

Secondly, PSA-risk analysis and especially agent-based modelling are open, relatively unstructured processes. It is an art more than a science (Bonabeau, 2002; Sparrow, 2000). This meant that the experts were challenged to work with a very open method. The need to make continuous choices and to systematically process information about a complex socio-technical system made the risk analysis process cognitively demanding. In the current research, the experts were very motivated to participate in the risk analysis process, which offset the demands in terms of cognitive effort (Westbrook & Braver, 2015). The current research thus has shown that it is possible to engage experts with the PSA-risk analysis, despite the considerable novelty of the approach. However, the interest of the experts declined once the conceptual model was presented to them. This shows that, despite being motivated,

complex systems thinking that is required for problem-solving is a skill that does not come naturally to experts with no background in systems thinking (Nikolic et al., 2013).

This research thus indicates that Sparrow (2000) might talk too lightly of implementing problem-solving risk analysis within the regulatory organisation. Merely bringing together the resources, the experts and the analyst is insufficient to solve problems, as this does not guarantee integration of knowledge creation to create solutions within the organisation. When experts do not take ownership of the problem-solving process, it remains a solitary modelling exercise that does not spur innovation within the regulatory agency.

10. Conclusion

In this section, conclusions will be drawn. First, the sub-questions will be answered. Then, by the synthesis of the sub-questions, the main research question will be answered. Lastly, the contribution of the research to science and society will be discussed and directions for future work will be presented.

10.1 Answering the sub-questions

Below, the sub-questions will be answered. Combined, the answer to these sub-questions will provide the answer to the main research question.

Sub-question 1: What are the characteristics of a PSA-risk analysis and how do these characteristics compare to risk analysis in other regulatory paradigms?

The main characteristics of PSA-risk analysis that have been identified are:

- It is a problem-based process that is undogmatic in its choice of analysis.
- It is aimed at disaggregating risks in as many ways as possible to create tailormade interventions.
- It is located at the heart of the regulatory agency and is performed with the help of analysts and experts alike.

Risk analysis in other regulatory paradigms differs fundamentally from PSA-risk analysis. In risk-based regulation, the focus is on the risk factors pertaining to the regulated actors. Furthermore, the analysis methods are procedurally defined, as the same type of analysis is repeated for every type of problem. The goal of the analysis is to assess risk and to prioritize firms for inspections, to be able to spend organisational resources on the highest risk actors. The analysis usually is performed by a central department, it is mostly technocratic and involvement of domain experts is minimal. This type of risk analysis thus is more predefined and includes predetermined outcome measures, which distinguishes it from PSA-risk analysis.

Responsive regulation does not mandate any form of risk analysis. Responsive regulation is concerned with when risk manifests itself, namely after an inspectee commits a crime. The main difference with PSA-risk analysis is thus that in PSA-risk analysis, risks are analysed with the intention to proactively reduce the greatest risks whilst in responsive regulation risks are allowed to materialize and then acted upon.

Risk analysis in really responsive risk-based regulation is performed to assess a risk and the firms' expected compliance to find a firm-specific suitable intervention strategy. It uses a risk analysis procedure that is adapted to the context of the regulator. The focus is on the regulated actors. Thus, even though this risk analysis approach is more focused on reducing the risks at actor level than mere risk-based analysis, it is still more predefined and less focused on finding tailormade solutions to problems than PSA-risk analysis.

Sub-question 2: How can expert domain knowledge be used to create an agent-based model?

Expert domain knowledge was gathered via semi-structured discussion sessions. This information was summarized (see Section 4) and based on this information, a conceptual model was created by the analyst of which a written version was checked by the experts. The conceptual model was then formalized to an agent-based model through definition of the agents, agent behaviour and model parameters.

The main concepts driving system behaviour were identified as the end-users' goal to acquire a PPP that cures their crop once it has a disease, the traders' goal to satisfy its customers to make sufficient profit, the context of the legal applications of plant protection products and the trust of the agents in the buying methods available to them to reach their goal.

Sub-question 3: How can an agent-based model be used to find risk concentrations in a complex regulatory problem?

Risk concentrations were found through the use of an ABM with the help of five steps that were followed during this research:

1. Identify natural forms of risk disaggregation as indicated by the experts.
2. Create a conceptual model based on the indicated risk disaggregation.
3. Formalize the model and include the possibility to study the influence of the identified risk factors.
4. Use the EMA workbench to study the risk factors over the scenario space.
5. Interpret the results to report back risk concentrations to the regulatory agency.

By implementation of these five steps, risk concentrations have been found for the Dutch PPPs case. A major risk concentration that was found is the EUO traders, as these are the gatekeepers of which plant protection products reach the end-user. Agent characteristics that were found to contribute to the problem were the voluntary willingness to comply, with combinations of high and low compliance in different agent groups being especially problematic. Furthermore, the percentage of crop-disease combinations that is covered by legal products was found to be a very important context variable, which has a large effect on the behaviour of the agents if few crop-disease combinations are covered. Other variables were excluded as (contributing to) high risk concentrations, namely the percentage of samples for which chemical profiling is performed, the structure of the Dutch PPPs chain, the number of inspectors in the simulation, the minimum profit to be made by the traders and the number of PPPs inspected upon inspection of a trader.

Sub-question 4: How can an agent-based model be used to experiment with possible measures to counteract these risk concentrations?

In this research, optimization and robustness testing were performed. The optimization rendered only one solution. This was thought to be caused by the use of only two similar KPIs, i.e. the cost of the measures was not included in the simulation, as the experts had not indicated interest in these costs. Therefore, seven more user-specified policies were defined to test the effect and robustness of three intervention parameters: inspecting EUO traders, inspecting TO traders and the number of inspectors. It was found that intervention strategies which included the inspection of EUO traders were more effective (lower mean percentages of illegal PPPs reaching the end-user) and more robust (lower standard deviation and maximin values) than strategies which inspected TO traders only or no traders. Furthermore, it was found that increasing the number of inspectors did not have an effect on the KPIs, nor did it increase the robustness of the inspection strategies. Inspecting at the right actor group was thus found to be more effective than inspecting with a larger number of inspectors.

It was thus possible to use the ABM to experiment with possible measures to counteract the risk concentrations and to give an indication to the regulatory agency as to which intervention strategies might prove effective and are worth exploring further.

Sub-question 5: To what extent does the agent-based modelling process fulfil the requirements of a PSA-risk analysis?

It was found that the agent-based modelling process is very suitable for performing PSA-risk analysis. The model was centred around the problem as proposed by the experts of the NVWA and it was used to synthesize the expert knowledge on the Dutch PPPs chain. It was thus problem-based. Furthermore, the model was used to disaggregate the risk of illegal plant protection products in various ways, amongst which were the different types of actors in the PPPs chain. This rendered insight into the greatest risk concentrations, namely the end-user only traders, and the context in which the highest risk existed, namely a low coverage of all disease-crop combinations. Some of the insights were new to the NVWA and have the potential to be used to change current practices. It has thus been shown that agent-based modelling can contribute to disaggregating problems to create tailormade interventions.

The analysis had not really reached the heart of the regulatory agency, as experts were unfamiliar with the method of ABM and left the actual modelling to the analyst. Thus, the experts were consulted to gather input and discuss the PPPs chain and the final model results. Even though the experts were positive about the final model results and were looking for further implementation of the model, it is to be questioned whether this has placed the modelling process at the heart of the organisation. From an agent-based modelling point of view it can be questioned whether it is relevant that the experts understand the model, as long as the model provides relevant insights (Nikolic et al., 2013). From a PSA-risk analysis perspective, it is important that experts and analysts work together to create tailormade solutions to problems (Sparrow, 2000). However, the current research indicates that bringing together the experts and the analyst is not sufficient to let the experts take ownership over the problem-solving process. The cognitive effort and systems thinking that the PSA-risk analysis requires due to its openness regarding its methods can be taxing (Westbrook & Braver, 2015). Were PSA-risk analysis to be implemented at a larger scale at the NVWA, experts could be trained in the basics of systems thinking and be helped by the analyst to take ownership over the problem-solving process.

10.2 Answering the main research question

The main research question that this research aims to answer is:

How can an agent-based model aid a regulatory organisation in performing a PSA-risk analysis through analysing risk concentrations in a complex problem?

This research has shown that the process of participatory agent-based modelling can be useful to a regulatory organisation in analysing risk concentrations in a complex problem. The discussion sessions with the experts led to an initial system overview of the plant protection products chain in the Netherlands that included the explicit and tacit knowledge of the domain experts. Thus, a greater system understanding was achieved through the discussion sessions. The model conceptualization was then used to integrate the most important aspects of the system overview. The formalized agent-based model could then be used to check whether the system overview that was sketched by the experts led to plausible model behaviour. Furthermore, using the EMA workbench to perform a Sobol analysis, optimization and robustness testing rendered insights into the risk concentrations of the system and to guidelines for thinking about new regulatory interventions. These insights were thought to be relevant by the experts and generated new questions that prompted further research. The five steps of the participatory modelling process that were followed, namely identifying forms of risk disaggregation with the experts, creating a conceptual model, formalizing the model, using the EMA workbench to study the model and interpreting the results to insights for the NVWA, have thus been

shown to be able to aid a regulatory organisation in performing a PSA-risk analysis. The *process* of agent-based modelling can thus be considered a valuable contribution to the problem-solving toolbox of the NVWA.

Agent-based modelling as a tool has been shown to be well suitable for PSA-risk analysis. This is because the tool resonates with Sparrow's (2000) adage of fixing important problems: the experts advanced the illegal PPPs on the Dutch PPPs market as important and the agent-based model was built from the narrative that was provided by the experts on the problem. Furthermore, agent-based modelling as a tool matched the type of problem the experts proposed, as they naturally disaggregated the problem in terms of actors, actor behaviours and context. This increases the confidence in agent-based modelling as a tool that can be used in PSA-risk analysis for regulatory problems. Lastly, creating an agent-based model from the discussion sessions allowed for experimentation with various means of disaggregation of the problem, whilst otherwise the importance of the identified factors would have remained putative. Especially in the face of a lack of quantitative data as with the Dutch PPPs case, this means of exploratory analysis has proven to be useful to provide insight in the importance of different risk concentrations. These insights were novel to the NVWA. For several years, the NVWA has been interested in adopting a chain-perspective towards regulation. The current research suggests that this is a very useful endeavour, as end-users may not pose the highest risk in the chain. However, in the domain of plant protection products, the inspections were still mostly carried out at the end-user, whereas the current research indicates that it is more effective to focus on EUO traders. This shows that agent-based modelling as a tool can be used to generate new insights for regulatory organisations that call for tailormade solutions.

This research could have benefitted from some improvements. The model itself remains a caricature of the Dutch PPPs chain, which is very useful as a first attempt to sketch the system, but currently it cannot be used beyond generating ideas. The model could benefit from expansion and validation by being subjected to expert discussion sessions with different experts and other stakeholder groups. As the model currently only includes the knowledge and viewpoints of the experts of the NVWA, it is likely that the model will be partially invalidated through these discussion sessions. This underwrites the necessity of the modelling endeavour, as it shows the need to create a solid system understanding of the PPPs chain. Furthermore, data could be collected to quantify and operationally validate the model. Beyond the model, the PSA-risk analysis participatory modelling process could also benefit from some improvements. The first improvement is that there is a closer feedback loop between the analyst and the experts. The analyst can consult the experts on smaller parts of the conceptualization and summarize the results of the previous discussion session to check whether the conceptualization matches the experts' ideas before presenting the finished conceptualization in one piece. This will also help the experts take ownership over the risk analysis process. Familiarization is also thought to play a role in the adaption of agent-based modelling within a regulatory organisation. Therefore, to successfully implement agent-based modelling as a PSA-risk analysis tool within the NVWA, it would help if the NVWA intended to implement agent-based modelling agency-wide to solve problems and that it supported early projects even if they failed. In addition, as systems thinking is a learned skill, the experts that engage in agent-based modelling for PSA-risk analysis could potentially benefit from a systems thinking workshop that helps them understand the basics of complexity in sociotechnical systems. With these recommendations, agent-based modelling can help regulatory organisations perform PSA-risk analyses that render innovative, tailormade solutions to their greatest regulatory challenges.

10.3 Scientific contribution

When Sparrow (2000) first advanced the problem-solving approach, it was unique in that it shifted away the focus from regulatory agencies from bean counting input hours and fixed intervention strategies towards problem-solving. Within the problem-solving approach, intervention planning and analysis is central. Problem-solving risk analysis places new demands on regulatory agencies (Sparrow, 2000). This research has defined what makes PSA-risk analysis unique, by comparing it to other regulatory paradigms. This will contribute to future studies on methods for PSA-risk analysis to upfront identify whether a given method will be suitable for PSA-risk analysis and to evaluate the suitability of the method after use.

With the characteristics of PSA-risk analysis clearly defined, the suitability of agent-based modelling for PSA-risk analysis has been studied by applying agent-based modelling to a case provided by a regulatory agency. Agent-based modelling has not previously been applied to a case of regulation in the context of PSA-risk analysis and the value of the tool in this context has to date not been explored. Previous literature has already established that agent-based modelling offers open exploration of a problem and is used to explain how a phenomenon arises from agent interactions (Edmonds et al., 2019; Nikolic & Kasmire, 2013). The current research has found that ABM as a method is very suitable to PSA-risk analysis, as this research has shown that an ABM can be used to study a regulatory problem, to disaggregate the problem in terms of actors, interactions and context and that via this, new insights for designing regulatory interventions can be found. Furthermore, it was found that ABM lends itself for collaboration with experts, especially in the case of the Dutch PPPs chain, for which few data is available and a caricature of the problem had to be created as a first step towards greater system understanding (Axtell & Epstein, 1994). It was learned that the validity of the model could be increased by more and shorter feedback cycles between experts and the modeller (as for example proposed by Jakeman et al. (2006)). By establishing the potential of ABM as a PSA-risk analysis method, this research places ABM amongst the PSA-risk analysis tools in the regulator's craft shop (Bynum, 2001; Perry et al., 2013; Tayebi & Glässer, 2016). It is hoped that, by showing the potential of ABM for problem-solving for public regulation, the current research inspires further research on how agent-based modelling can help regulators in finding effective solutions to societal problems.

10.4 Societal contribution

The current research has shown that agent-based modelling is a suitable tool for PSA-risk analysis. By having another method in their regulatory toolbox, regulators are able to perform PSA-risk analyses better, i.e. find risk concentrations more easily and understand problems better. This will allow regulators to design interventions that are more targeted at the problem at hand. Via this, regulatory agencies are one step closer to effective regulation, as a sound analysis is the first step to create more effective interventions (Sparrow, 2000).

Furthermore, this research has shown the value that an agent-based model can have to a regulatory organisation when it is applied to a case. The modelling process has rendered an overview of the current knowledge within the NVWA about the Dutch PPPs chain. The model has provided new insights to the NVWA, i.e. the gatekeeper function of the EUO traders. This will lead to further investigation of the Dutch PPPs chain and ultimately to new intervention strategies. In addition, the modelling process has acquainted the NVWA with agent-based modelling and shown the pros and cons of this modelling technique, which sparked interest in further agent-based modelling projects within the organisation. Thus, the current research has contributed to a greater understanding of the sociotechnical systems that are regulated by the NVWA. As regulation is pertinent to the functioning of societies (Prosser, 2010), hopefully this research can be another small step towards improving the effectiveness of regulatory agencies.

10.5 Future research

The current research shows that ABM can be a suitable tool to PSA risk analysis. However, two major tracks of future research spring from this research: one track on how ABM can be useful to regulatory organisations and another track on how PSA-risk analysis with ABM can be integrated within regulatory organisations. To tailor ABM even better to the needs of regulatory organisations, multiple types of future studies must be performed. Firstly, it is essential that ABM is used in more PSA-risk analyses than this case study, to study the suitability of ABM over a range of problems that are relevant to regulators. In these studies, the experts can be interviewed to provide an account of their thoughts on the suitability of ABM to PSA-risk analysis, to ensure the method is also found to be suitable in practice. Secondly, research should be performed to characterize the types of problems for which ABM is a useful tool, as the current research only indicates the potential of ABM for PSA-risk analysis but does not provide any guidance on which specific regulation problems to use it for. Thirdly, it should be studied whether making multiple ABMs of a single problem can help to disaggregate the problem in new ways and whether this is relevant to the regulator. Lastly, it should be studied whether it is useful to create one general ABM of the problem, search for risk concentrations and then make smaller, more detailed ABMs of these risk concentrations. Perhaps this can help to disaggregate the problem even further and provide even more insight into the patterns underlying the problem.

To facilitate implementation of PSA-risk analysis with ABM within regulatory organisations, more research can be performed on the necessity of a systems thinking perspective. So far, most research on the problem-solving approach in real cases has been done in terms of effects on the KPIs (Sparrow, 2018). Based on this research, it would be interesting to study the *conditions* that support an effective problem-solving process. A case study could be devised in which two groups of experts and analysts work separately on the same regulatory problem and one group gets a short two-day systems thinking introductory workshop. It can then qualitatively be studied whether the two groups experience similar processes and reach the similar conclusions to see if increasing systems thinking knowledge has any impact on the problem-solving process. Depending on the case, the interventions that the groups devised can be carried simultaneously and performance can be compared. This would give a first indication of whether the systems thinking knowledge of the experts influences the PSA-risk analysis.

11. References

Abar, S., Theodoropoulos, G. K., Lemarinier, P., & O'Hare, G. M. P. (2017). Agent Based Modelling and Simulation tools: A review of the state-of-art software. *Computer Science Review*, *24*, 13–33. https://doi.org/10.1016/j.cosrev.2017.03.001

Akanle, O. M., & Zhang, D. Z. (2008). Agent-based model for optimising supply-chain configurations. *International Journal of Production Economics*, *115*(2), 444–460. https://doi.org/10.1016/J.IJPE.2008.02.019

Andretta, M. (2014). Some Considerations on the Definition of Risk Based on Concepts of Systems Theory and Probability. *Risk Analysis*, *34*(7), 1184–1195. https://doi.org/10.1111/RISA.12092

Axtell, R. L., & Epstein, J. L. (1994). Agent-based modeling: understanding our creations. *The Bulletin of the Santa Fe Institute*, *9*(4), 28–32.

Baldwin, R., & Black, J. (2008). Really Responsive Regulation. *The Modern Law Review*, *71*(1), 59–94. https://doi.org/10.1111/j.1468-2230.2008.00681.x

Baldwin, R., & Black, J. (2016). Driving Priorities in Risk-Based Regulation: What's the Problem? *Journal of Law and Society*, *43*(4), 565–595. https://doi.org/10.1111/JOLS.12003

Baldwin, R., Cave, M., & Lodge, M. (2012). *Understanding Regulation: Theory, Strategy, and Practice* (2nd ed.). Oxford University Press.

Black, J. (2005). The emergence of risk-based regulation and the new public risk management in the United Kingdom. *Public Law*, 510–546. https://www.academia.edu/1295947/The_emergence_of_risk_based_regulation_and_the_new_public_risk_management_in_the_United_Kingdom

Black, J. (2010). Risk-based Regulation Choices, Practices and Lessons Being Learnt. In OECD (Ed.), *Risk and Regulatory Policy Improving the Governance of Risk* (pp. 185–224). OECD Publishing. https://doi.org/https://doi.org/10.1787/9789264082939-en

Black, J., & Baldwin, R. (2010). Really responsive risk-based regulation. *Law and Policy*, *32*(2), 181–213. https://doi.org/10.1111/j.1467-9930.2010.00318.x

Boba, R. (2003). *Problem Analysis in Policing*. www.policefoundation.org

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *PNAS*, *99*(3), 7280–7287. www.pnas.orgcgidoi10.1073pnas.082080899

Braithwaite, J. (2011). The Essence of Responsive Regulation. *University of British Columbia Law Review*, *44*(3), 476–520.

Buie, J. (1996). Methods of Risk Analysis : Traditional and Ecological Approaches. In *Wetlands Program Technical Report no. 96-8* (Issue 96). https://doi.org/10.21220/m2-m83f-wp96

BuRO. (2019). *De risico's van de bloembollenketen*. https://www.nvwa.nl/documenten/consument/eten-drinken-roken/vlees-en-vleesproducten/risicobeoordelingen/risicobeoordeling-roodvleesketen

Bynum, T. S. (2001). *Using Analysis for Problem-Solving*.

Chan-Lau, J. A. (2017). *ABBA : An Agent-Based Model of the Banking System*.

Cuppen, E., Nikolic, I., Kwakkel, J., & Quist, J. (2020). Participatory multi-modelling as the creation of a boundary object ecology: the case of future energy infrastructures in the Rotterdam Port Industrial Cluster. *Sustainability Science*, *16*(3), 901–918. https://doi.org/10.1007/S11625-020-00873-Z

de Bruijn, H., & Ten Heuvelhof, E. H. (2019). *Handhaving - Het spel tussen inspecteur en inspectee* (2nd ed.). Boom Uitgevers.

Dechesne, F., Ghorbani, A., & Yorke-Smith, N. (2014). Introduction to the special issue on agent-based modelling for policy engineering. *AI & SOCIETY*, *30*(3), 311–313. https://doi.org/10.1007/S00146-014-0535-X

Department of Economic and Social Affairs. (2015). *Transforming our world: the 2030 Agenda for Sustainable Development*. https://sdgs.un.org/2030agenda

Dijkema, G. P. J., Lukszo, Z., & Weijnen, M. P. C. (2013). Introduction. In Koen H. van Dam, I. Nikolic, & Z. Lukszo (Eds.), *Agent-Based Modelling of Socio-Technical Systems* (pp. 1–8). Springer. https://doi.org/10.1007/978-94-007-4933-7

Eck, J. E., & Eck, E. B. (2012). Crime Place and Pollution: Expanding Crime Reduction Options Through a Regulatory Approach. *Criminology & Public Policy*, *11*(2), 281–316. https://doi.org/10.1111/j.1745-9133.2012.00809.x

Edmonds, B., Le Page, C., Bithell, M., Chattoe-Brown, E., Grimm, V., Meyer, R., Montañola-Sales, C., Ormerod, P., Root, H., & Squazzoni, F. (2019). Different modelling purposes. *Journal of Artificial Societies and Social Simulation*, *22*(3). https://doi.org/10.18564/jasss.3993

Ford, C. (2013). Prospects for scalability: Relationships and uncertainty in responsive regulation. *Regulation & Governance*, *7*(1), 14–29. https://doi.org/10.1111/J.1748-5991.2012.01166.X

Freebairn, L., Atkinson, J.-A., Kelly, P. M., McDonnell, G., & Rychetnik, L. (2018). Decision makers' experience of participatory dynamic simulation modelling: methods for public health policy. *BMC Medical Informatics and Decision Making*, *18*, 131. https://doi.org/10.1186/S12911-018-0707-6/TABLES/2

Galán, J. M., López-Paredes, A., & del Olmo, R. (2009). An agent-based model for domestic water management in Valladolid metropolitan area. *Water Resources Research*, *45*. https://doi.org/10.1029/2007WR006536

Haines, F. (2013). Three Risks, One Solution? Exploring the Relationship between Risk and Regulation. *The ANNALS of the American Acadamy of Policital and Social Science*, *649*(1), 35–51. https://doi.org/10.1177/0002716213490884

Hamarat, C., Kwakkel, J. H., Pruyt, E., & Loonen, E. T. (2014). An exploratory approach for adaptive policymaking by using multi-objective robust optimization. *Simulation Modelling Practice and Theory*, *46*, 25–39. https://doi.org/10.1016/j.simpat.2014.02.008

Hansson, S. O. (2005). Seven Myths of Risk. *Risk Management*, *7*(2), 7–17. https://www.jstor.org/stable/3867684?seq=1&cid=pdf-

Hayes, R., Paddrik, M., Todd, A., Yang, S., Beling, P., & Scherer, W. (2012). Agent based model of the E-Mini Future: Application for policy making. *Proceedings of the 2012 Winter Simulation Conference*, 1–12. https://doi.org/10.1109/WSC.2012.6465037

Hinkle, J. C., Weisburd, D., Telep, C. W., & Petersen, K. (2020). Problem-oriented policing for reducing crime and disorder: An updated systematic review and meta-analysis. *Campbell Systematic Reviews*, *16*(2), 1–86. https://doi.org/10.1002/cl2.1089

Hutter, B. M. (2006). Risk, Regulation and Management. In P. Taylor-Gooby & J. O. Zinn (Eds.), *Risk in Social Science* (pp. 202–227). Oxford University Press. https://ebookcentral-proquest-com.tudelft.idm.oclc.org/lib/delft/reader.action?docID=430625&ppg=203

Jakeman, A. J., Letcher, R. A., & Norton, J. P. (2006). Ten iterative steps in development and evaluation of environmental models. *Environmental Modelling & Software*, *21*(5), 602–614. https://doi.org/10.1016/j.envsoft.2006.01.004

Jaxa-Rozen, M., & Kwakkel, J. H. (2018). Tree-based ensemble methods for sensitivity analysis of environmental models: A performance comparison with Sobol and Morris techniques. *Environmental Modelling & Software*, *107*, 245–266. https://doi.org/10.1016/J.ENVSOFT.2018.06.011

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*, *96*, 239–250. https://doi.org/10.1016/J.ENVSOFT.2017.06.054

Liefooghe, A., López-ibáñez, M., Paquete, L., & Verel, S. (2018). Dominance, Epsilon, and Hypervolume Local Optimal Sets in Multi-objective Optimization, and How to Tell the Difference. *Proceedings of the Genetic and Evolutionary Computation Conference*, 324–331.

Louie, M. A., & Carley, K. M. (2008). Balancing the criticisms: Validating multi-agent models of social systems. *Simulation Modelling Practice and Theory*, *16*(2), 242–256. https://doi.org/10.1016/j.simpat.2007.11.011

Lowrance, W. W. (1976). *Of Acceptable Risk: Science and the Determination of Safety.*

Macal, C. M. (2016). Everything you need to know about agent-based modelling and simulation. *Journal of Simulation*, *10*, 144–156. https://doi.org/10.1057/JOS.2016.7/TABLES/2

Maier, H. R., Razavi, S., Kapelan, Z., Matott, L. S., Kasprzyk, J., & Tolson, B. A. (2019). Introductory overview: Optimization using evolutionary algorithms and other metaheuristics. *Environmental Modelling and Software*, *114*, 195–213. https://doi.org/10.1016/j.envsoft.2018.11.018

Malleson, N., Heppenstall, A., & See, L. (2010). Crime reduction through simulation: An agent-based model of burglary. *Computers, Environment and Urban Systems*, *34*(3), 236–250. https://doi.org/10.1016/J.COMPENVURBSYS.2009.10.005

McMahon, J. (2015). Behavioral economics as neoliberalism: Producing and governing homo economicus. *Contemporary Political Theory*, *14*(2), 137–158. https://doi.org/10.1057/cpt.2014.14

Mcphail, C., Maier, H. R., Kwakkel, J. H., Giuliani, M., Castelletti, A., & Westra, S. (2018). Robustness Metrics: How Are They Calculated, When Should They Be Used and Why Do They Give Different Results? *Earth's Future*, *6*, 169–191. https://doi.org/10.1002/eft2.280

Mobus, G. E. (2018). Teaching systems thinking to general education students. *Ecological Modelling*, *373*, 13–21. https://doi.org/10.1016/j.ecolmodel.2018.01.013

Nardini, J. T., Baker, R. E., Simpson, M. J., & Flores, K. B. (2021). Learning differential equation models from stochastic agent-based model simulations. *Journal of the Royal Society Interface*, *18*, 1–23. https://doi.org/10.1098/rsif.2020.0987

Nikolic, I., Dam, K. H. van, & Kasmire, J. (2013). Practice. In K. H. van Dam, I. Nikolic, & Z. Lukszo (Eds.), *Agent-Based Modelling of Socio-Technical Systems* (pp. 73–137). Springer. https://doi.org/10.1007/978-94-007-4933-7_3

Nikolic, I., & Kasmire, J. (2013). Theory. In Koen H. van Dam, I. Nikolic, & Z. Lukszo (Eds.), *Agent-Based Modelling of Socio-Technical Systems* (pp. 11–71). Springer. https://doi.org/10.1007/978-94-007-4933-7

NVWA. (2012). *POORTWACHTER 2011 - Onderzoek naar het voorschrijfgedrag van dierenartsen met betrekking tot antibiotoca in de vleeskuikenhouderij*.

NVWA. (2018a). *Domein gewasbescherming 2018 - Beeld van ontwikkelingen op het domein*.

NVWA. (2018b). *Integrale risicoanalyse pluimveevleesketen*.

NVWA. (2019a). *Integrale ketenanalyse voedergewassen en diervoeder*.

NVWA. (2019b). *Ons verhaal bij de organisatiekoers*.

NVWA. (2020). *Tussentijdse Verantwoording 2020*.

NVWA. (2021). *Jaarplan 2022*.

Object Management Group. (2013). *Business Process Model and Notation (BPMN) Version 2.0.2*.

Olan, M. (2003). Unit testing: Test early, test often. *Journal of Circuits, Systems and Computers*, *19*(2), 319–328.

Paredes-Frigolett, H., Gomes, L. F. A. M., & Pereira, J. (2015). Governance of Responsible Research and Innovation: An Agent-Based Model Approach. *Procedia Computer Science*, *55*, 912–921. https://doi.org/10.1016/J.PROCS.2015.07.113

Perry, W. L., McInnis, B., Price, C. C., Smith, S. C., & Hollywood, J. S. (2013). *Predictive Policing: The Role of Crime Forecasting in Law Enforcement Operations*. www.rand.org

Pinyol, I., & Sabater-Mir, J. (2013). Computational trust and reputation models for open multi-agent systems: a review. *Artificial Intelligence Review*, *40*(1), 1–25. https://doi.org/10.1007/s10462-011-9277-z

Prosser, T. (2010). Introduction: Two Visions of Regulation and Four Regulatory Models. In *The Regulatory Enterprise* (pp. 1–20). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199579839.003.0001

Röckmann, C., Ulrich, C., Dreyer, M., Bell, E., Borodzicz, E., Haapasaari, P., Hauge, K. H., Howell, D., Mäntyniemi, S., Miller, D., Tserpes, G., & Pastoors, M. (2012). The added value of participatory modelling in fisheries management - what has been learnt? *Marine Policy*, *36*(5), 1072–1085. https://doi.org/10.1016/j.marpol.2012.02.027

Saltelli, A., & Annoni, P. (2010). How to avoid a perfunctory sensitivity analysis. *Environmental Modelling and Software*, *25*, 1508–1517. https://doi.org/10.1016/j.envsoft.2010.04.012

Sparrow, M. K. (2000). *The Regulatory Craft: Controlling Risks, Solving Problems & Managing Compliance*. Brookings Press.

Sparrow, M. K. (2008). *The Character of Harms: Operational Challenges in Control*. Cambridge University Press.

Sparrow, M. K. (2016). Measuring performance in a modern police organization. *Perspectives on Policing: Selected Papers on Policy, Performance and Crime Prevention*, 119–150. www.NIJ.gov,

Sparrow, M. K. (2018). Problem-oriented policing: matching the science to the art. *Crime Science*, *7*(14). https://doi.org/10.1186/s40163-018-0088-2

Streloke, M. (2018). *Illegal trade of plant protection products: a highly profitable way to smuggle chemicals*. https://doi.org/10.1007/s00003-018-1177-6

Tayebi, M. A., & Glässer, U. (2016). Social Network Analysis in Predictive Policing. In M. A. Tayebi & U. Glässer (Eds.), *Social Network Analysis in Predictive Policing* (1st ed., pp. 7–14). Springer International Publishing. https://doi.org/10.1007/978-3-319-41492-8_2

van der Voort, H. (2018). Data science als de eeuwige belofte? *Tijdschrift Voor Toezicht*, *9*(2–3), 79–85. https://doi.org/10.5553/tvt/187987052018009002008

Vennix, J. A. M. (1999). Group model-building: tackling messy problems. *System Dynamics Review*, *15*, 379–401.

Voinov, A., Jenni, K., Gray, S., Kolagani, N., Glynn, P. D., Bommel, P., Prell, C., Zellner, M., Paolisso, M., Jordan, R., Sterling, E., Schmitt Olabisi, L., Giabbanelli, P. J., Sun, Z., Le Page, C., Elsawah, S., BenDor, T. K., Hubacek, K., Laursen, B. K., … Smajgl, A. (2018). Tools and methods in participatory modeling: Selecting the right tool for the job. *Environmental Modelling and Software*, *109*, 232–255. https://doi.org/10.1016/j.envsoft.2018.08.028

Wajsman, N., Burgos, C. A., & Davies, C. (2017). *The economic costs of IPR infringement on the pesticides sector*. www.euipo.europa.eu

Westbrook, A., & Braver, T. S. (2015). Cognitive effort : A neuroeconomic approach. *Cognitive, Affective, & Behavioral Neuroscience*, *15*(February), 395–415. https://doi.org/10.3758/s13415-015-0334-y

Appendix A: Example of the Mural board

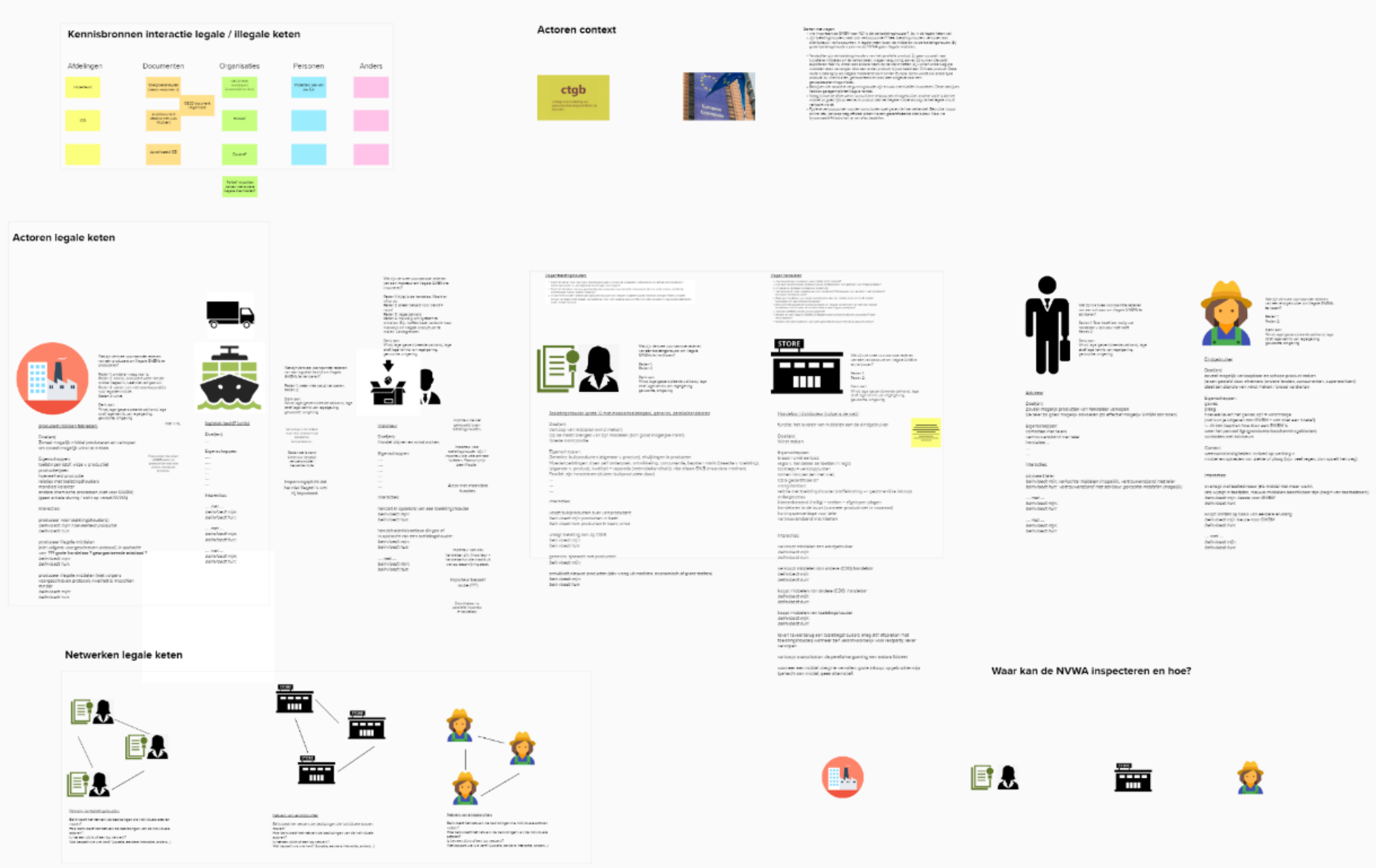


Figure A.1. Example of the Mural board after three discussion sessions with the NVWA experts.

Appendix B: Actor pools

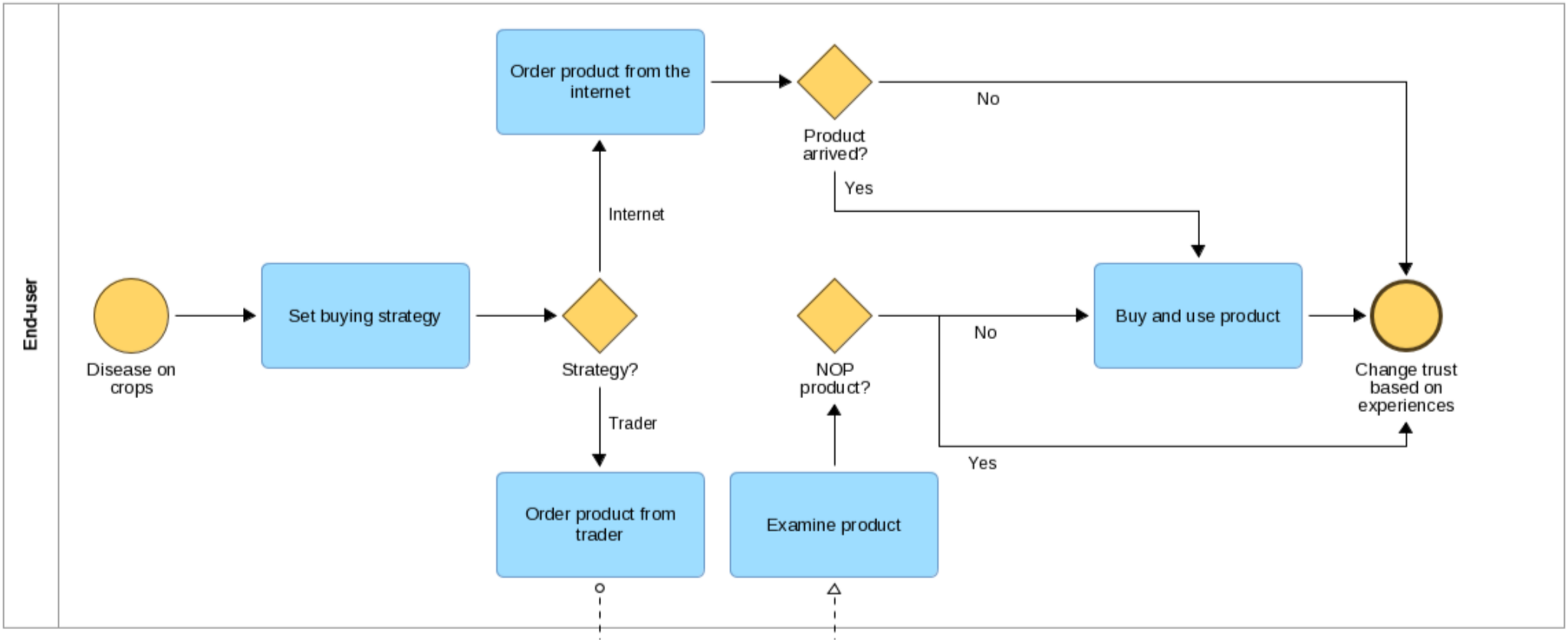


Figure B.1. Actor pool of the end-user.

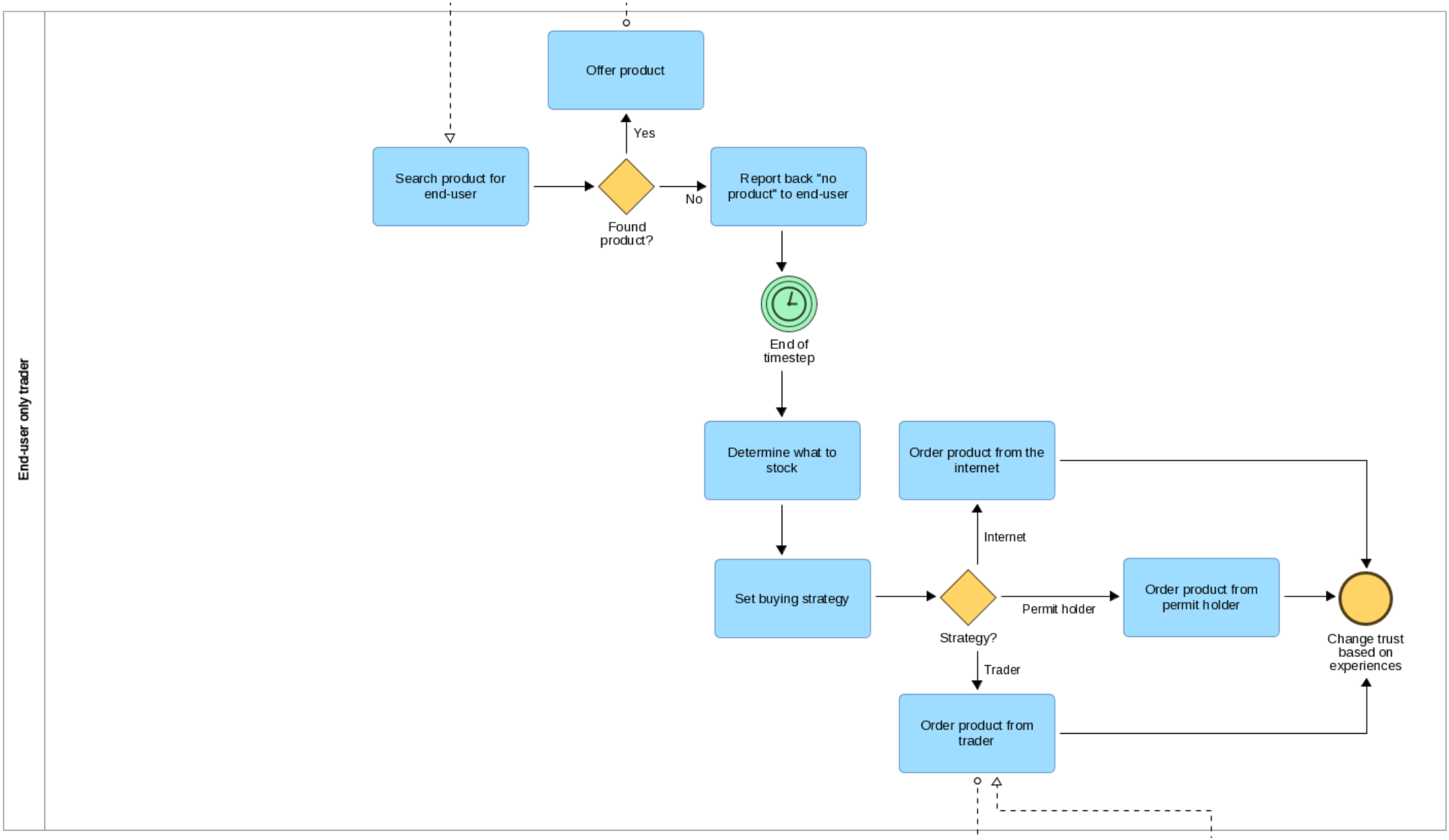


Figure B.2. Actor pool of the end-user only trader.

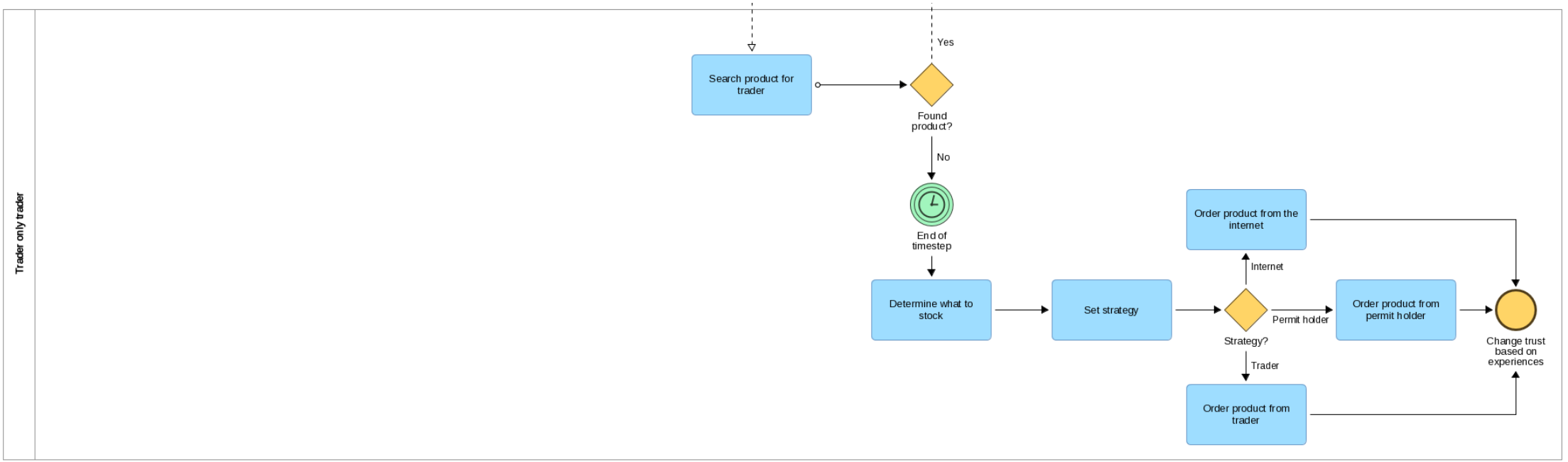


Figure B.3. Actor pool of the trader only trader.

Appendix C: Verification details

In this appendix, details are provided on the verification tests that have been performed.

C.1 Unit testing

During unit testing, every function has been tested individually. The following tests have been performed:

Setup unit tests

Unit test 1: set seed
1a. Test if the fixed seed stays fixed when the set-seed? option is set to true.
1b. Test if the fixed seed changes when the set-seed? option is set to false.

Unit test 2: create list of crops
2a. Test if lengths of the list of available crops and of the list of diseases in the model correspond to the user input.

Unit test 3: create end-users
3a. Test if end-users are set-up correctly and whether they have the correct initial variable values.

Unit test 4: create traders
4a. Test if traders are set-up correctly and whether they have the correct initial variable values.
4b. Test if end-users connect to a trader as their local trader.

Unit test 5: create inspectors
5a. Test if inspectors are created.

Unit test 6: create mother authorisations
6a. Test if the right number of mother authorisations are created based on various user-specified percentages of coverage of crop-disease combinations by legal products.
6b. Test if the mother authorisations that are created have the correct combinations of crops and diseases.

Unit test 7: create bulk authorisations
7a. Test if a bulk product is created when a mother authorisation is present in the simulation.
7b. Test if the properties of the bulk product match that of the mother authorisation for the properties that should match and check whether the properties that should not match do not match.

Unit test 8: set up initial stock of traders
8a. Test if an order of stock is created for the trader.
8b. Test if the properties of the order are correct.
8c. Test if the correct number of total orders is created.

Unit test 9: create online offer of traders
9a. Check if an appropriate number of PPPs are offered online by traders.

Unit test 10: create NOP products
10a. Test if any NOPs are created based on a mother authorisation.
10b. Test whether the NOP is the same as the original product except for the variables on which it should differ.

Unit test 11: create products that are illegal in the EU
11a. Test if an appropriate number of illegal PPPs is created based on a set number of legal products.
11b. Test if the products that are illegal in the EU have the correct properties.

Unit test 12: create illegal online offer
12a. Test if an appropriate number of online orders is created based on the available illegal PPPs.
12b. Test if the online orders have the correct PPPs in them.

Model run unit tests

Unit test 13: yearly updating of traders
13a. Test if a trader performs the yearly check.
13b. Test if the trader only performs the yearly check once a year.

Unit test 14: adjust trust
14a. Test whether the trust changing procedure increases and reduces trust correctly.
14b. Test if trust limits are not exceeded (above 100 or below 0).
14c. Test if trust is not modified in the fixed trust period.

Unit test 15: check profit (traders)
15a. Test if trust is altered according to whether the trader has met the minimum profit criterium.

Unit test 16: update client request data (traders)
16a. Test if the first year of client request data (no data) is removed correctly.
16b. Test if the second year of client request data is removed correctly.
16c. Test if the third year of client request data is removed correctly.

Unit test 17: plants get diseases (end-users)
17a. Test if end-users get diseases on their crops according to the user-specified percentages of end-users who get a crop on their disease every tick.

Unit test 18: end-users set strategy
18a. Test if end-users only buy from traders during the fixed trust period.
18b. Test if the strategy is set correctly after the fixed trust period.

Unit test 19: traders make money
19a. Test if the profit made is calculated correctly for an original PPP with no previous owners.
19b. Test if the profit is calculated correctly for an original PPP with two previous owners.
19c. Test if the profit is calculated correctly for a NOP product with no previous owners.
19d. Test if the profit is calculated correctly for a NOP product with two previous owners

Unit test 20: register KPIs
20a. Test if KPIs are registered correctly for the three different types of PPPs (legal, illegal in the EU and NOP).

Unit test 21: change trust of the end-user
21a. Test if the trust of the end-user is changed correctly based on trust reductions in the two different buying methods.

Unit test 22: the disease of the crop of the end-user is cured
22a. Test if the curing of the disease alters the relevant variables of the trader correctly and whether the KPI is registered.

Unit test 23: trade product
23a. Test if a product is traded from a trader to an end-user correctly, in terms of creating a new order, reducing the number of products in stock of the trader and updating the trust of the end-user.
23b. Test if the original order is up for deletion when it is empty (the trader is out of stock for this product).

Unit test 24: the disease of the crop of the end-user is not cured
24a. Test if the trust of the end-user is altered correctly when a suitable product is available and the disease is not cured.
24b. Test if the trust of the end-user is altered correctly when a second-best option is available (a product for the disease but not for the crop of the end-user) and the disease is not cured.
24c. Test if the trust of the end-user is altered correctly when its crops die.

Unit test 25: use product (end-users)
25a. Test if the disease is cured and trust is altered correctly for a product with full effectiveness.
25b. Test if the disease is not cured and trust is altered correctly for a product with zero effectiveness.

Unit test 26: traders set stocking strategy
26a. Test if traders set their stocking strategy correctly based on various values for their trust in different buying methods.
26b. Test variations of settings of not choosing the internet even though it is the most trusted buying method (but perceived risk is too high or propensity to violate is too low).

Unit test 27: decide what to stock (traders)
27a. Test whether a dictionary is created containing all the individual requests of the traders or end-users for PPPs to this trader.
27b. Test if the products that are currently in stock of the trader are correctly subtracted from the dictionary, as these products do not have to be bought.

Unit test 28: send package
28a. Test whether products that are illegal in the EU are always found and NOP products with a low similarity to the original product are found.

Unit test 29: order products from permit holders or the internet (traders)
29a. Test if the correct order is created when one legal product is requested and available.
29b. Test if no order is created and trust of the trader in the buying method is decreased when the requested product is not available.
29c. Test if no order is created and trust is decreased with an illegal product and a 100% catch rate at the Dutch border.
29d. Test if the correct is created for an illegal product with a 0% catch rate at the Dutch border.

Unit test 30: change trust based on selling method
30a. Test if the trust of the trader in various selling methods of the order are updated correctly.

Unit test 31: order products from traders (traders)
31a. Test if the correct order is created when one legal product is requested and available and if the stock of the selling trader is reduced correctly.
31b. Test if no order is created and trust of the trader in the buying method is decreased when the requested product is not available.
31c. Test if the selling trader is prompted to order new products when they sell out on one of their products.

Unit test 32: end-users with diseases ask their traders for PPPs
32a. Test if the trust in the buying method is reduced and the selling trader is prompted to restock if the trader has no product available for the end-user.
32b. Test if the disease of the end-user is cured and a new order is created if the trader has a suitable, very effective product available.
32c. Test if the selling trader is prompted to restock if they only have a second-best product available for the end-user.

Unit test 33: end-users with diseases search the internet
33a. Test if the end-user orders a product if there is a product available via a trader with online offer.
33b. Test if the end-user orders a product that is not owned by a trader.
33c. Test if the end-user does not order a product and decreases its trust in buying from the internet if no suitable products is available.

Unit test 34: create inspection list
34a. Test if the right, user-defined targets for inspection (types of agents) are added to the inspection list.

Unit test 35: catch and fine (inspectors)
35a. Test if the end-user decreases its trust in the buying method of the inspected order upon being caught.

Unit test 36: to inspect (inspectors)
36a. Test if the inspection of a trader with only legal products increases the trader's trust in the buying method.
36b. Test if the inspection of a trader with only PPPs that are illegal in the EU reduces the trader's trust in the buying method.
36c. Test if the inspection of a trader with only NOP products that have no similarity to the original product reduces the trader's trust in the buying method.
36d. Test if the inspection without chemical profiling of a trader with only NOP products that have 100% similarity to the original product increases the trader's trust in the buying method.
36e. Test if the inspection with only chemical profiling of a trader with only NOP products that have 100% similarity to the original product reduces the trader's trust in the buying method.
36f. Test if the inspection of an end-user with only illegal PPPs reduces the end-user's trust in the buying method.

Unit test 37: inspect random (inspectors)
37a. Test if inspectors are assigned to end-users and whether inspection results comply with whether the end-users own legal or illegal products.
37b. Test if no inspections are carried out when every agent is already being inspected.

C.2 State variable checking

Through state variable checking, of multiple simulations with twenty end-users and five traders, the following aspects of the model were confirmed:

- end-users buy PPPs that sometimes cure the disease on their crops. If the disease is not cured within three ticks, the disease gets set back to "none" which symbolizes that the crops die.
- end-users set their strategy to the buying method that they trust most.
- end-uses have a stock of orders of the products they used in the previous five ticks.
- some end-users lose faith in their trader if the disease on their crops does not get cured.
- traders set their strategy to the buying method that they trust most.
- traders add the product that is requested by one of their end-users to their requested products list.
- traders update their requested products every year.
- traders gain profit for every sale.
- once a year, traders reset their profit for that year to 0.
- traders are prompted to buy new products when they have no product available for one of their clients.

C.3 Interaction testing

Through minimal interaction testing, with one end-user and two traders, the following aspects of the model were confirmed:

- traders and end-users can change their buying method if their current buying method is unsatisfactory.
- traders and end-users buy PPPs from the strategy they trust most.
- traders can buy from another trader.
- orders are created only for the products requested by the end-user.
- end-users cannot acquire illegal products if their local trader buys legal products and the end-user buys from its local trader.
- end-users can access products via the internet from a trader who sells its products online.
- if no traders offer their products online, the end-user can only buy illegal products via the internet.
- if a trader does not choose the other trader as its buying method, it cannot access the PPPs of this trader to buy them.
- inspections are carried out at the agent types specified by the user.
- inspections increase the trust of the agent in its buying method if it is legal and decrease the trust in the buying method if the PPP is found to be illegal.

C.4 Multi-agent testing

Multi-agent testing has been performed with 500 end-users and 20 traders. The following sanity checks were performed:

- carrying out a minimal number of inspections reduced the number of illegal products arriving at the end-user compared to performing no inspections. Performing inspections with 1 vs. 10 inspectors further reduced the number of illegal PPPs arriving at the end-user.
- an increase in the minimum profit increased the number of illegal PPPs arriving at the end-users (more traders are driven to illegal methods).
- when the inspection chance at the Dutch border is increased to 100%, the number of illegal PPPs arriving at the end-user decreases.
- a 100% voluntary compliance rate brings of both actors reduces the number of illegal PPPs arriving at the end-user to 0.
- a higher coverage of crop-disease combinations of legal PPPs reduces the number of illegal PPPs arriving at the end-user.

Appendix D: Parameter settings variability testing

Table D.1. Parameter settings variability testing.

Model parameter	**Value**
%_always_comply_end_users	60
%_always_comply_traders	90
%_traders_end_user_only	70
%_coverage_of_disease_crop_combinations_legal_products	70
Nr_of_inspectors	0
Inspect_end_users?	False
Inspect_end_user_only_traders	False
Inspect_trader_only_traders	False
Minimum_profit	1000
%_avg_change_to_get_disease	5
Inspection_chance_NL_border	5
Fine-to-profit ratio	0.3
%_profiling_used	0
nr_of_PPPs_inspected_upon_visit_trader	24
nr_of_PPPs_inspected_upon_visit_end_user	0

Appendix E: Sobol sensitivity tables

Table E.1. Sobol sensitivity analysis values of the % NOP products arriving at the end-user.

	ST	ST_conf	S1	S1_conf
%_always_comply_end_users	0.04	0.02	0.00	0.04
%_always_comply_traders	0.49	0.23	0.03	0.12
%_coverage_of_disease_crop_combinations_legal_products	0.17	0.09	0.05	0.09
%_profiling_used	0.02	0.01	0.02	0.03
%_traders_end_user_only	0.03	0.01	0.01	0.04
Nr_of_inspectors	0.03	0.02	0.03	0.05
inspect_end_user_only_traders_EMA	0.53	0.27	0.34	0.17
inspect_trader_to_trader_only_traders_EMA	0.19	0.14	0.01	0.06
inspection_chance_NL_border	0.12	0.07	0.07	0.09
minimum_profit	0.01	0.01	-0.00	0.02
nr_of_PPPs_inspected_upon_visit_trader	0.04	0.05	0.03	0.03

Table E.2. Sobol sensitivity analysis values of the % total illegal products arriving at the end-user.

	ST	ST_conf	S1	S1_conf
%_always_comply_end_users	0.13	0.07	0.03	0.10
%_always_comply_traders	0.47	0.26	0.01	0.14
%_coverage_of_disease_crop_combinations_legal_products	0.34	0.17	0.09	0.12
%_profiling_used	0.01	0.01	0.00	0.03
%_traders_end_user_only	0.02	0.01	-0.00	0.03
Nr_of_inspectors	0.02	0.02	0.03	0.04
inspect_end_user_only_traders_EMA	0.45	0.26	0.21	0.19
inspect_trader_to_trader_only_traders_EMA	0.09	0.06	-0.02	0.06
inspection_chance_NL_border	0.06	0.04	0.04	0.07
minimum_profit	0.01	0.00	-0.01	0.02
nr_of_PPPs_inspected_upon_visit_trader	0.02	0.03	0.00	0.03