Bio-economic modelling of brown rot in the Dutch potato production chain

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Abstract

Brown rot, a quarantine disease caused by *Ralstonia solanacearum* race 3, biovar 2, comprises a major threat to the Dutch potato production chain. To avoid export losses, the Dutch government has implemented a costly control policy. However, it is unknown whether this policy is optimal from a cost-effective point of view. This thesis describes the development of a bio-economic model that can be used to evaluate the cost-effectiveness of brown rot control policies in the Netherlands.

Two conceptual epidemiological models, a state-variable model and an individual-based model (IBM), were developed and compared for their suitability to model brown rot dynamics within the potato production chain. The IBM was selected for further development into a spatially explicit epidemiological model. Applications of this model illustrated how it can enhance insight into brown rot dynamics within the Dutch potato production chain. The epidemiological model was integrated with an economic model into a bio-economic model, which quantifies the costs and benefits of a control strategy on the basis of its effect on brown rot incidence in the chain. Model applications showed amongst others that export losses are of decisive importance in determining the cost-effectiveness of a control policy, and that conclusions on the cost-effectiveness are affected by the period over which the effect of a policy on brown rot dynamics is observed. Results of an impact analysis of model parameters on the incidence and economic consequences of brown rot revealed that policy and sector factors in particular have a large impact on the cost-effectiveness of control, while exogenous and economic factors are of lesser importance. Scenario studies based on the results of the impact analysis indicated that highly cost-effective control requires cooperation of the government and sector.

The research described in this thesis shows that bio-economic modelling can facilitate the design and implementation of optimal brown rot control policies, by (1) enhancing insight into the incidence and economic consequences of brown rot in the potato production chain, (2) enabling *ex ante* evaluation of control strategies for their cost-effectiveness, and (3) enabling objective communication on brown rot control towards the sector. The modelling approach and the general insights obtained in this research are applicable to other quarantine diseases as well.

Keywords: quarantine disease, brown rot, *Ralstonia solanacearum*, control policy, bio-economic model, individual-based model, spatially explicit, export losses, impact analysis, Design of Experiments, metamodel, The Netherlands.

Voorwoord

Dit was het dan, mijn periode als AIO zit er bijna op. Een reis van vier jaar, eindigend bij dit proefschrift. En zoals met de meeste reizen het geval is: de tijd is omgevlogen! Dacht ik in het begin nog allerlei interessante zijwegen te kunnen bewandelen; gaandeweg bleek dat de hoofdweg naar dit proefschrift toch ook al aardig lang was, en voorzien van de nodige bochten en kuilen. Maar gelukkig waren er steeds mensen die met mij mee liepen, mij steunden of aanmoedigden, waardoor ik nu trots kan zeggen: ik heb de eindstreep gehaald! Graag wil ik deze mensen in dit voorwoord persoonlijk bedanken.

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Annemarie

Contents

CHAPTER 1

General introduction

1.1 Background

Potatoes are an important cash crop in the Netherlands. The total yearly production is approximately 7 million tonnes, and consists of 50% ware potatoes, 35% starch potatoes, and 15% seed potatoes (CBS, 2006). The yearly production value is more than 700 million euros, which represents approximately one-third of the total production value of arable crops (Berkhout and Van Bruchem, 2006). The majority of ware and seed potatoes are exported, whereas starch potatoes are almost completely processed in the Netherlands. Dutch seed potatoes represent more than 55% of the global seed potato trade volume (United Nations, 2005).

Since 1995, the Dutch potato production chain has been hit by several outbreaks of brown rot, a bacterial disease caused by *Ralstonia solanacearum* race 3, biovar 2. Brown rot comprises a major threat to potato production world wide; particularly in warm, humid growing areas, it can be very destructive (Hayward, 1991; Elphinstone, 2005). Symptoms of the disease are wilting of the plants, browning of the vascular tissue in tubers, and the exudation of white slime from broken or cut vascular bundles. *R. solanacearum* has a narrow host range, the most important other hosts being tomato and a number of solanaceous weeds. The pathogen can easily be spread through latently infected seed potatoes and other vegetative propagation material. Another important infection source is the irrigation of potatoes with contaminated surface water. Brown rot bacteria can enter the surface water through infected plants of the host weed bittersweet (*Solanum dulcamara*), which can grow on watersides with its roots floating in the water (CABI/EPPO, 1997).

Within the European Union, *R. solanacearum* has a quarantine status. This means that it is ‘of potential economic importance to the endangered area and not yet present there, or present but not widely distributed and being officially controlled’ (FAO, 1999). Obligations for EU member countries to control brown rot are recorded in the European Plant Health Directive (European Union, 2000) and Brown Rot Control Directive (European Union, 1998). The European and Mediterranean Plant Protection Organization (EPPO), an intergovernmental organization for international cooperation in plant protection, has assigned the A2 status to *R. solanacearum*. This status is given to pests that (1) can be very damaging and are difficult to control when introduced into a new environment, and (2) are already present in parts of the EPPO region and should be prevented from further spread (EPPO, 2006).

In the Netherlands, climatic conditions are less favourable for development of disease symptoms and infections generally remain symptomless. Nevertheless, the economic consequences of presence of the disease are considerable, because the risk of establishment of brown rot as an endemic disease threatens the Dutch export of seed potatoes. To avoid economic losses from reduced export, the Dutch government has implemented an intensive control policy, aimed at eradication of the disease from the potato production chain.

1.2 Problem statement

The eradication policy in the Netherlands during the last decade has resulted in a strong decline of brown rot incidence, from more than a hundred detections in several years of the late nineties to less than ten in recent years (Hendriks and Höfte, 2004; Janse, 2006). Nevertheless, it has not led to a full eradication of the pathogen, and it is questionable whether this is achievable given the permanent presence of brown rot in Dutch waterways. At the same time, preventive measures, including an intensive monitoring program and restrictions on the use of surface water, lead to considerable yearly costs for both the government and stakeholders in the potato production chain.

From this follows that there is a trade-off between reducing the costs of control and minimising the risk of new outbreaks – and thus of incurring export losses. In order to control brown rot in a cost-effective way, a balance must be found between these two objectives. So far, this task suffered from a lack of knowledge of the effect of control measures on the incidence and economic consequences of brown rot. Although the major risk factors involved in introduction and dispersal of brown rot have been identified, insight into their relative importance is still poor. Moreover, information on the economic impact of control measures is limited, and the potential consequences of export restrictions are unknown.

Improved insight into brown rot dynamics within the potato production chain, and the effect of control measures on it, would enable prediction of the effectiveness of control strategies. Better knowledge of the economic consequences of control measures and potential export restrictions would allow evaluation of the costs and benefits of a control policy prior to its implementation. In other words, the design of a cost-effective control policy would be greatly facilitated if the effect of control strategies on the incidence and costs of brown rot could be quantified.

1.3 Research objectives

The objective of the research described in this thesis is to develop a bio-economic model and use it to evaluate the effect of control strategies on the incidence and costs of brown rot in the Dutch potato production chain. This model can serve as an instrument for scenario analyses to support the design of cost-effective control strategies. To achieve this objective, the following three sub-objectives were identified:

1. development of an epidemiological model, to obtain more insight into brown rot behaviour in the Dutch potato production chain and the effect of control measures on it;
2. development of an economic model and integration with the epidemiological model into a bio-economic model, by which control strategies can be evaluated for their cost-effectiveness;
3. scenario analyses with the bio-economic model to explore options for a cost-effective brown rot control policy.

1.4 Outline of the thesis

The thesis is arranged according to the three sub-objectives (Figure 1). Chapter 2 deals with the question which approach to use for modelling brown rot dynamics. Two conceptual models are developed and compared for their strengths and weaknesses in simulating the behaviour of brown rot within the potato production chain. On the basis of this comparison one of the modelling concepts is chosen for the rest of the study. In chapter 3, the selected conceptual model is further developed into a quantitative epidemiological model that simulates the introduction and dispersal of brown rot within the potato production chain. The model is applied to study brown rot dynamics under the current Dutch control policy and the effect of reducing monitoring intensity on it.

Chapter 4 describes the development of an economic model to quantify the costs and benefits of controlling brown rot. The economic model is combined with the epidemiological model into an integrated bio-economic model. This model enables the evaluation of the economic consequences of a control strategy on the basis of its effect on brown rot incidence. The bio-economic model is applied to two scenarios, to provide insight into the different types of costs related to brown rot.

In Chapter 5, an impact analysis is performed to quantify the effect of different model parameters on the incidence and economic consequences of brown rot. Parameters included in the analysis represent policy options, characteristics of different actors in the sector (e.g. farmers, trading companies), economic inputs, and environmental and social circumstances. The results of the impact analysis are used to perform scenario studies, which provide insight into the interactions between the government and sector in determining the cost-effectiveness of controlling brown rot.

Chapter 6 summarizes the general insights provided by the bio-economic model and their implications for the design of cost-effective control strategies. It discusses the applicability and imperfections of the model and provides directions for further research. The chapter concludes by discussing the possible contribution of the bio-economic model to the cost-effective control of brown rot, and of quarantine diseases in general.

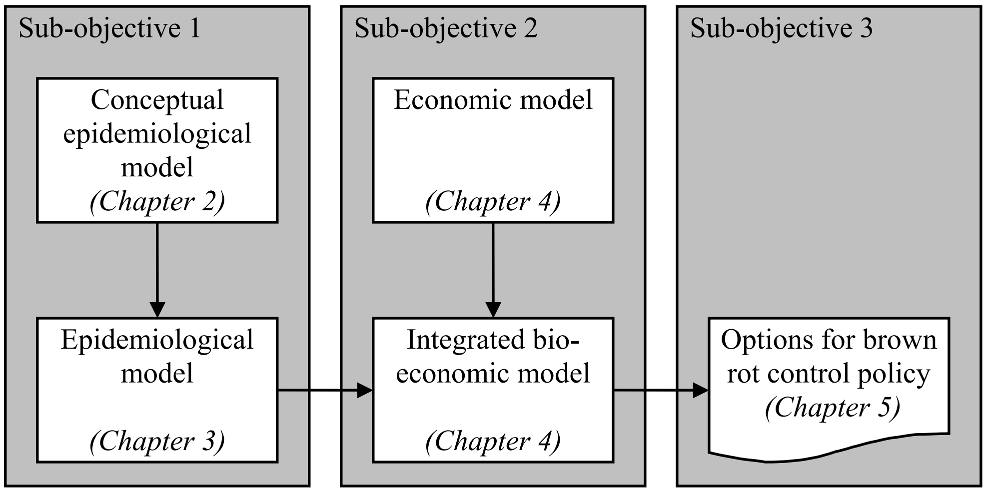

Figure 1.1. Objectives and outline of the thesis.

Chapter 2

Modelling of brown rot prevalence in the Dutch potato production chain over time: from state variable to individual-based models

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Abstract

Brown rot (*Ralstonia solanacearum*) comprises a major threat to the Dutch potato production chain. Eradication of the disease has not been achieved thus far, due to insufficient knowledge of the relative importance of possible risk factors with respect to brown rot prevalence and dispersal in the potato production chain. To study the relationship between brown rot infections in potatoes and possible risk factors, we evaluated two epidemiological models, i.e. a compartmental state-variable model and a spatial individual-based model (IBM). Our approaches differ from most existing ecological applications of the two modelling techniques in that they focus on disease epidemiology within the industrially defined dynamics of the brown rot pathogen in the potato production chain.

The state variable model proved useful for obtaining insight into the basic principles of brown rot dispersal. It showed that the dynamics of the fraction of infected seed lots in the total potato lot population forms the key to a general understanding of brown rot epidemics. However, this model was unable to reflect the large fluctuation in yearly number of infections that is inherent to brown rot epidemics. To give a more detailed and realistic representation of the fraction of infected seed lots, a conceptual IBM was developed. As in this IBM a specific location is assigned to each individual potato lot, it becomes straightforward to include spatial heterogeneities based on detailed data on the potato production sector. In contrast to the state-variable model, the IBM enables us to study the effects of specific brown rot control policies in spatially-defined areas. Moreover, the inherent high level of detail makes the IBM a convenient technique for policy application. The IBM will be further developed and extended to a bio-economic model for application in brown rot control strategy analysis.

2.1 Introduction

Potato brown rot is a bacterial disease caused by *Ralstonia solanacearum* race 3, biovar 2. In warm growing areas in particular, such as the Mediterranean region, brown rot can be very destructive and yield losses are considerable (Elphinstone, 2001). In the European Union, the pathogen has a quarantine status. This means that it is of potential economic importance to this area, but not yet widely distributed and officially controlled by the government (FAO, 1999). In the Netherlands, where potatoes are the main cash crop (CBS, 2002), over 300 brown rot infections have been found since the first appearance of the disease in 1995. The temperate climate in the Netherlands is not optimal for brown rot, and infected potatoes often do not show any symptoms. Despite this fact, brown rot prevalence has serious consequences for the Dutch potato production chain as a consequence of an elaborate sanitation policy, costly preventive regulations, and in the long term potential export bans.

For affected farms, the economic losses related to a brown rot infection are considerable, as strict sanitation measures are imposed on the whole farm for several years. Preventive measures also affect growers who have not recently dealt with a brown rot infection. For example, a ban on the use of surface water for potato cultivation will lead to significantly lower yield levels as potato production in the Netherlands is water-limited. Little information exists on the economic impact of brown rot, but insurance claims resulting from outbreaks in the Netherlands in 1999 exceeded four million euro (Elphinstone, 2001). Since 65% of the seed potatoes traded on the world market are produced in the Netherlands (Van Vaals and Rijkse, 2001), brown rot establishment in the Netherlands would jeopardise the Dutch potato export market with negative effect for the Dutch economy. On a global scale, brown rot was estimated to have affected around 80 countries during recent years, the damage caused by infestations exceeding 800 million euro annually (Elphinstone, 2005).

Since brown rot has a quarantine status, obligations for control regulations are recorded in the European Plant Health Directive (European Union, 2000) and Brown Rot Control Directive (European Union, 1998). The control policy applied by the Dutch government is in conformance with the EU regulations except for the survey intensity, which is much higher than prescribed. Apart from an obligatory national survey, all seed potato lots are tested in the Netherlands each year. The implied control strategy has resulted in a reduction of brown rot cases to less than 0.01% of all tested lots (Elphinstone, 2001; Elphinstone, 2005). Nevertheless, brown rot infections are still occasionally found. It remains unclear how these few infections can be prevented. A major reason for this is the poor knowledge of the importance of possible risk factors with respect to brown rot prevalence and dispersal in the potato production chain. The development of an epidemiological model will help clarifying the relationship between risk factors and brown rot infections in potatoes, and give more insight into the relative contribution of these factors to total brown rot prevalence. This model serves as a basis for the development of a bio-economic model that can be used as a management tool to evaluate different brown rot control strategies as to their cost-efficiency.

In this chapter, two different epidemiological modelling strategies for brown rot in the Netherlands are presented, each with its own purpose. The first is a compartmental state variable model that is not (explicitly) spatial (Winston, 1991), the second approach is an explicitly spatial individual-based model (IBM) (DeAngelis and Gross, 1992). Both types of models are commonly applied in the study of dynamic processes in natural environments (see e.g. LePage and Cury, 1997; Yerkes and Koops, 1999; Hagenaars et al., 2000; Ahearn et al., 2001). Our objective is to explore the use of these epidemiological and ecological modelling techniques in a new context, namely the industrially defined dynamics of the brown rot pathogen in the potato production chain.

2.2 Modelling context

2.2.1 The Dutch potato production chain

The production of potatoes takes place by a vegetative multiplication system, which spans several years. Starting with a single plant (initial clone), in vitro plantlets, or minitubers, three to five years of multiplication under very controlled circumstances eventually result in a pure clone of seed potatoes of the highest category of health status, class S. These high-quality seed potatoes are then further multiplied for several years by potato growers. Seed potatoes automatically decrease one quality class per year and are classified subsequently as S, SE, E, A, and sometimes even as class B and C. Roughly 70% of all seed potatoes yearly produced in the Netherlands are exported, as are most ware potatoes and processed potato products (Van Vaals and Rijkse, 2001). The seed lots that remain within the country are split into a number of clonally related ‘daughter’ lots, and are planted for further propagation at the same or another farm the following year. Depending on the variety of seed potatoes, they will be grown for production of ware or starch potatoes after three to six years.

The cultivation of starch potatoes, including seed potatoes grown for starch production, is limited to a region in the Northeast of the Netherlands that was formerly known as the ‘Veenkoloniën’. Because of lower quality demands, starch potato cultivation falls under less strict regulations which are referred to as ‘tbm’ (teelt beschermende maatregelen, which means cultivation protecting measures). Also seed potatoes grown for the starch industry can be grown under tbm legislation, but only if they are multiplied for the last time and grown as starch potatoes on the same farm in the following year. In conclusion, the starch potato production chain differs from the ware potato production chain from various points of view, and for the time being we regard the two chains as separated from each other.

In the Netherlands, all seed lots except tbm seed lots are tested for brown rot presence after harvest. The sample size depends on lot size; one sample of 200 tubers is taken per 25 tonnes of potatoes[1]. The test has a specificity of 100%, which means that all tested samples that are found positive are indeed infected with brown rot. The sensitivity of the test, i.e. the detection probability of an infected lot, is 95% at an infection level of 1.5%, and increases with increasing infection level (Janse and Wenneker, 2002). Ware, starch, and tbm seed lots are tested at random, and in these categories only one sample is taken per tested lot. Potato lots that are highly suspected of being infected but give negative test results are given the status 'probably infected'. This occurs for example if another lot on the same farm is infected, or if at least two sister lots (i.e. lots from the same parent lot) are infected. Probably infected seed lots are downgraded to ware (or starch) potatoes and are marketed under certain restrictions.

With respect to the Dutch potato production chain, the following modelling assumptions can be made:

1. Brown rot infections in seed potatoes do not occur in the highest quality classes, since these seed potatoes are cultivated on a small scale under very high standards of hygiene. Therefore, the highest class included in the model is class S.
2. The age of a seed potato lot, indicated by its class, does not affect its infectivity or susceptibility to infection;
3. The decrease in potato national production caused by destruction of infected potato lots is negligible compared to the yearly natural fluctuations in total yield of seed potatoes caused by weather conditions.

A logical consequence of focussing on the production chain is that we have defined the potato lot as smallest host unit. As can be concluded from the description of the production chain, the potato lot is the trading unit and can be monitored throughout its lifetime within the chain. Thereby, the consequences of an (undetected) infection on brown rot dispersal can be quantified. Moreover, the potato lot is the smallest unit in which brown rot is detected: if only few tubers in a lot are found to contain the pathogen, the whole lot is classified as infected and destroyed. Defining an aggregated 'individual' as basic unit is only rarely observed in modelling plant disease dynamics. Although applying a more general population unit is not technically different from modelling the individual organism, in IBMs in particular, the biological individual (in this case a potato plant or tuber) is usually taken as the conceptual unit (Van den Bosch et al., 1999; Berec, 2002).

[1] The Dutch control measures as described in this chapter refer to the brown rot policy that was in force until the end of 2004. As of 2005, the sampling strategy of seed potatoes is one sample per lot.

2.2.2 Brown rot infection pathways

Large parts of the Dutch waterways are contaminated with the brown rot bacterium as a result of its presence in the weed bittersweet (*Solanum dulcamara*). Brown rot can enter the potato production chain by irrigation or spraying with this contaminated surface water. Infection through contaminated surface water is called primary infection, because the source of infection is outside the potato production chain. Once brown rot has entered the potato production chain, the pathogen can disperse through the chain by horizontal and vertical transmission mechanisms. Horizontal transmission implies infection of a healthy potato lot where the source is another infected lot, and can – for instance – be caused by the use of contaminated machinery or equipment. Vertical transmission, also referred to as infection through clonal relationships, indicates transmission of the disease from parent to offspring and occurs with the splitting of an infected but yet undetected seed lot into daughter lots, which are subsequently replanted.

Horizontal transmission could also occur as a result of persistence of brown rot bacteria in soil. In field experiments performed in the Netherlands, the maximum persistence duration of the pathogen in soil on which infected potatoes had been grown was found to be 10 to 12 months (Van Elsas et al., 2000). In the past, experiments in other countries have shown similar results, even in the presence of volunteers (Elphinstone, 1996). The maximum growing frequency for potatoes in the Netherlands is once every three years, except for tbm potatoes, which may be grown more frequently. However, also for this category of potatoes, the applied frequency of cultivation is often less than once per two years. Consequently, in practice crop rotation prevents transmission through infested fields, and for the time being soil is not considered a transmission source.

Figure 2.1 is a simplified representation of a part of the potato production chain, in which the three infection pathways are shown. The squares and circles correspond to on- and off-field potato lots, respectively. Seed lots are shown in white, while ware lots are shaded. At any time in the chain, potato lots belong to a certain farm or company, represented by the large shaded blocks. Circles and squares are coded with a number and a letter, indicating the location and ID of a lot. In Figure 2.1, seed potato field A1 is irrigated by contaminated surface water and thereby becomes infected. Through unhygienic and possibly shared use of machinery, the infection may be horizontally transmitted to field A2 or B1, thereby affecting a second farm. Horizontal transmission may also occur during or after storage, through unhygienic transport or improper separation of lots in the storage facility. At the end of the winter, seed lots are split, causing vertical transmission to the lots T1 and T2, which are clonally related to their parent lot A1. After storage, potato lots are replanted as seed or ware lots at different locations, resulting in dispersal of the infection to farms C and D, and possibly farm E.

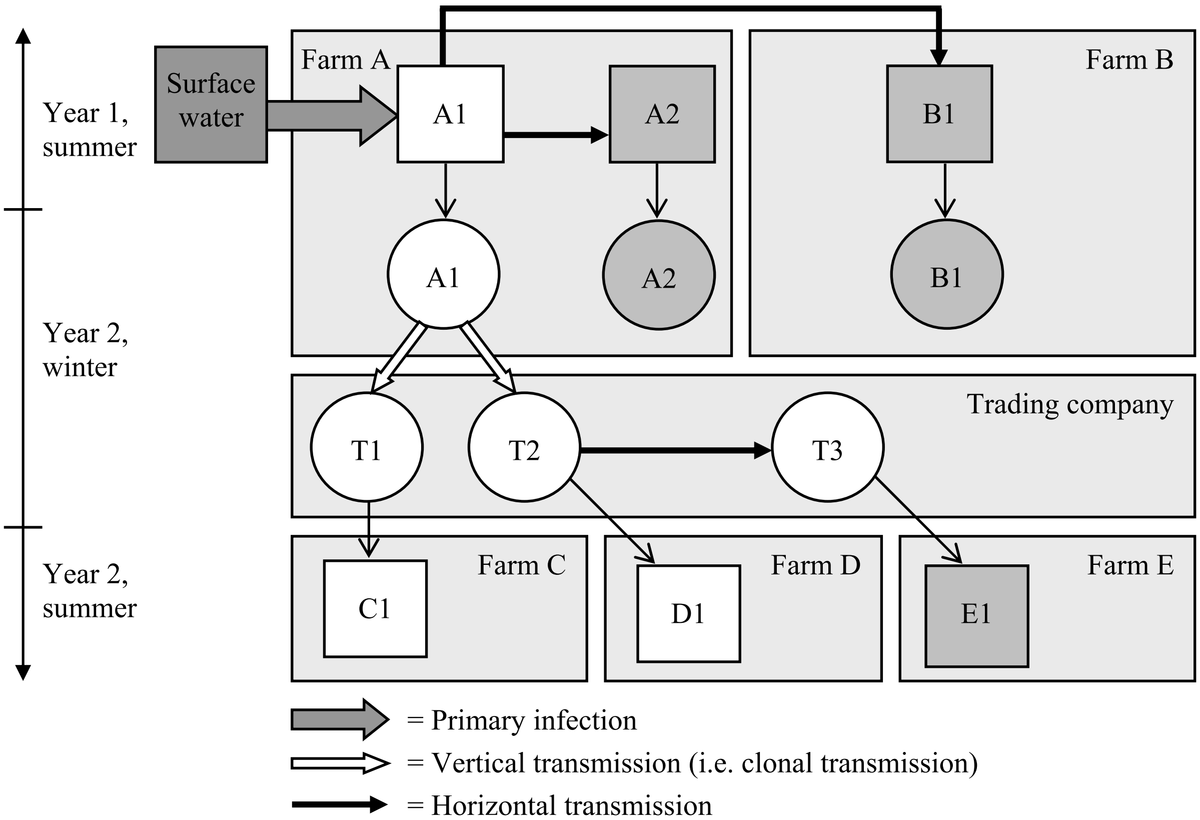

Figure 2.1. Schematic representation of the three major brown rot dispersal pathways. Squares indicate on-field lots, whereas circles indicate off-field lots. Seed lots are white, ware lots are shaded. Each lot is coded with a letter and number, which together determine its ID.

2.3 The state variable model

2.3.1 Modelling approach

In the state variable model, individual potato lots are aggregated into a small number of groups or compartments, each described mathematically by a state variable (France and Thornley, 1984). The change in distribution of potato lots over these classes is described by a set of difference equations, which together determine brown rot prevalence over time. An important strength of this approach is that the simplification obtained through aggregation allows one to keep the model relatively transparent and parameter sparse. This is helpful in interpreting its results and thus in understanding what, given the assumptions embodied in the model, are the essentials of brown rot epidemiology and control (France and Thornley, 1984; Webster West and Thompson, 1997; Railsback, 2001; Strayer et al., 2003). Clearly, the simplifying assumptions of a state variable description, such as the assumption that all healthy potato lots within a sub-population of lots of a certain kind experience the same risk of infection, ignore possible further heterogeneities and may thus miss important elements of brown rot epidemiology (Huston et al., 1988; Van der Werf et al., 1995; Shirley et al., 2003). This argument forms part of our motivation for developing an individual-based model, as described later in this chapter.

2.3.2 State variables and transition probabilities

In this section, we discuss the development of a state variable model concept for the ware potato production chain. A model that describes the starch potato production chain will have the same structure, only the parameters differ. We seek to model the yearly composition of the total population of seed and ware potato lots in the Netherlands in autumn, after completion of the field period and testing. Starting from a matrix modelling perspective, the population at that time of the year can be represented by vector v(k), which contains the number of potato lots in each of six different states: healthy seed lots (S_H), infected but undetected seed lots (S_I), detected seed lots (S_D), healthy ware lots (W_H), infected but undetected ware lots (W_I), and detected ware lots (W_D).

Figure 2.2 shows the relationships between the various states. The arrows represent possible transitions from one state to another. The scheme shows that out of the six classes, only two ‘reproduce’ into the next year whereas four classes are end-stations after which a lot is removed from the production chain. The ‘reproducing’ states are healthy seed potatoes and infected but undetected seed potatoes. Detected seed and ware lots are destroyed in practise and therefore removed from the model. Healthy and undetected infected ware lots are retailed or processed during the following winter, and thus also leave the system. Export is not included in the model and the total number of seed lots in the model is kept constant over time; the number of seed potato lots that remain in the Netherlands to be replanted the following year compensates exactly for the removal of detected potato lots and ware potato lots. From the class of healthy seed potatoes, all other states can be reached. A healthy seed lot can acquire an infection through transmission from another seed lot during its storage period or the following on-field period, which may or may not be detected. In theory, transmission from ware lots to seed lots could also occur, during storage and transport preceding the processing of a ware lot. However, since storage of ware and seed potatoes is separated and transport has to comply with a hygiene protocol, including disinfection of equipment after every transport, this probability is assumed very small and will be neglected. At the end of the growing season, the seed lot may turn into a ware lot or remain a seed lot. Undetected infected seed lots will remain in the production chain for at least another year, but once they are infected, they can never become healthy again.

As can be concluded from Figure 2.2, the two reproducing states S_H and S_I substantially determine the dynamics of brown rot in the potato production chain. As four of the six states are absorbing (i.e. potato lots that enter those states will never leave them again), the 6x6 transition matrix derived from this figure consists mainly of zero-elements. Therefore, to describe the development of brown rot in the potato production chain, modelling the change of S_H and S_I is sufficient.

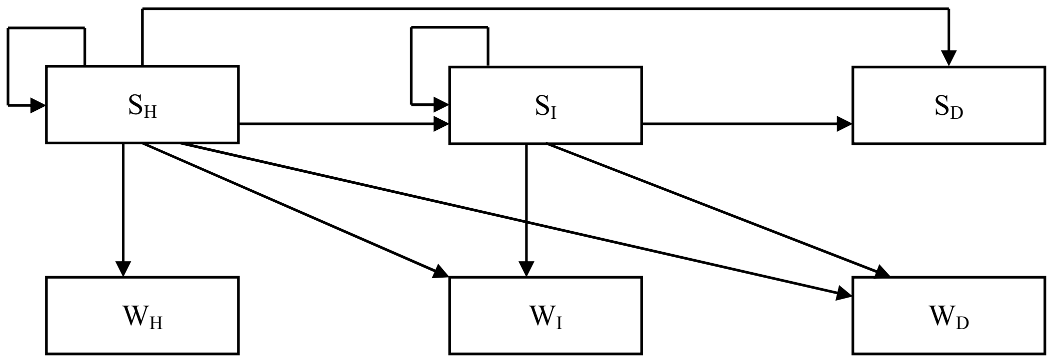

Figure 2.2. Schematic representation of the states and possible transitions between the states. S_H: seed potatoes, healthy; S_I: seed potatoes, infected but undetected; S_D: seed potatoes, detected; W_H: ware potatoes, healthy; W_I: ware potatoes, infected but undetected; W_D: ware potatoes, detected.

2.3.3 Difference equations for the fractions of S_H and S_I

The proportions of S_H, S_I and S_D to the total number of seed lots S_{tot}, are denoted as σ_H, σ_I and σ_D. As was mentioned before, the total number of seed potato lots is assumed to be constant over the years. Since the relative infection level of brown rot in the Netherlands is very low, σ_I and σ_D will remain small, so we can write:

$$\sigma_H = \sigma_{tot} - (\sigma_I + \sigma_D) \approx 1 \tag{2.1}$$

Although the value of σ_I is very small compared to σ_H, its relative change over time is important in determining the development of brown rot prevalence. The change in the fraction of infected seed lots depends on the probabilities of primary infection and transmission of existing infections. The fraction σ_I in year k is defined as

$$\sigma_I(k) = \lambda \cdot \sigma_I(k-1) + \varepsilon(k) = \lambda^k \cdot \sigma_I(0) + \sum_{j=0}^{k-1} \lambda^j \cdot \varepsilon(k-j) \tag{2.2}$$

Here, λ is the yearly multiplication factor of an existing infection, also referred to as the net reproduction factor of σ_I. $\varepsilon(k)$ is the fraction of infected but undetected seed lots that originate from primary infection during year k, including transmission of these primary infections within the same year.

The k-dependency of $\varepsilon(k)$ is introduced to account for a gradual increase in area of contaminated surface water. λ is a product of the yearly growth factor of an existing infection (R) and the probability that an infection is not detected during testing (c):

$$\lambda = c \cdot R \tag{2.3}$$

The yearly growth factor R in turn is given by one (i.e. the existing infection) plus the number of new infections (ρ_{tot}) arising from an existing infection:

$$R = 1 + \rho_{\text{tot}} \tag{2.4}$$

In order to get insight into the contributions of the summer and winter seasons to the transmission over a year, it is useful to introduce the notation ρ_{s} (ρ_{w}) for the number of new infections per existing infection during the summer (winter). R is then given by

$$R = (1 + \rho_{\text{s}})(1 + \rho_{\text{w}}) = 1 + (\rho_{\text{s}} + \rho_{\text{w}} + \rho_{\text{s}} \cdot \rho_{\text{w}}) \tag{2.5}$$

From equations 2.4 and 2.5 we see that ρ_{tot} is equal to the sum of the separate contributions of the summer and winter season plus a combined effect $\rho_{\text{s}}{\cdot}\rho_{\text{w}}$.

From equations 2.2 to 2.4 it follows that the yearly number of new and undetected infections caused by transmission is given by $c\rho_{\text{tot}}\sigma_{\text{I}}(k\text{-}1)$. This formulation follows from a standard 'mass-action' term $c\rho_{\text{tot}}\sigma_{\text{I}}(k\text{-}1)\sigma_{\text{H}}(k\text{-}1)$ (De Jong, 1995) and from noting that $\sigma_{\text{H}}(k\text{-}1)$ is in excellent approximation equal to one (equation 2.1).

The factor ε in equation 2.2 represents not only the fraction of primary infections through surface water, but also the transmission from these infections within the same year. Assuming that a primary infection takes place on average halfway through the summer, the transmission is expected to be half of the summer transmission ρ_{s}. Consequently, ε can be formulated as:

$$\varepsilon(k) = c \cdot \left(\frac{\rho_s}{2} + 1 \right) \cdot \delta(k) \tag{2.6}$$

where δ is the probability of primary infection through surface water, which is a product of the following three probabilities: presence of contaminated surface water (k-dependent), use of surface water for irrigation, and transmission to the potato tubers.

The model given above can be further elaborated and refined to distinguish different sub-populations of seed and ware potato lots, based on some other important characteristics. For example, the seed lot fractions could be subdivided according to their quality class. Since not all infections are detected each year, the prevalence of brown rot may vary among different quality classes of seed potatoes, the reason being that seed lots of a lower quality class have been grown for more seasons than higher-quality seed lots. Another factor that could potentially be included is the infection level of a lot. The longer an infection remains undetected, the higher will be the population density of brown rot, which increases a lot's probability of being detected. Although not shown here, the model can be readily adopted to account for these aspects of brown rot epidemiology.

2.3.4 A model application: analysis of Dutch brown rot epidemics since 1995

Table 2.1 shows the number of farms that had a brown rot infection since the introduction of the pathogen in the Netherlands. Information about the exact number of infected lots per year is incomplete, but in general each infected farm had only one infected lot. The category of seed potatoes is split into ‘regular seed’, which include all seed potato lots that are grown under normal regulations and are thus integrally tested, and ‘tbm seed’, comprising the seed potato lots grown under tbm. The yearly brown rot prevalence as represented by Table 2.1 probably is a small underestimation of the actual infection level. There are two reasons for this. Firstly, no information is available about the yearly number of probably infected lots, i.e. undetected but highly suspected lots that are downgraded to ware lots with marketing restrictions. These lots are not classified as infected, yet it is plausible that some of these lots are indeed infected. Secondly, the detection probability at a 1.5% infection level is only 95%; a small number of infected lots will thus remain undetected each year. The probably infected and the infected but undetected lots are not included in Table 2.1.

Table 2.1. Number of infected farms per potato category for the years 1995 – 2003. Regular seed: integrally tested seed potatoes grown under normal regulations. Tbm seed: seed potatoes grown under tbm regulations and thus only tested at random.

Year	Category				Total
	Regular seed	Tbm seed	Ware	Starch	
1995	50	-	34	10	94
1996	9	5	-	-	14
1997	15	5	5	1	26
1998	12	96	-	2	110
1999	11	15	3	15	44
2000	11	3	13	2	29
2001	10	1	5	-	16
2002	5	2	8	-	15
2003	10	-	1	-	11

To fit our model to these data,, the numbers from the categories ‘regular seed’ and ‘tbm seed’ were translated into fractions. For simplicity we assume that ε is time-independent; i.e. the area of contaminated surface water remains constant over time. The previously defined regression equation for $\sigma_I(k)$ (equation 2.2) can then be reformulated as

$$\sigma_I(k) = \lambda \cdot \sigma_I(k-1) + \varepsilon = \lambda^k \cdot \sigma(0) + \frac{1-\lambda^k}{1-\lambda} \cdot \varepsilon \qquad (2.7)$$

For very large k and $\lambda<1$, $\sigma(k)$ approximates to $\varepsilon/(1-\lambda)$, which is the horizontal asymptote. Under these conditions, the brown rot epidemic stabilises to a constant fraction of infected lots per year.

Two regression analyses were performed on the yearly fractions of ‘regular seed’ and ‘tbm seed’, to obtain the parameters λ and ε that best describe the observed brown rot dynamics. The results are shown in Figure 2.3 (continuous lines). For the regular category, the best fitting regression equation approaches the actual situation to a reasonable extent, but has a negative value for λ (-0.148). A λ of higher than 1 implies net population growth, whereas between 0 and 1 the population declines; a value below 0 is biologically impossible. The model describing the dynamics of the tbm category has a very low, but positive value for λ (0.001), which is relatively low compared to ε ($6.49 \cdot 10^{-3}$). This implies that there is almost no transmission and that the fraction infected potatoes in year k almost completely depends on ε. The equilibrium situation of 0.65% infected tbm seed lots per year is much higher than the observed fraction in most years.

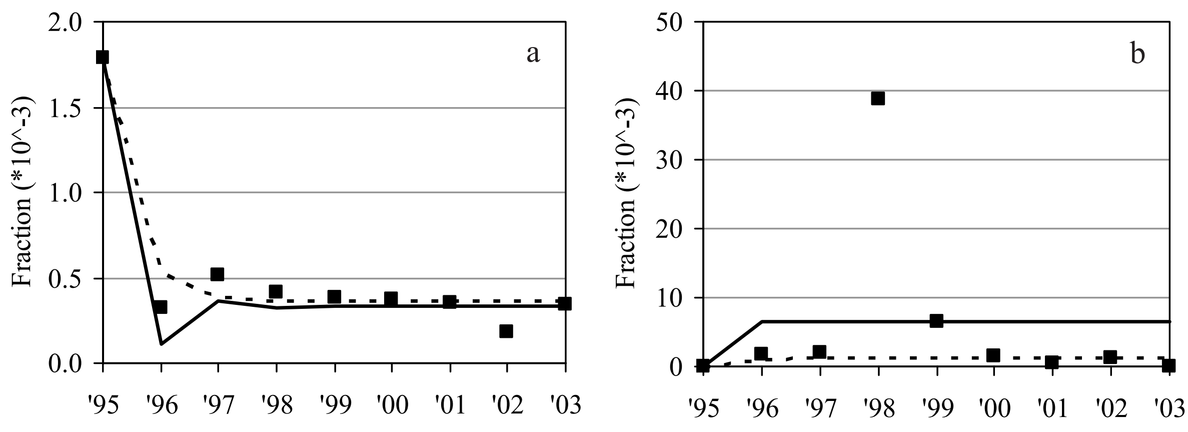

Figure 2.3. Yearly modelled amount of infected seed potatoes as fraction of total amount of seed potatoes, from 1995 to 2003, with $\sigma_I(0)$ set equal to the fraction observed in 1995. Observed fractions are represented by ■. (a) $\sigma_I(k)$ of regular seed potatoes, based on regression analysis on actual data of all years (continuous line, λ=-0.148 and $\varepsilon=0.38*10^{-3}$) and of all years except 1995 (dotted line, λ=0.117 and $\varepsilon=0.32*10^{-3}$). (b) $\sigma_I(k)$ of tbm seed potatoes, based on regression analysis on actual data of all years (continuous line, λ=0.001 and $\varepsilon=6.49*10^{-3}$) and of all years except 1998 (dotted line, λ=0.134 and $\varepsilon=1.04*10^{-3}$).

In conclusion, neither of the two regression analyses produces satisfactory results. Hypothesizing that the unrealistic outcomes are caused by extreme values in the two data series, another regression analysis was performed on each data set, this time leaving the year 1995 in the regular category and 1998 in the tbm category out of the analysis. The extreme values in these years are, respectively, caused by a latent increase of brown rot prevalence in the years before 1995, when the presence of the pathogen was still unnoticed, and by the unusual splitting of an infected but undetected parent lot into more than 80 daughter lots. The new regression analyses resulted in much higher values of λ (0.117 and 0.134) and lower values of ε ($0.32 \cdot 10^{-3}$ and $1.04 \cdot 10^{-3}$). As shown in Figure 2.3 (dotted lines), the two models are a reasonable approximation of the actual situation in periods when the infection level remains fairly constant or changes only gradually. However, both models are unable to describe the strong fluctuations that are occasionally observed in practice. The fact that the estimated value of λ is only slightly larger for infected tbm seed potatoes than for infected regular seed potatoes does not enhance confidence in these results. Regular infected seed potatoes are expected to have a much lower probability of remaining undetected (parameter c), because all lots are tested, as compared to only a small percentage of tbm seed lots. Moreover, because regulations are stricter for this category, transmission probabilities will be lower, resulting in a lower growth factor R. Since λ is a combination of c and R, we would expect the difference in λ between 'tbm seed' and 'regular seed' to be larger than observed in the results of the regression analysis.

2.3.5 Insights obtained from the state variable model

As was concluded from the transition diagram (Figure 2.2), the dynamics of the fraction of infected seed lots (σ_1) forms the key to a general understanding of brown rot epidemics. Since the first brown rot outbreak in the Netherlands in 1995, the brown rot infection prevalence per year has remained low; the number of infected farms per year is over-all decreasing, with an exception of two 'extreme' years (Hendriks and Höfte, 2004). Apparently, the currently employed control strategy results in a net reproduction factor λ that is too small to cause a major outbreak, although new introductions of the pathogen regularly occur through contaminated surface water. Nevertheless, transmission can lead to a latent increase of undetected low-level infections, resulting in an increased number of detected lots in a year when climate conditions are favourable for multiplication of the pathogen.

A consequence of the low average yearly number of brown rot infections is that even a small absolute variation in the number of infections will have a relatively large impact, i.e. the fluctuation and occurrence of outliers in number of infections determine for a large part the effectiveness of a brown rot policy. As a consequence, stochastic modelling is needed to obtain a quantitative insight into the dynamics of outbreaks, in particular the risk of a relatively large outbreak. It is possible to reformulate the model described above, and extend it with further subdivisions of classes based on the important factors that were mentioned, in a stochastic context. However, such disaggregation of the model might easily result in a number of compartments that is comparable to or larger than the expected yearly number of infections. Consequently, it is computationally more efficient to track each of the infected lots individually instead of dividing them into classes, thus arriving at an individual-based approach.

An individual-based stochastic approach has several advantages, such as the possibility to include potentially relevant details at the individual level (Dijkhuizen and Morris, 1997; Grimm, 1999). Including GIS information of potato lots and fields in the model will allow the inclusion of realistic spatial heterogeneity in the distribution of potato lots and brown rot prevalence. A GIS relates descriptive information to space, thereby providing a visualisation of the model output in a way that is easily understood and communicated (Bian, 2003). Moreover, spatial explicitness of a model supports the analysis of possible impacts of different brown rot control strategies (Deal et al., 2000). In particular, it provides the possibility to check for regional differences in brown rot prevalence and, proceeding from this, to examine the perspectives of a region-specific control policy. In conclusion, the inclusion of stochasticity is a prerequisite for usefully modelling brown rot epidemiology in the Dutch potato chain. Furthermore, an individual-based model might be convenient if more details are desired than the compartmental model offers.

2.4 The individual-based model (IBM)

2.4.1 Modelling approach

An IBM is defined as a model in which one separately tracks the dynamics of all entities, taking into account the individuals' unique properties and their interactions with each other (Huston et al., 1988). It is this typical characteristic of an IBM that makes it possible to investigate types of questions that can often not be answered by using a state variable approach (Nugala et al., 1998). Yet, another property of IBMs is that they link different hierarchical levels of the potato production chain (Huston et al., 1988), which in our case allows for observing the effect of brown rot prevalence both in the potato lot population and at farm level. The IBM described in this article is spatial explicit, in that it assigns a location to each individual, thus including the interactions between an individual and its environment. One disadvantage of IBMs is that they are often very extensive and carry a lot of information, which makes it a challenge to keep the model transparent (Grimm, 1999). Moreover, because rules are formulated at the individual level, the interpretation of mechanisms responsible for fluctuations at the population level may be difficult (McCauley et al., 1993). In the following sections, an IBM approach to model brown rot epidemics is described, as well as its intended application for the Dutch situation.

In this chapter, only the concepts and structure of the IBM are presented. A full description, including parameterisation and analysis, will be given in Chapter 3.

2.4.2 Objects

As mentioned in section 2.2.1, the trading units of the potato production chain are potato lots. Potato lots are grown on fields, which belong to farms. The three nouns in this last sentence comprise the main concepts of the production cycle and are logically translated into classes of the IBM. Since we are interested in the prevalence, and in a later stage also the economic consuences of brown rot, the model needs to monitor the infected lots over time and over the farms and fields to which they belong. Healthy lots do not play any role in brown rot dispersal and by no means affect the state of the model. Therefore, only infected lots are included as objects in the model. A new infected lot is created at the moment it becomes infected, and always has to be derived from a field object in order to know the size and category of the lot. If transmission occurs when potatoes are not on the field, the model 'reasons' from which fields the lot that becomes infected might originate, and selects one of them to derive from it a new infected lot.

Figure 2.4 shows how the three types of objects are related to each other. Each farm is linked to one or more fields on which potato lots are grown in a certain year. Because of crop rotation, the number of available fields has to be much higher than the number of fields used for potato cultivation per year. Only the selected potato fields contain a link to the farm to which they belong. If an infected lot is or has been grown on a potato field, this field will contain a link to the lot until the end of the production cycle, when new potato fields are selected for the next growing season. Field objects thus constitute the connection between infected lots and farms. Infected lots remain linked to the field from which they are derived during their lifetime. If an infected lot has originated through vertical transmission, the parent lot is retained, so that the parental lineage of an infected lot can always be traced. The daughter lot contains a link to the parent lot, and vice versa.

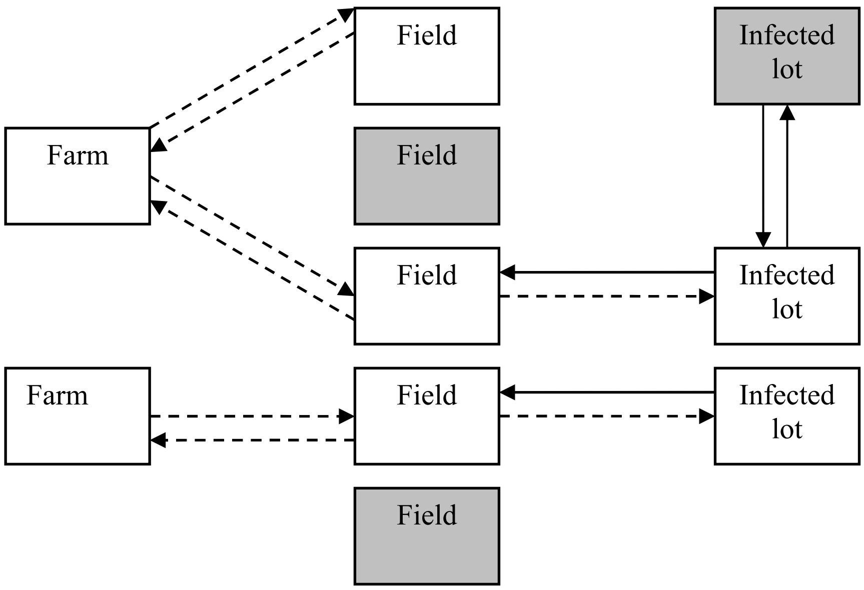

Figure 2.4. Relations between farm, field, and infected lot objects in the model. Shaded fields do not take part in the potato production cycle in the outlined situation. The arrows show how objects are linked with each other; continuous lines represent permanent relations, whereas dotted lines represent temporary relations.

2.4.3 Object characteristics: attributes

The unique properties of objects are determined by the values of predefined attributes. Below, the most important attributes of each class are discussed, starting with those of the farm objects. Firstly, because the model has to be spatial explicit, each farm has an x- and y- coordinate. Next, the attributes ‘farm type’ and ‘farm size’ provide information on the share of potato production to the total farm activities and income, and consequently on the impact of a brown rot infection on the farm. Unlike the other types of objects, farm objects also contain a number of attributes that characterise behaviour. Among these are the hygiene level of a farm and ownership of equipment (private or shared), which affect, respectively, the infection probability of a potato lot on the farm and the distance over which transmission may occur. To know whether a farm has recently had an infection and whether phytosanitary regulations are imposed on the farm, farm objects also contain the attribute ‘infection status’.

Similar to farm objects, field objects contain unique coordinates by which they can be spatially located. Another important, field-specific spatial attribute is its location with respect to contaminated surface water. A field can either be inside a contaminated area or not. Other properties included as attribute are the size of a field, the most recent year of selection for potato cultivation, and (if it is selected) the category of potatoes that is grown on the field. Each field object also has an infection status, which informs the model about the most recent year in which an infected lot was grown on it.

Infected lots are the only objects that are mobile in the potato production chain, so they cannot be given any coordinates. They can be located, however, because every infected lot is linked to a field. The infected lot attribute ‘detection status’ is the key attribute of the model, since the value of this attribute informs the user about the number of undetected infected lots in the chain, thus indirectly about the effectiveness of brown rot control. Another very informative attribute is the ‘infection source’, which indicates during which process of the potato production cycle the lot became infected. Attributes affecting the testing process and detection probability of a lot are ‘infection level’, ‘lot size’, and ‘potato category’.

2.4.4 Processes and events

The production cycle of potatoes spans one year, and can be separated in an on-field period and an off-field period. Both periods contain a number of processes, which may go together with specific events that change the attribute values of objects and with it brown rot prevalence. The difference between processes and events is not always clear. Generally, processes are the activities that actually take place in practice during a production cycle, whereas events involve the change in the unique characteristics of objects as a result of these processes. Processes occur on a large scale, whereas events affect individual objects. For example, during the planting process, one event could be infection of a seed lot, but there may be many other events as well. One process may thus go together with many events. Figure 2.5 gives a schematic representation of the processes of the production cycle as they affect the state of the model.

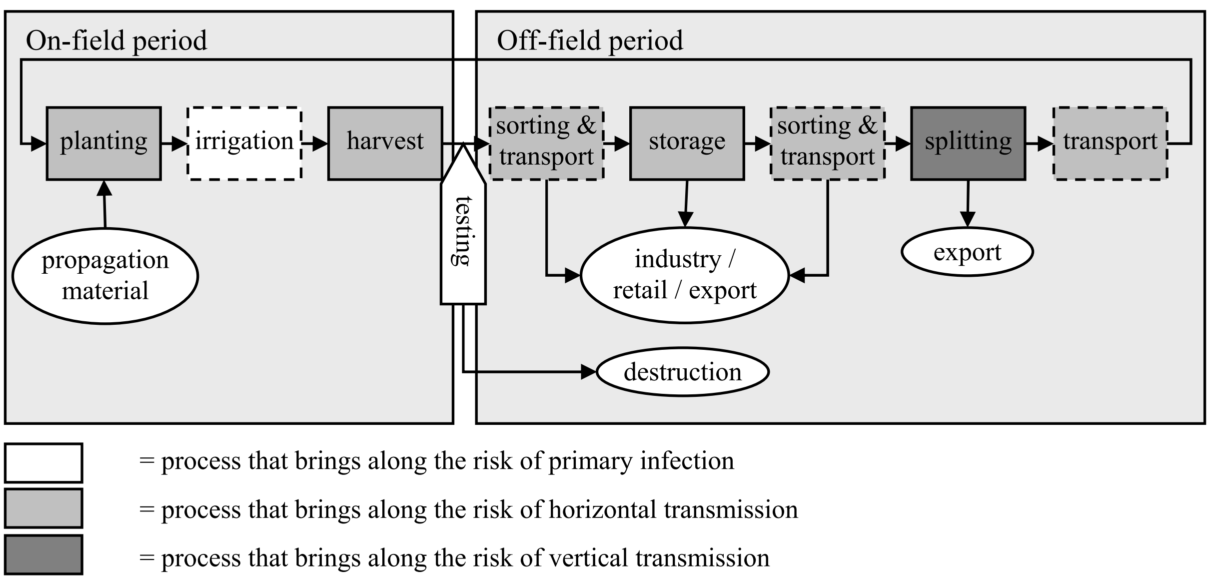

Figure 2.5. Processes of the potato production cycle, divided in an on-field period and an off-field period. Rectangles stand for processes, whereas the ovals indicate removal from or input in the model. Processes shown in dotted-line rectangles are not necessarily part of a potato production cycle.

The on-field part of the production cycle lasts from planting to harvest. During the growing season, potato fields are usually irrigated and sprayed several times. As mentioned before, both processes may involve the use of surface water. The possible effect of irrigation on brown rot prevalence is much greater than that of spraying; therefore, spraying will not be modelled as separate process. After harvest, all seed lots are stored, as are most ware potatoes before they are processed, retailed, or exported. Starch lots are always transported to starch companies immediately after harvest. Lots that are to be stored may be sorted and transported before or after storage, depending on their category and storage location. Within the first weeks after harvest, testing of potato lots takes place. Detected and probably infected lots as well as all traded and processed lots are removed from the model during the storage period. At the end of the winter, seed lots are split into small daughter lots, which are exported or transported within the Netherlands to the location where they will be planted. They can also be replanted on the same farm.

The events of major interest in the model are infection and detection. As shown in Figure 2.5, all mentioned processes except testing bring along a risk of infection. Primary infection can only occur during the process of irrigation, if surface water is used and the irrigated field is located in a contaminated area. Infected seed lots that are still undetected by the time of splitting inevitably bring along vertical transmission. During splitting, a number of daughter lots are created, which inherit the infection from their parent lot. Horizontal transmission may occur during planting, harvest, and sorting, through contact with contaminated machinery and equipment. Also transport can lead to secondary infection if a truck is not thoroughly cleaned after transport of an infected lot, though the recent introduction of the transport protocol is supposed to exclude this risk. Storage includes a risk of infection through direct contact between poorly separated lots that are stored in bulk. Horizontal transmission during a certain process can only take place in the presence of an already infected lot in the production chain, and leads to at maximum one new infection per 'source' lot. Whether transmission actually occurs depends on the process and is simulated individually for each infected lot that is present in the production chain at that time.

Detection of a lot is only possible during the process of testing. When at least two lots with the same parent lot are found infected, all undetected sister lots are defined probably infected. The same occurs with undetected lots that are from the same farm as detected lots. The farm and field to which a lot is linked at the moment of detection are put in quarantine for, respectively, three and five years. Other important events included in the model are the increase in size of a lot at the end of the growing season, downgrading of potato lots at the time of splitting, increase of infection level depending on the age of an infection, and selection of fields per farm at the end of the off-field period. Selection of fields for potato cultivation depends on values of attributes such as field location, farm location, crop rotational plan of a farm, and quarantine status of a field. For all selected fields, the attribute 'time since last potato cultivation' obtains a value of zero; for all other fields, this value is increased by one year.

2.4.5 Model output and possible application

Although the IBM is not completely developed yet, the intended model output and possible applications are illustrated to assess the suitability of the IBM. As the principal aim of the model is to show brown rot prevalence over time, the yearly number of infected lots is of primary interest. However, the object-oriented modelling approach also offers the opportunity to obtain more specific information about every infected lot. First of all, in order to analyse the effectiveness of a control strategy, it is important to know the fraction of all infected lots in a certain year that is detected, and of which potato category the undetected infected lots are. After all, only undetected infected seed lots contribute to brown rot preservation and dispersal. Next, since all infected lots are linked to fields with x- and y-coordinates, the locations where infections occurred can be made spatially explicit. Through the linked fields, also the owner farms of infected lots can be identified. Finally, of each infected lot the source of infection is registered by the model, so it is possible to determine the share of each process in the total number of brown rot infections.

The information given by the model output can be very valuable in a later stage of the project, when different control strategies are to be compared. As not only the brown rot dispersal, but also the costs of brown rot prevalence determine the applicability of a strategy, the magnitude of a brown rot epidemic at farm level needs to be assessed. For example, a relatively high number of infected lots belonging to only few farms may have a lower economic impact than only a few infected lots, each connected to a different owner farm. Also the category and area of potatoes grown on a farm considerably affect the sanitation costs. Furthermore, analysis of the infected farms will reveal if certain farms are more vulnerable to brown rot infection than others. By mapping all brown rot infections, also regional differences in risk of brown rot infections may be identified, which could lead to regional imposition of brown rot measures. In fact, by imposing an irrigation ban on potatoes in regions with contaminated surface water, the Dutch government already applies a regional brown rot control strategy. Further optimisation of brown rot control policy may ensue from the analysis of the infection sources of infected lots. The outcome of such analysis will provide insight in the relative importance of different risk factors, and makes it possible to develop measures aimed at those factors that contribute most to brown rot prevalence.

2.5 Discussion

In this chapter, we have introduced two models on brown rot dynamics in the potato production chain. The models follow different approaches: the first is a deterministic and compartmental state variable model, whereas the second is a stochastic, individual-based, and spatially explicit model. As will be discussed in detail below, both models are useful tools for elucidating qualitative and quantitative characteristics of brown rot epidemiology and control, focussing on the Dutch situation. State variable population models usually abstract from details at the level of individuals (Uchmanski, 2000; Shirley et al., 2003) and are frequently applied to obtain insight into the basic principles of disease dynamics. In the context of brown rot epidemiology, they are especially suitable for analysing the general trend of prevalence over several years, as shown by the illustrative example in section 2.3.4. The application described in this section demonstrated that a state variable model approaches the real situation fairly well for as long as changes in the level of brown rot prevalence over years are relatively small. A major strength of the model is that it is relatively simple and well suited for system analysis, since important indicators such as growth factor and equilibrium state of the potato lot population are easily derived from the model. However, it cannot deal with the peaks in brown rot prevalence observed in practice every now and then. Fitting the model to data with extreme values results in unrealistic parameters, as indicated by the negative λ. Probably, the model fit could at least partly be improved by using a larger data set. However, covering a larger period does not diminish the fact that a state variable model without stochasticity is unable to reflect the strong fluctuations that are characteristic of brown rot epidemics.

To overcome this disadvantage, the second, individual-based model was considered. The complexity of this model is high compared to the state-variable model. Besides, the model provides less insight into the general factors affecting disease dynamics (McCauley et al., 1993; Wilson, 1998), and is therefore less suitable for a general analysis of brown rot epidemics. However, since it includes the individuals' unique properties and local interactions, the IBM will resemble brown rot prevalence over time at a more detailed level than the first model. Moreover, the inclusion of detailed and spatial data on the potato production sector may uncover relations between brown rot prevalence and certain characteristics of the potato sector, which would otherwise remain unnoticed.

The over-all aim of the epidemiological brown rot model is eventually to extend it to a bio-economic model for evaluating brown rot control strategies as to their cost-efficiency at national level. In this respect, the IBM is more appropriate for application, from several points of view. Firstly, the costs of brown rot are incurred mainly at farm level, whereas the disease epidemics take place within the potato lot population. As mentioned already in section 2.4.5, the IBM output can directly give the desired output, whereas results of a state variable approach would first need to be translated to farm level. The results of an IBM are thus more ready to use for subsequent economic analysis than those of the state variable model. Next, the aggregated level of the state variable model leads to a 'flattening' of the effect of different brown rot policies, because control measures on a very detailed level will have to be generalised. Moreover, since the model does not show any peaks in brown rot prevalence over time, the effect of measures aimed at avoidance of latent brown rot dispersal is less apparent. Consequently, the effectiveness of control strategies may be underestimated.

Last but not least, by combining the IBM with a GIS, the model output is easily spatially visualised, which greatly enhances the interpretability of results. In addition, mapping brown rot infections makes it possible to analyse spatial variation in brown rot prevalence, which may result in the regional imposition of control measures. Another advantage of spatial explicitness is that it increases imaginative power of the model. The final bio-economic model will be used for testing several different control strategies and the output should be communicated to managers and policy makers, who are often not familiar with modelling techniques. For this target group, the IBM is perceived as a more practical device for evaluating brown rot policy options than a rather abstract state variable model. A major drawback of the inclusion of GIS is the need for specific input data that comes with it.

These arguments illustrate how the context in which a model will eventually be used affects the choice of modelling technique (DeAngelis and Gross, 1992; Mooij and Boersma, 1996). Application of the IBM thus offers several practical advantages, most of them being somehow related to the fact that the epidemic model will eventually be extended to a bio-economic model that is to be applied in an institutional environment. Therefore, the IBM model will be further developed and refined in the near future. However, as mentioned above, the IBM approach certainly has its weaknesses, the most important one being the difficulty of interpreting results at higher aggregated, population levels. The non-spatial state variable model discussed in section 2.3 could help in interpreting the main characteristics of the results obtained from the more detailed spatial one.

CHAPTER 3

Individual-based models in the analysis of disease transmission in plant production chains: an application to potato brown rot

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Abstract

Spread of plant disease in production chains of planting material is a process of great economic importance, but has received little attention from plant disease epidemiologists. Disease control in production chains is therefore often based on rules of thumb and expert judgement by regulatory bodies, rather than on an explicit analysis and evaluation of the epidemiological and economic consequences of alternative strategies. This chapter puts forward the idea that individual-based models may be used as a framework to simulate the spread of disease causing organisms in plant production chains. The 'individuals' in this context are the trading units (e.g. batches, lots) of a production chain. The quarantine disease 'potato brown rot', caused by the bacterium *Ralstonia solanacearum*, is used as an illustrative example. The model simulates the spread of potato brown rot over all potato growing farms and fields in the Netherlands over a chosen time frame. It addresses the relevant infection pathways for this disease in potato production and is spatially explicit.

Model outputs of simulations based on the control strategy as applied in the Netherlands until 2004 are presented. Besides, the effects of minor adjustments to this strategy are investigated. The simulations show an irregular pattern of brown rot dynamics in the potato production chain, as is observed in practice. Simulations quantify the relative importance of different infection pathways, and elucidate the effect of testing frequency on these pathways and on the overall brown rot incidence. The study shows that individual-based modelling (IBM) provides a powerful platform for modelling the epidemiology and impact of diseases in plant production chains. IBM can be effectively used for the analysis, evaluation and design of cost-effective disease management policies.

3.1 Introduction

Plant production chains are important pathways for the transmission of infectious diseases. The threat of disease outbreaks in these chains is increasing as a result of the expansion of long-distance travel and international trade in agricultural products, which facilitates the introduction of pathogens in areas that were previously free of them (Mumford, 2002; Weiss and McMichael, 2004). The risk of disease transmission is particularly high for production chains consisting of a vegetative propagation system and multiple production cycles. Once pathogens have been introduced in such chains, they can survive in the tissue or on the surface of propagation material from one production cycle to the next (Van der Plank, 1963). Thereby, they have an opportunity to multiply and disperse, which may eventually result in an epidemic. A major problem in controlling diseases in production chains occurs when infected entities remain asymptomatic, while being capable of transmitting the disease. Quantitative information on transmission and dispersal risks of pathogens within chains is often limited (Leach et al., 2002; Meentemeyer et al., 2004). A better insight into the behaviour of infectious diseases in plant production chains would greatly support the design or optimisation of control strategies.

This chapter presents the development of a modelling concept to simulate disease dynamics at the level of the plant production chain, using an individual-based modelling (IBM) technique. The application of the IBM concept to disease propagation in plant production chains is novel, as models for plant diseases generally focus on epidemics at plant or field level (Bertschinger et al., 1995; Van der Werf et al., 1989; Webb et al., 1999), covering only one growing season or production cycle (Willocquet and Savary, 2004). The distinguishing feature of IBMs is that they acknowledge and explicitly represent the principle that each individual is unique in its characteristics and interactions with other individuals. An IBM traditionally defines the individual organism as the logical basic modelling unit instead of using aggregated state-variables to describe population dynamics (Huston et al., 1988). Whereas in conventional IBMs entities are concrete individuals, in our application the commercial production entities (e.g. lots, consignments) in the production chain are defined as the modelling units. The unique characteristics of these entities do not only reflect their biological state, but also their management and position within the chain.

The model is applied to brown rot dynamics in the Dutch potato production chain. Brown rot is caused by the bacterium *Ralstonia solanacearum* biovar 3 (race 2) and comprises a major threat to potato production worldwide. Particularly in warm growing areas, such as the Mediterranean region, brown rot infections can cause considerable yield loss (Elphinstone, 2001). Outbreaks have been reported in many European countries, and within the EU and numerous other countries, brown rot has been awarded a quarantine status (Elphinstone, 2005). That is: the disease is of potential economic importance to the area endangered thereby and not yet present there, or present but not widely distributed and being officially controlled (FAO, 1999). In the Netherlands, the climatic conditions are not optimal for brown rot and infections usually remain asymptomatic. However, the risk of establishment of brown rot as an endemic disease in the Netherlands threatens the Dutch export of seed potatoes (Van Vaals and Rijkse, 2001). Moreover, the extensive preventive and sanitation measures that are imposed to eradicate brown rot from the chain are costly and have serious economic consequences for the entire Dutch potato sector (Elphinstone, 1996; Janse et al., 1998).

Although the number of brown rot cases (i.e. infected lots) in the Dutch production chain has been reduced to less than ten per year since the first outbreak of the disease in 1995, complete eradication of brown rot from the potato production chain has still not been achieved despite substantial efforts, and knowledge about the importance of several risk factors on brown rot prevalence is still poor. The IBM described in this chapter is designed to give more insight into the relative importance of different risk factors affecting the prevalence of brown rot and its dispersal in the potato production chain. Also, it can be used to evaluate the effectiveness of control strategies, and thereby support the development of an effective brown rot management strategy. In the following sections, the modelled system is described, after which the structure and contents of the IBM are explained. Next, the parameterisation and validation of the model are presented after which model performance and possible applications are highlighted and discussed.

3.2 The modelled system

3.2.1 The potato production chain

The production of potatoes takes place by vegetative multiplication and comprises several production cycles of one year. Starting from a single selected potato plant, in vitro plantlets, or minitubers, after two to five years of multiplication a pure clone of seed potatoes of the highest health status is obtained. These seed potatoes are then propagated for several more years at successively larger scales by seed potato growers. Propagation material is certified each year by the Dutch General Inspection Service for Agricultural Seed and Seed Potatoes (Nederlandse Algemene Keuringsdienst voor zaaizaad en pootgoed, NAK-AGRO) according to a classification system that describes health status.

Depending on their variety, seed potatoes are eventually grown for production of ware or starch potatoes. Ware potatoes are sold for consumption or processed into potato products, such as chips; starch potatoes are destined for the starch industry. Since ware potatoes have a much larger profit margin than starch potatoes, they are produced from seed potatoes of a higher health status. About 70 percent of all seed potatoes produced yearly in the Netherlands are exported (almost 700,000 tonnes), as well as a large part of all ware potatoes and a small part of the starch potatoes (together over 800,000 tonnes). The production and processing of starch potatoes is concentrated in a region in the North-East of the Netherlands, called the 'Veenkoloniën'. Seed potatoes are mainly grown in the Northern provinces and in the impoldered province of Flevoland. Ware potatoes are grown all over the country, but generally not in the same regions as starch potatoes.

Up to now, all seed lots are tested after harvesting for the presence of brown rot. Ware and starch lots are tested at random at a low frequency. If a lot is found to be infected, it is destroyed, and quarantine measures are enforced on the farm that owned the lot and on the field on which it was grown in order to prevent further spread of the disease. Besides, all lots that are clonally related to the detected lot, or may have been in contact with it, are traced back and tested for brown rot. Lots that are not found to be infected in a test but that are nevertheless strongly suspected of being infected are defined 'probably infected'. These lots must be marketed under restrictions. The brown rot policy is currently being reconsidered as the number of detections has declined over the past years, indicating that the brown rot epidemic in the Netherlands is under control.

3.2.2 Brown rot infection pathways

There are different pathways through which a potato lot can become infected with brown rot. Firstly, infections may be caused by irrigation or spraying of potatoes with contaminated surface water, in which brown rot bacteria can occur because of the presence of the host weed bittersweet (*Solanum dulcamara*). Large parts of the Dutch waterways are contaminated with brown rot and serve as a permanent external reservoir of brown rot bacteria. Infection through surface water, also referred to as primary infection, is the only way through which an infection can enter the production chain. As part of the brown rot control policy, the Dutch Plant Protection Service takes samples of the Dutch surface water several times during a growing season. Regions in which surface water is found to be contaminated with brown rot bacteria are designated as 'prohibition areas', where the use of surface water is prohibited.

Once brown rot has entered the potato production chain, the pathogen can disperse through the chain by horizontal and vertical transmission mechanisms. Vertical transmission, also referred to as infection through clonal relationships, indicates transmission of the disease from 'parent' to 'offspring', i.e. from one generation to the next. Vertical transmission results as a rule in an increase in the number of infected lots because an infected parent seed lot is split into daughter lots. Horizontal transmission means infection of a healthy potato lot where the source is another infected lot, and can – for instance – be caused by direct contact between different potato lots during storage. As the pathogen can survive for a few days up to several months on materials such as iron and rubber, indirect contact between two lots through machinery or equipment may also lead to transmission of the disease (Janse et al., 1998). Another source of horizontal transmission is infested soil. Field experiments have shown a survival period of brown rot in soil varying from a few months to almost two years (Elphinstone, 1996; Van Elsas et al., 2000). The current opinion is that a minimum crop rotation of 1:3 in combination with control of volunteers (i.e. unharvested potatoes) reduces the risk of soil transmission to a negligible level.

3.3 Modelling concepts

3.3.1 Individual-based modelling

In an IBM, each individual is included as an object of a certain type or 'class'. The characteristics of an object are described by a set of variables, called 'attributes'. Objects of the same class have the same set of attributes. The values for these attributes vary among objects and define each object as a unique individual. In the model presented here, the most important objects are farms, fields, and potato lots.

The modelled production cycle is represented by a series of processes. During these processes, changes in the state of objects are caused by 'events'. For each process in the production cycle, the model checks which events are associated with it and which objects are affected by these events. Examples of events are 'primary infection of a lot' during the irrigation process, or 'detection of infection in a lot', which is related to the process of testing. The occurrence of an event is stochastic. The duration of processes and the time interval between them is not taken into account because only the order in which events take place is important. The model thus 'jumps' from the end of one process to the start of the next process, which is comparable to what happens in discrete-event simulation (Baveco and Smeulders, 1994). A detailed description of the conceptual model can be found in Chapter 2.

3.3.2 Model framework

The model covers the Dutch potato production chain from the cultivation of high-quality seed potatoes until export or transport of ware or starch potatoes to retail or processing companies. The propagation of starting material preceding large-scale cultivation of seed lots occurs under very hygienic and controlled circumstances and is not included in the model because the risk of brown rot infections at this level is negligible. Neither is the industrial processing of potatoes included in the model; transmission at this level is only possible to other lots that have already left the production chain and will therefore have no consequences for brown rot dispersal. In the past, brown rot bacteria were incidentally found in wastewater of processing industries. Nowadays, however, potato processing industries in the Netherlands have wastewater purification systems that eliminate *R. solanacearum*.

As shown in Figure 3.1, the brown rot model consists of three phases: an initialisation phase, a dynamic phase, and a termination phase. The dynamic phase covers all processes of the potato production cycle that can affect the number of infected lots in the chain. Potatoes are planted in the spring and harvested in the autumn. The growing season starts with planting and ends with harvesting of potatoes. During the growing season, they may be irrigated. Other practices applied in this period do not affect brown rot dynamics. After harvest, potatoes are graded and subsequently stored. During or shortly after harvest, a potato lot may be tested for the presence of brown rot; the result of this test will be available by the time it is in storage. Ware and starch lots may be transported to industry or retail directly after harvest; these lots leave the production chain so transport of infected lots at this time is without risk of transmission to potato lots that remain in the production chain. After storage, seed lots are sorted and split into daughter lots. Finally, all lots are transported to their final destination, which can be a farm, industry, or retail. To enable a simulation to start from a situation in which brown rot is already present in the chain, one or more 'initial infections' can be created at the beginning of the first production cycle.

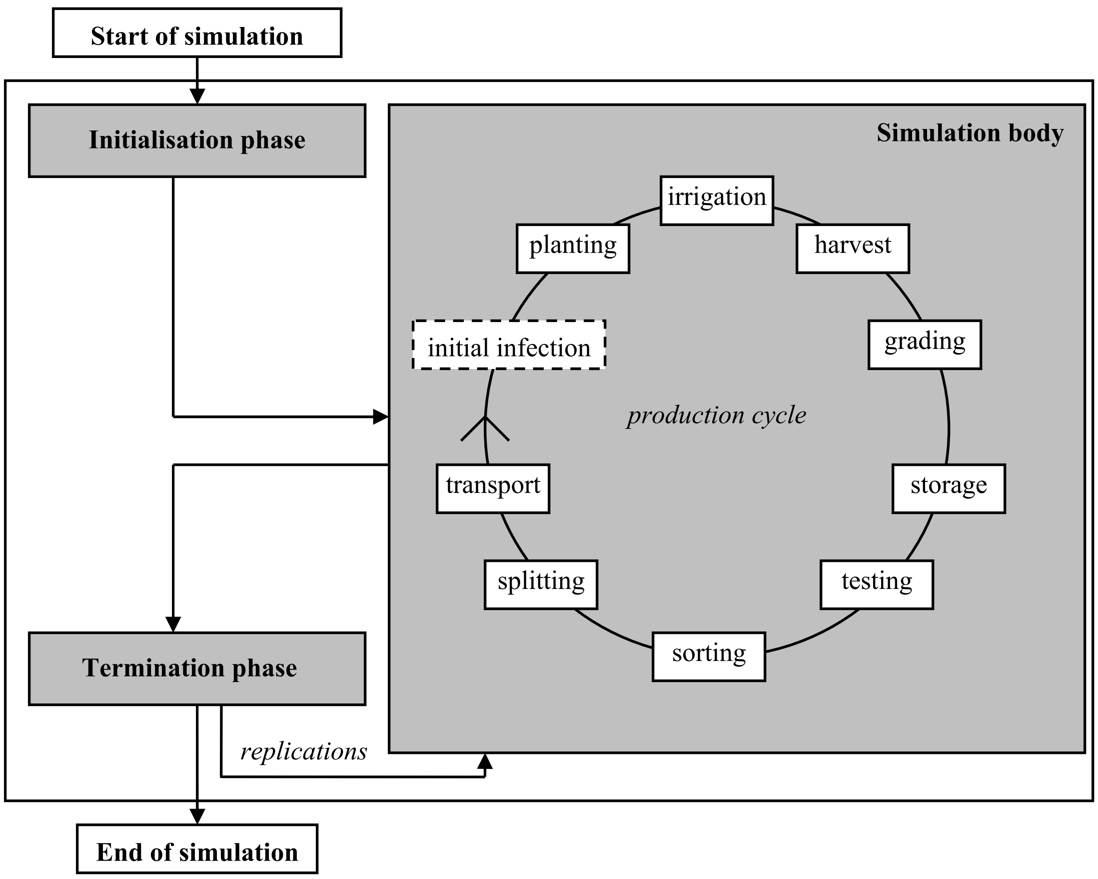

Figure 3.1. Schematic representation of the simulation model. The process of 'initial infection' is optional and can only be passed during the first production cycle of a simulation run.

3.4 Description of objects

All farms and arable fields that are part of the potato production chain are defined as individual objects in the model. Healthy potato lots are not explicitly represented. Their existence is implied by the representation of fields grown with potatoes. Individual farms, fields, and infected lots are represented in the model as objects. Table 3.1 provides an overview of the most important attributes that characterise each class of objects, and the possible values the attributes may take. Objects are permanently or temporally linked to other objects. For example, each farm is linked to the fields it has in use in a certain year, and each infected lot contains a link to the field on which it is or has been grown. For seed lots, it is possible that several lots are grown on the same field, in which case the field may be linked to more than one lot. To enable tracing of clonally related lots when an infected lot is detected, clonally infected lots are linked to their parent lot.

The model is omniscient, i.e. it represents a virtual reality and – as such – represents all infected lots that are present in the chain at any moment in a simulation run. Some infected lots may be detected during testing whereas others may remain undetected. 'Detected' here means that the actors in the chain obtain knowledge about the infection. As soon as the status of an infected lot changes from 'undetected' to 'detected', it is removed from the simulated production chain and thus cannot be a source of transmission anymore.

3.5 Input data and parameterisation

3.5.1 Farm and field data

The physical characteristics of all farm and field objects included in the model are based on actual data of all potato farms (n = 11746) and arable fields (n = 404773) in the Netherlands (data from 2003), which were provided by the Dutch Agricultural Economics Research Institute (Landbouw Economisch Instituut, LEI). To determine the location of fields with respect to contaminated surface water, an additional GIS database of all prohibition areas (i.e. areas in which brown rot bacteria have been found in the surface water), of the Dutch Plant Protection Service (Plantenziektenkundige Dienst, PD) was used (data from 2002). The model includes the possibility of expansion of the area with contaminated surface water. In the current application this option is not applied.

The qualitative characteristics stored in farm objects (e.g. hygiene level, storage facility, machinery use, risk behaviour) are confidential and are therefore randomised over the farms. Consequently, model results do not apply to the actual individual farms, although they are applicable to the farm *community*. The frequencies of the possible values for machinery use and

Table 3.1. Overview of major fixed and variable attributes per class.

Class	Attribute	Description	Type of variable (units)
Farm	FarmID	Unique ID of farm	Discrete (-)
	FarmX, farmY	Geographical position	Continuous (meters)
	Acreage Seed	Acreage of seed potatoes	Continuous (hectares)
	Acreage Ware	Acreage of ware potatoes	Continuous (hectares)
	Acreage Starch	Acreage of starch potatoes	Continuous (hectares)
	Hygiene level	General hygiene level applied	Ordinal (low; medium; high)
	Storage facility	Presence and type of storage facility	Nominal (none; bulk storage; packed storage)
	Machinery use	Machinery use	Nominal (private; shared; rent)
	Risk behaviour	Likelihood of applying risky practices	Nominal (risk-seeking; risk-averse)
	Farm infection	Presence of infected lot(s)	Nominal (true; false)
Field	FieldID	Unique ID of field	Discrete (-)
	FieldX, fieldY	Geographical position	Continuous (meters)
	Area	Size of the field	Continuous (meters)
	Surface water area	Status of surface water at location of the field	Nominal (contaminated; not contaminated)
	Field type	Potato category grown on field	Nominal (seed; ware; starch; no potatoes)
	Crop rotation	Time since last potato production on field	Discrete (years)
	Field infection	Number of years the field will still remain infectious	Ordinal (4, 3, 2, 1)
Infected lot	LotID	Unique ID of infected lot	Discrete (-)
	Infection year	Year of simulation in which lot was created	Discrete (years)
	Infection source	Source that caused infection	Nominal (irrigation, planting, harvesting,, etc.)
	Lot size	Acreage covered when planted	Continuous (hectares)
	Lot category	Potato category of infected lot	Nominal (seed, ware, starch)
	Lot status	Detection status of an infected lot	Nominal (untested, undetected, detected, probably infected)
	Infection level	Infection level of a lot	Ordinal (0^+, 1, 2, 3)

storage facility within the farm population are based on data from the LEI farm accountancy network, which contains farm level data of a representative sample of about 200 potato cultivating farms. According to this database, machinery use is correlated with potato acreage, while the presence of a storage facility shows a correlation with the potato categories grown on a farm. The frequencies of hygiene levels and risk behaviour among farms were formulated after consultation of experts (see next sub-section). The hygiene level depends on the categories of potatoes grown on the farm, and the risk behaviour in turn is correlated with the hygiene level that prevails on the farm.

3.5.2 Expert elicitation of parameters

The model contains two different types of parameters: sector parameters, which represent general characteristics of the potato production chain, and epidemiological parameters, comprising infection and detection probabilities. Epidemiological parameters are inherent to the biological system. Changes in the production chain do not affect these parameters but are reflected in the sector parameters. Adjusting the values of sector parameters, for instance the fraction of farmers that are risk-seeking, will in turn affect the frequency at which infections may occur.

Sector parameters of which no statistical data were available were determined by consultation of experts from various segments of the potato production chain. Epidemiological parameters were difficult to obtain quantitatively; although the different transmission pathways are qualitatively well-known, the probabilities for introduction and spread through these pathways have never been quantified. Therefore, a questionnaire was developed in which brown rot experts were asked to estimate the minimum, most likely, and maximum probability of an event to occur, given a specific situation. The selection of experts consisted of ten Dutch and nine foreign epidemiologists or bacteriologists, working at research institutes or national plant protection services in the Netherlands or countries with a comparable brown rot situation and climate. Of these experts, eleven responded, while four selected experts stated that they had insufficient knowledge to fill out the questionnaire. The model parameters were calculated as the average of all 'most likely values' as estimated for that parameter by each of the participating experts.

As the number of brown rot cases found in practice until now is far too limited to validate the model on the basis of empirical data, an expert workshop was organised to validate the epidemiological results and parameters against an assessment by an expert panel. Five of the experts who had filled out the questionnaire (all Dutch) participated in this workshop. During this workshop, results of different simulations were presented, based on the average most likely parameter values as well as averages of the estimated minimum and maximum values. The experts were asked to reflect on model outputs and to assess the plausibility of the simulation results with respect to observed yearly numbers of infections and contributions of infection sources to the total number of infections. All five experts found simulated infection dynamics and relative importance of infection sources based on most likely parameter values plausible. They also judged the estimated parameter values as credible, even though these values sometimes differed significantly from their own estimates. The broad range of individual parameter estimates reflects the uncertainty about epidemiological parameters and underscores the importance of a sensitivity analysis, of which the results are presented in section 3.6.3.

3.5.3 Epidemiological parameters

This section discusses the epidemiological parameters that are included in the model, grouped by type of event. The parameters, including their values, are summarised in Table 3.2.

Primary infection. Primary infection is only possible on potato fields that are located in an area with contaminated surface water. The probability that primary infection indeed occurs on such a field is given by two parameters: the probability that a farmer uses surface water for irrigation in a prohibition area, which is a farm-related sector parameter, and the probability of infection when contaminated surface water is used (p_primInfection). Both probabilities depend on the type of summer climate, which can be normal or conducive to brown rot.

Horizontal transmission. Horizontal transmission can occur through direct or indirect contact between an infected lot and healthy lot. Transmission through direct contact is only possible during storage; during all other processes, the only possibility for transmission is through indirect contact by contaminated machinery or equipment. Lots grown on the same field are assumed to be planted in spatial isolation from each other, which excludes the possibility of direct contact and disease transmission. Furthermore, it is assumed that an infected lot can cause horizontal transmission to at maximum one other lot during a certain process.

The probability of horizontal transmission generally depends on the infection level of the 'source' lot. Several additional aspects play a role, depending on the process that leads to transmission. The probability of transmission through contaminated machinery (p_transmMachinery), which may occur during planting, harvest, grading, or sorting, depends on the hygiene level of the owner farm of the lot. Shared use of machinery does not affect this probability but may cause the infection to be transmitted to a lot owned by another farm. The probability of transmission during storage (p_transmStorage) is affected by hygiene level and type of storage on the farm, as transmission can only occur if lots are poorly separated from each other. Transport transmission (determined by parameter p_transmTransport) can occur when transport takes place in bulk.

Transmission through soil comprises an exception to the other types of horizontal transmission in that its occurrence does not depend on the actual presence of infected lots, but on historic events, i.e. presence of an infected lot on the same field in previous years. Soil transmission may occur on each field that is in use for potato production in the actual year and on which an infected lot has been grown in any of the past four years. The probability decreases with the number of years that have elapsed since the infected lot was grown on the field.

Horizontal transmission is not simulated if the newly infected lot does not affect prevalence of brown rot in the potato production chain. For instance, transmission to a ware lot during storage is not included in the model because this lot will leave the production chain before it could cause transmission.

Vertical transmission. Vertical transmission, i.e. the splitting of a seed lot into daughter lots, is simulated for seed lots that are replanted in the Netherlands. Approximately 70% of all seed lots are exported. Consequently, each infected, undetected seed lot in the model has a probability of 0.3 to be split into daughter lots, which subsequently remain in the chain. Splitting is simulated by creating new infected lot objects that represent the daughter lots of the infected seed lot. The multiplication factor of a seed lot during one production cycle is seven, so new daughter lots are created until their total size is approximately seven times as large as the size of the parent lot.

Detection. The probability of detection of a lot depends on the probability of testing, the number of samples taken per lot, and the sensitivity of the test, i.e. the probability that an infected sample is tested positive (p_detection). The first two probabilities are determined by the control strategy and are thus user-defined. The probability of an infected sample to be tested positive depends on the infection level of a lot (i.e. incidence of brown rot within the lot) and on sample size. In the current application, the detection probability per sample is based on the statistical detection probability, given a specific infection level and the Dutch standard sample size of 200 tubers (Janse and Wenneker, 2002).

Table 3.2. Overview of epidemiological parameters, grouped by type of event.

Event	Parameter	Value
Primary infection	p_primInfection	0.38^{a}, 0.56^{b}
Horizontal transmission	p_transmMachinery, low hyg. level	0.0^{0+}, 0.037^{1}, 0.36^{2}, 0.55^{3}
	p_transmMachinery, medium hyg. level	0.0^{0+}, 0.0029^{1}, 0.030^{2}, 0.34^{3}
	p_transmMachinery, high hyg. level	0.0^{0+}, 0.0^{1}, 0.0^{2}, 0.0^{3}
	p_transmStorage, low hyg. level	0.0^{0+}, 0.015^{1}, 0.17^{2}, 0.33^{3}
	p_transmStorage, medium/high hyg. level	0.0^{0+}, 0.0^{1}, 0.0^{2}, 0.0^{3}
	p_transmTransport	0.0^{0+}, 0.0029^{1}, 0.028^{2}, 0.35^{3}
	p_fieldTransm	0.042^{y1}, 0.024^{y2}, 0.012^{y3}, 0.0012^{y4}
Testing	p_detection*	0.018^{0+}, 0.18^{1}, 0.63^{2}, 0.95^{3}

Explanation of indices: a: normal summer, b: conducive summer; 0^{+}, 1, 2, 3: infection level of source lot; y1, y2, y3, y4: number of years that have past since field became infested. *: detection probabilities as shown are based on a sample size of 200 tubers.

3.6 Model performance

3.6.1 Default scenario

The model was applied to simulate brown rot dynamics given the brown rot control strategy that prevailed in the Netherlands until 2004. This strategy, which will further be referred to as the default scenario, includes a testing frequency of seed potato lots of 100% (as compared to 7% for ware and starch potatoes), and a ban on the use of surface water for potato cultivation in contaminated areas. It is assumed that fields in use by risk-seeking farms have a probability of 1% to be irrigated despite this ban. The simulation was performed for a period of 15 years (i.e. production cycles) and was replicated 100 times with the same initial conditions but a different random seed number. At this number of replications, the change in the running mean of the average yearly number of infections per simulation is less than 0.5%, and the total duration of a simulation is still acceptable.

Figure 3.2 shows the simulated number of infected lots present in the chain at the end of each year. Average disease prevalence reaches a plateau at which disease transmission and disease elimination from the chain (as a result of inspection) are in dynamic equilibrium. At this equilibrium, the average yearly number of infected lots is almost 15. The distribution of the number of outbreaks per year is skewed to the right, causing the average yearly number of infections to be greater than the median, which lies around 10 infected lots per year. Due to stochasticity, single model replicates may show large deviations from the average trend. The range of observed number of infections per year is wide, indicating important variability between replicates. Year to year variation is also important, as shown by the example of a randomly selected simulation run. This between-years and between-replications variation corresponds with the erratic dynamics of brown rot observed in practice (Hendriks and Höfte, 2004).

As the model is spatially explicit, the infected lots in a simulation run can also be mapped, as illustrated in Figure 3.3. Almost all infections that occurred in the presented run occurred in regions with contaminated surface water, and many of them originated through irrigation (Figure 3.3a). Thus, surface water appears to be an important infection source. Also, relatively few infections occur in seed lots (Figure 3.3b), which is explained by the fact that the probability of a farm to be risk-seeking, and thus to irrigate in a prohibition area, is smaller for farms that produce seed potatoes than for other farms.

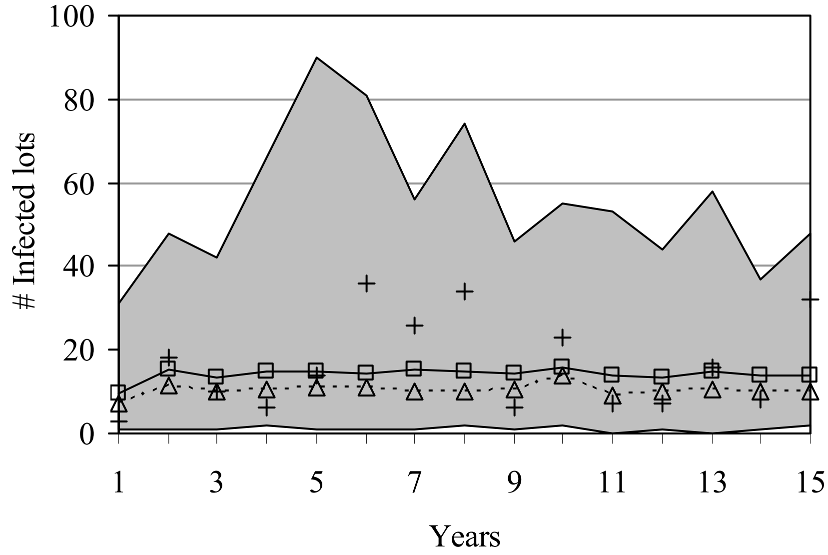

Figure 3.2. Brown rot dynamics simulated over a period of ten years at a 100% testing frequency for seed lots, based on 100 replications. The figure shows the range (grey area), mean (□, continuous line) and median (Δ, dotted line) of the yearly number of infections over 100 replications, and the output of one randomly selected replication (+).

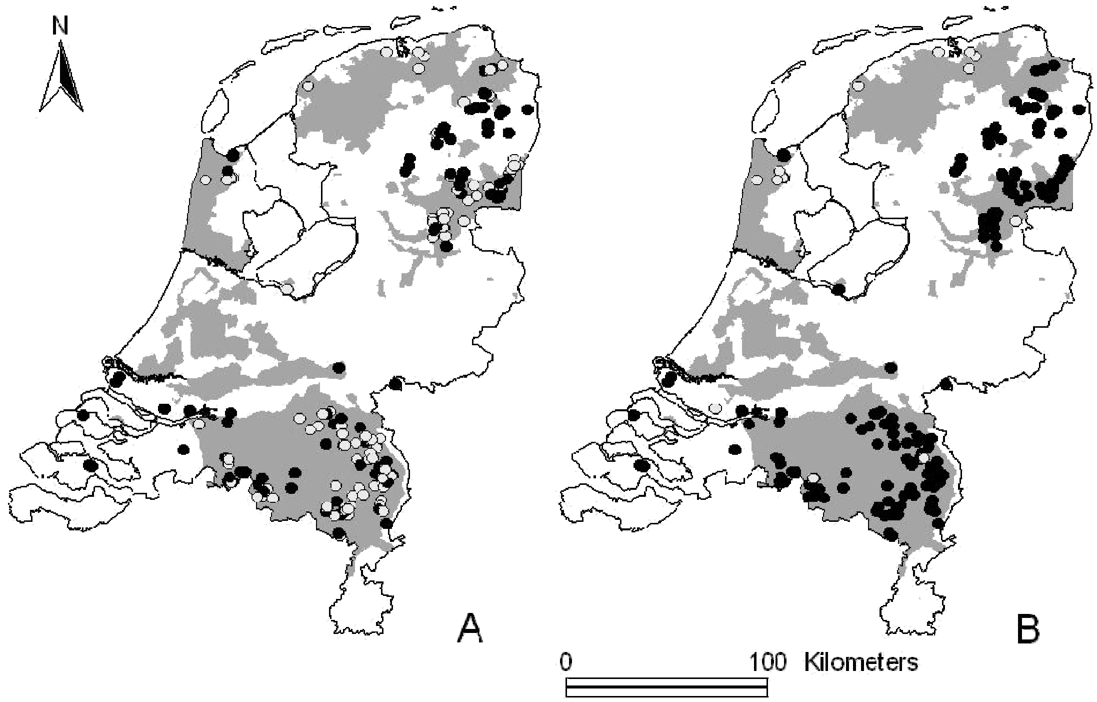

Figure 3.3. Spatial representation of all infected lots in one simulation run (ten years). Grey areas represent prohibition areas, infected lots are indicated with circles. 3a: lots infected through contaminated surface water (○) versus lots infected through other sources (●). 3b: infected lots of category seed (○) vs. infected lots of other categories(●).

Figure 3.4 shows the contribution of different infection mechanisms to the total number of infections. The calculations are based on infections occurring in the years 6 to 15 of the simulations to exclude initial transitory effects before a dynamic equilibrium has been achieved. As was already suggested by Figure 3.3, surface water is of major importance, accounting for about 60% of all infected lots in the chain. This result is consistent with retrospective source identification of detected lots so far (Schans and Steeghs, 1998). Horizontal transmission can only occur in the presence of infected lots in the chain and has a small probability of occurrence (Table 3.2), resulting in an accordingly low frequency of the corresponding infection sources. Although the probabilities of transmission through machinery are the same during planting, harvest, grading, and sorting, the planting and sorting process causes fewer infections than harvesting and grading. Planting takes place before irrigation, when there are few infected source lots in the chain, whereas harvesting and grading take place after some lots have become infected through irrigation with contaminated surface water. Sorting takes place after testing, when most infected lots have been removed from the chain. Clonal infection accounts for roughly 20% of all infections, which is caused by the limited sensitivity of the brown rot test, especially at low infection levels.

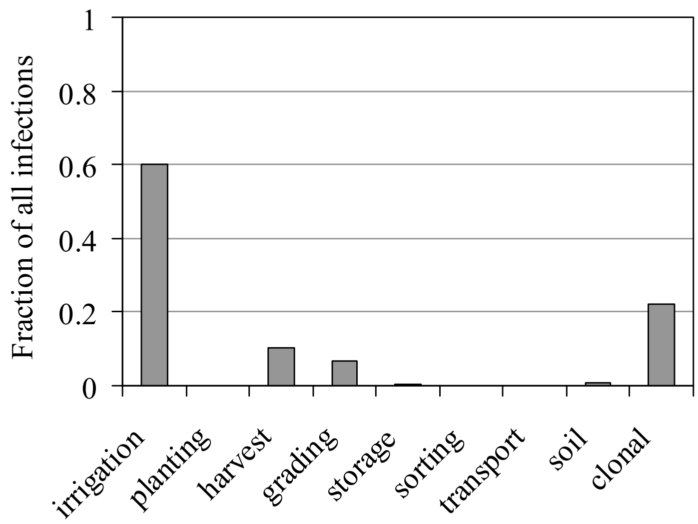

Figure 3.4. Relative contribution of each infection source to the total number of infected lots. Irrigation = primary infection; clonal = vertical transmission; all other sources represent horizontal transmission.

3.6.2 Alternative strategies

Figure 3.5 shows the yearly number of infections when the testing frequency of seed lots is decreased from 100% to 75, 50, 25, 10, or 5%. As before, the first five years of simulation are excluded from the calculation of averages. A decrease in testing frequency causes a more or less exponential increase in brown rot prevalence, which is almost completely due to an increase in the number of clonal infections in the steady state. The relationship between testing frequency and number of clonal infections is non-linear, because an infected seed lot that is not detected and not exported may lead to an extended progeny of daughter lots in the following years. Decreasing testing frequency does not affect the number of primary infections, as primary infection is independent of the number of infected lots already present in the chain. In contrast, the occurrence of horizontal transmission is directly related to the presence of infected lots in the production chain. However, most horizontal transmission probabilities are relatively low, resulting in a minor absolute effect of decreasing testing frequency on the number of infections caused by horizontal transmission.

It may be concluded from Figure 3.5 that applying a 100% testing frequency leads to an average reduction in brown rot incidence of 40% compared with a 10% testing frequency. So far, however, we have only focused on the average brown rot incidence. Figure 3.6 shows the total range of infections over all simulation runs, as well as the output of one simulation run, for a testing frequency of 10%. A comparison with Figure 3.2 shows that decreasing the testing frequency causes the variability in number of infections per year to increase approximately twofold compared to a 100% testing frequency. Decreasing testing frequency increases the likelihood of an epidemic because infections have a higher probability to remain in the production chain for several years.

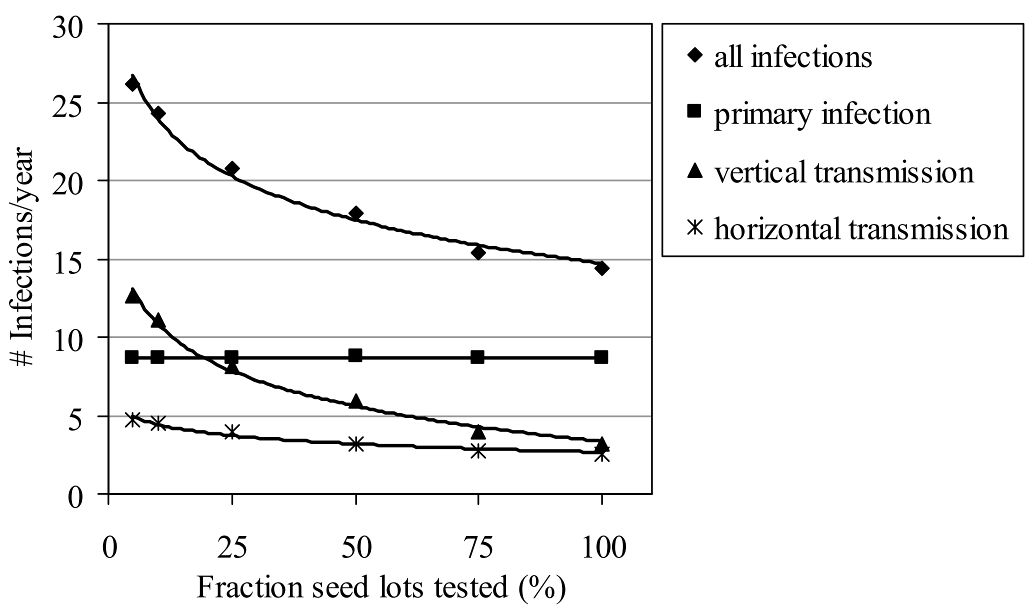

Figure 3.5. Average yearly number of infections at different test frequencies of seed potatoes, shown in total and per infection pathway.

Another effect of a lower test frequency on model behaviour is that it takes more years after the start of a simulation before the system reaches equilibrium. This is because the number of 'later generation' clonally infected lots needs time to build up. Due to the accumulation of undetected clonal infections in seed lots and the horizontal transmissions resulting from these, a higher equilibrium level of new infections per year is reached at a low testing frequencies (Figure 3.6) compared to a 100% testing frequency (Figure 3.2).

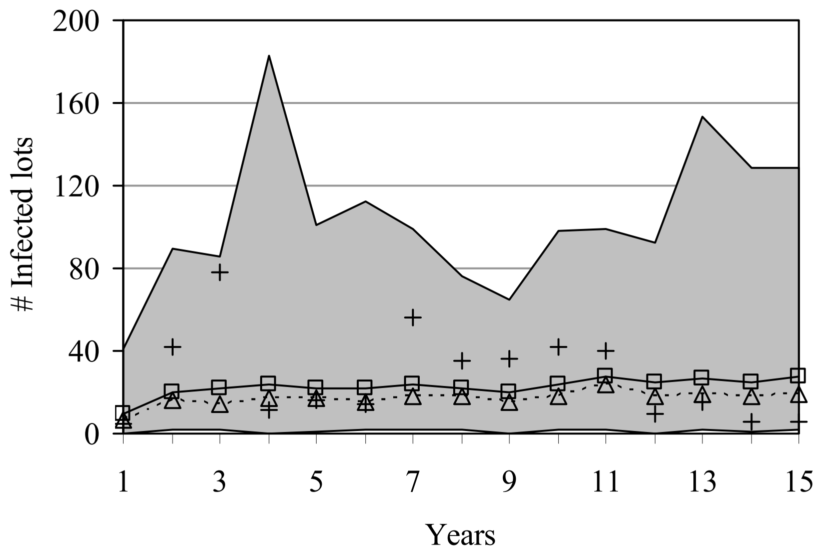

Figure 3.6. Brown rot dynamics simulated over a period of ten years at a 10% testing frequency for seed lots, based on 100 replications. The figure shows the range (grey area), mean (□ , continuous line) and median (△ , dotted line) of the yearly number of infections over 100 replications, and the output of one randomly selected replication (+).

3.6.3 Sensitivity analysis

A local sensitivity analysis of epidemiological parameters was conducted to evaluate possible deviations in model output resulting from different parameter estimates. Table 3.3 shows the effect of a 10% change of the parameters per infection mechanism on the average brown rot incidence at dynamic equilibrium and the relative importance of the corresponding infection sources. The probability of primary infection is an important parameter with a large effect on the total incidence of brown rot, but changing this parameter has no effect on the fraction of infections caused by surface water. This is because a change in the number of primary infections also affects the number of secondary infections. Thus, the ratio between primary and secondary infections is not substantially affected. The yearly number of infections showed little or no sensitivity to changes in horizontal transmission parameters, while the contribution of horizontal transmission sources was only sensitive to changes in the probability of machinery transmission.

Table 3.3. Effect of a 10% decrease or increase per parameter set on average yearly simulated number of infections and on the fraction of infections caused by the corresponding infection source.

	Yearly number of infections			Contribution to disease incidence (%)		
Infection source (parameter set)	-10%	Default situation	+10%	- 10%	Default situation	+ 10%
Irrigation (p_primInfection)	13.1 (-9.0%)	14.4	15.6 (+8.3%)	60.1 (-0.0%)	60.1	61.2 (+1.8%)
Planting, harvest, grading, sorting (p_transmMachinery)	14.8 (+2.8%)	14.4	14.6 (+1.4%)	15.3 (-10.0%)	17.0	17.9 (+5.3%)
Storage (p_transmStorage)	14.7 (+2.1%)	14.4	14.8 (+2.8%)	0.1[a] (-50%)	0.2	0.2 (+0.0%)
Transport (p_transmTransport)	14.8 (+2.8%)	14.4	14.8 (+2.8%)	0.0 (-0.0%)	0.0	0.0 (+0.0%)
Infested field (p_fieldTransm)	14.4 (-0.0%)	14.4	15.0 (+4.2%)	0.6[a] (-14.3%)	0.7	0.7 (+0.0%)

[a] Given the low contribution of the corresponding infection sources to total disease incidence, the relative change in contribution to disease incidence is mainly due to stochastic effects. A larger number of replications would probably reduce the observed sensitivity.

3.7 Discussion and conclusions

This chapter describes the development of a spatially explicit, individual-based modelling technique to simulate disease dynamics at the level of the plant production chain. The model was applied to the dynamics of brown rot in the Dutch potato production chain. Simulation results of the default scenario are in accordance with the current knowledge of, and experiences with brown rot in the Dutch potato production chain. Moreover, the model provides several new insights into brown rot behaviour within the chain. For instance, the model shows that primary infection accounts for approximately 60% of all infections under the default control strategy. Vertical transmission is responsible for roughly 20% of the infected lots; the remaining horizontal transmissions are mainly caused by harvesting (10.2%) and grading (6.6%). Another interesting result is the relationship between testing frequency of seed lots and disease incidence. Clonal infection increases with decreasing testing frequency, whereas the number of primary infections remains almost constant and the number of horizontal transmissions increases only slightly. Sensitivity analysis indicated that the model is robust to the values of most epidemiological parameters, except for the probabilities of primary infection and transmission through machinery. Adjusting the parameter values of machinery transmission only affects the ratio between the contributions of different infection sources to total brown rot incidence. A 10% change in the probability of primary infection, however, causes an increase or decrease of brown rot incidence by roughly one infection per year on average. Although a difference of one infection per year may seem of little concern, the impact of this change in model output on the Dutch potato sector could be considerable, given the elaborate sanitation policy and economic losses to the potato growers involved.

The model has several applications. For instance, it may be used to analyse brown rot prevalence in relation to climate conditions, as the model includes stochastic variables to reflect summer and fall climate. One could also analyse the role of sector parameters such as farm hygiene and machine use or transport logistics (separate versus mixed transport of seed and ware potatoes) on brown rot dynamics, to determine the ‘weakest links’ in the production chain. Furthermore, a sensitivity analysis on the sector parameters will identify which of these parameters predominantly affect model output. The results of such analyses support the development of future control measures, as they indicate which sector parameters should be affected by control measures in order to obtain the highest reduction in brown rot prevalence within the chain. Moreover, the model can be used to simulate brown rot dynamics based on different control strategies, and thus analyse their effectiveness. This makes the model a valuable policy support tool.

The complex structure of the model has two disadvantages. Firstly, it requires a large number of input data. All farm and field objects in the model are based on real farms and fields, of which the location and other physical characteristics are required. An alternative modelling strategy would be to let the model determine these characteristics stochastically, as is done for example in a model by Stoorvogel et al. (2004). However, even then, detailed information on the spatial distribution of the actual farms and fields, the possible values of other physiological characteristics, and possible interrelations between these characteristics, is required in order to obtain a representative set of objects. A second disadvantage is the high level of detail of the model, which goes at the cost of transparency. Contrary to analytical or relatively simple state-variable models (Chapter 2), common indicators describing trends in disease dynamics, such as the net reproduction factor of the number of infections (λ), cannot be analytically derived, although they can be readily derived from model outputs.

Why have IBMs been applied in plant epidemics only to a limited extent so far? The answer is probably that there was no need for such rather complex models. Existing plant epidemiological models approach disease dynamics mainly from a 'fundamental' point of view, i.e. they describe disease dynamics on the basis of the biological behaviour of the pathogen or its vector. This behaviour is often reasonably well described by general epidemiological theories such as logistic growth equations and dispersal gradients (Diekmann and Heesterbeek, 2000; Zadoks and Schein, 1979). However, when we change our focus to epidemics in managed plant production chains, the host plant or crop becomes mobile and infection dynamics are not dominated anymore by purely biological processes, in which case prevalent modelling techniques do not satisfy anymore. At this level, the populations of plants that comprise the trading units in these chains behave as 'aggregate' individuals for which the concepts of IBM apply. Modelling plant epidemics at this level is thus comparable to modelling epidemics in livestock, for which indeed the application of IBMs has been described as well (Jalvingh et al., 1999; Vonk Noordegraaf et al., 2000).

The model we have developed in this chapter can be applied to many diseases other than brown rot. The structure of the model represents that of the potato production chain and includes the major processes of the potato production cycle. The model could therefore be adopted to simulate other 'chain-related' potato diseases, such as ring rot (*Clavibacter michiganensis* subsp. *sepedonicus*) and blackleg (*Erwinia carotovora* subspecies). It is also possible to incorporate more than one disease in the same model, which would allow for studying the combined effects of control measures. Apart from application to the potato production chain, the modelling approach applied in this chapter can be used for modelling diseases in other production chains and other countries, provided that sector and disease parameters can be estimated and farm and field data can be obtained. To enable economic evaluations, the epidemiological model can be extended with an economic module, to calculate the costs of applying a certain set of control measures (e.g. costs of field inspections and sampling costs) as well as the economic consequences of disease prevalence under this set of measures (e.g. costs of removal of diseased plants or plant parts). The resulting bio-economic model provides information on both the effectiveness of a control strategy and its economic consequences. Such a model can be of great support to authorities and policy makers who are responsible for the implementation of effective and efficient control policies that are acceptable and feasible.

Chapter 4

Costs and benefits of controlling quarantine diseases: a bio-economic modelling approach

This chapter has been submitted as: Breukers, A., M. Mourits, W. van der Werf, and A. Oude Lansink.

Abstract

This chapter describes a bio-economic model to quantify the costs and benefits of controlling plant quarantine diseases. The model is unique in that it integrates the epidemiology and economic consequences of a quarantine disease. It allows for *ex ante* evaluation of control scenarios for their cost-effectiveness, taking into account potential export losses resulting from presence of the disease. The model is applied to brown rot in the Dutch potato production chain. Simulation results show that under the current control policy (2006) the average yearly costs of brown rot are 7.7 mln euros. Reducing monitoring frequency increases the costs to 12.5 mln euros, 60% of which are export losses. It is also shown that, due to potential long-term effects of a strategy, conclusions on cost-effectiveness of a strategy depend on the time frame over which costs are calculated. These applications illustrate the potential of the bio-economic model to facilitate the development of cost-effective and soundly based control policies.

4.1 Introduction

Quarantine diseases comprise a distinct class of plant diseases (Heesterbeek and Zadoks, 1987). A quarantine status is given to diseases that are 'of potential economic importance to the area endangered thereby and not yet present there, or present but not widely distributed and being officially controlled' (FAO, 1999). They are harmful to crops or ecosystems in particular areas, as a consequence of which efforts are made on an international scale to protect the areas threatened by introduction of these diseases. The presence of a quarantine disease in a country can lead to reduced export volumes, as the potential contamination of plants or plant parts will cause other countries to be reluctant to import from this country (Mumford, 2002; Myers et al., 1998).

For exporting countries, the threat of export losses is often the primary motive to implement an elaborate and costly control policy. However, as quantitative information on the potential magnitude of export losses is generally lacking, it is unclear whether such policy is cost-effective, i.e. whether the benefits of avoiding these losses exceed the costs of the control policy. Economic analyses of outbreaks of quarantine diseases (e.g. Brennan, et al., 1992, MacLeod, et al., 2004) illustrate how the cost-effectiveness of a control policy depends on the losses incurred in absence of this policy. Unfortunately, these analyses are usually performed *ex post¸* whereas policy makers prefer an *ex ante* assessment of a control policy in order to have insight in potential impacts of control policies.

Olson and Roy (2002) provide a theoretical framework for determining the economic optimal level of control of biological invasions in relation to their dispersal rate. Yet, they do not discuss how to actually quantify the costs of control. Several models have been developed that quantify the costs and benefits of controlling quarantine diseases (e.g. Cembali et al., 2003; Heikkila and Peltola, 2004; Hoddle et al., 2003). However, these models do not consider export losses, while those who do so (e.g. Stansbury et al., 2002; Wittwer et al., 2005) estimate export losses for a particular situation rather than describing a functional relationship between disease incidence and the frequency and height of export restrictions.

This chapter presents a method to quantify the costs of controlling a quarantine disease as well as the benefits of avoiding export losses, in relation to the effectiveness of control. An epidemiological model is integrated with an economic model into a unique, bio-economic simulation model that allows for *ex-ante* evaluation of control strategies for their cost-effectiveness. The chapter provides a description of the integrated approach with emphasis on the economic model; the epidemiological model is described in detail in Chapter 3. The model is applied to the case of brown rot control in the Dutch potato production chain. Brown rot (caused by the bacterium species *Ralstonia solanacearum* race 3, biovar 2) can cause substantial damage, particularly in warm and humid areas, and within the European Union, the disease has a quarantine status (Elphinstone, 2005). In the Netherlands, climatic conditions are such that infected potatoes usually do not develop any symptoms, so crop damage is negligible. However, the risk of establishment of brown rot threatens the Dutch export of seed potatoes, which comprise an important export product of the Netherlands (Lamont, 1993). To avoid economic losses resulting from reduced export, a costly control policy aimed at eradication of the disease from the chain is currently in force.

In section 4.2, the general structure of the bio-economic model is described. Section 4.3 elaborates the economic model and presents a method to quantify the relation between disease incidence and export losses. Next, the potential of the bio-economic model is illustrated by comparing the current Dutch brown rot control policy and a reduced monitoring policy in terms of their cost-effectiveness. The last section discusses major insights obtained from the model application and their implications for controlling quarantine diseases.

4.2 The bio-economic model

Figure 4.1 shows the structure of the integrated bio-economic model, specified for the case of brown rot in the Dutch potato production chain. The model consists of two individual models, which are represented by the grey boxes. The epidemiological model simulates the efficacy of a particular control strategy; the economic model determines the corresponding costs and benefits. The costs of brown rot prevalence and control can be subdivided into three categories (explained below), each of which are quantified by a separate module. Thick arrows link the two models with their respective output, while normal arrows link the required types of input with the models. Several types of inputs are based on expert knowledge. Below, the individual model components are described in detail.

4.2.1 Epidemiological model

The epidemiological model (Chapter 3) simulates the spread of brown rot over all potato growing farms and fields in the Netherlands for a sequence of years. It covers the Dutch potato production chain from the cultivation of high-quality seed potatoes until export or transport of ware or starch potatoes to retail or processing companies. The entities of the model are potato lots, farms, and arable fields. A potato lot is defined as a group of potato tubers or plants of the same variety and quality class, which are grown together on the same field and treated as one unit. The model represents all infected potato lots that are present in the chain at any moment in a simulation run. Some of these lots may be detected at a certain moment, while others will remain undetected throughout their lifetime in the production chain. During a simulation, the occurrence of infection or detection of a lot is stochastically determined by probabilities and local circumstances. Model parameters and data on the farms and fields in the model are

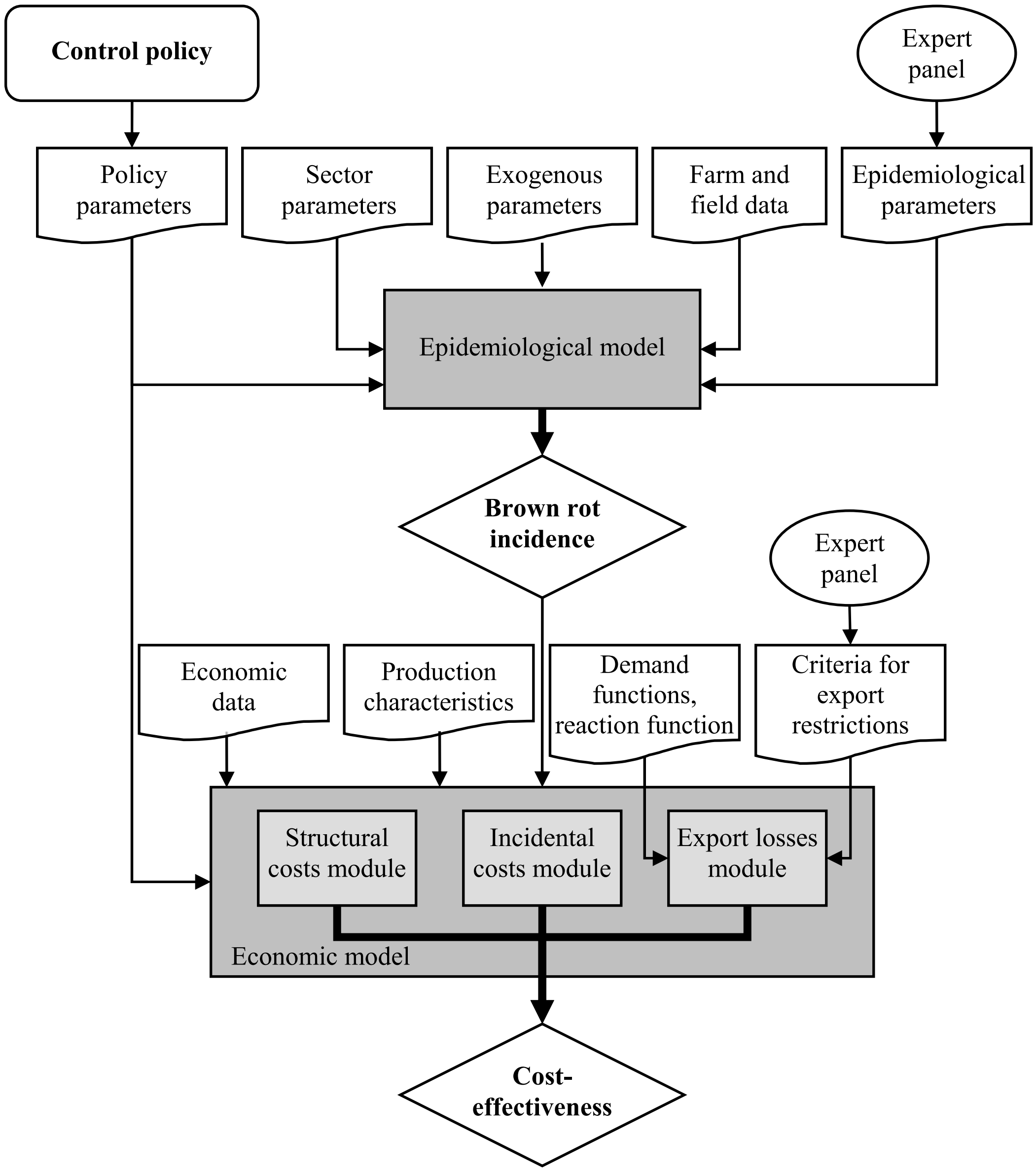

Figure 4.1. Schematic representation of the bio-economic model.

provided by input files (Figure 4.1). Policy parameters represent the brown rot control policy that is implemented, epidemiological parameters comprise infection probabilities, exogenous parameters represent social and climatic circumstances, and sector parameters describe the structure and characteristics of the potato production chain. Empirical information about the epidemiological parameters is very limited; therefore, the parameters were estimated by an expert panel.

Due to the stochastic nature of the model, simulation results vary per run, and repeated runs (i.e. replications) are necessary to assess expected brown rot incidence and its variability. Epidemiological model output provides detailed information on infected and detected lots and affected farms, for each year of each replication.

4.2.2 Economic model

The costs of presence and control of a quarantine disease are determined by the preventive and reactive measures and the damage caused by the disease. The enforcement of preventive measures is largely independent of the level of disease incidence, so the corresponding costs are referred to as structural costs. Costs incurred through reactive measures only apply when an outbreak of the disease occurs and are therefore referred to as incidental costs. The presence of a quarantine disease can lead to crop losses and export losses. For the case of brown rot in the Netherlands, only export losses are relevant so we will further refer to this cost category as export losses.

Actors experiencing economic consequences of brown rot are the government, potato growers, and trading companies. In order to quantify these costs, all modules of the economic model require basic information on production characteristics (e.g. total potato acreage, yield per hectare) and economic data (e.g. potato prices, revenue per hectare). The specific contents and requirements of each individual module are described in the following subsections. Because all costs are calculated for each year in each replication of a simulation, the economic model does not only calculate the expected (average) yearly costs, but also the year to year variation in these costs.

Structural costs module

Structural costs encompass costs of monitoring disease prevalence and costs resulting from restrictions to the cultivation of susceptible crops or plants. Monitoring of brown rot prevalence in the Dutch potato production chain comprises the sampling of potato lots as well as other potential host plants and surface water. Surface water can become contaminated with brown rot as a result of the presence of infected plants of a host weed, bittersweet (*Solanum dulcamara*), along the waterways. Dutch waterways are thus a permanent source of brown rot outside the potato production chain. Therefore, restrictions are imposed to the use of surface water for irrigation of potatoes.

The costs of monitoring depend on the monitoring intensity as specified by the control strategy and on the costs of taking and analysing samples. A ban on the use of surface water may lead to drought stress in areas where ground water is unavailable, resulting in yield and quality disorders. The corresponding losses are determined by the average reduction in yield per hectare and the reduction in price paid for potatoes with lower quality. Because structural costs do not depend on the level of brown rot incidence, they are rather constant over time.

Incidental costs module

Reactive measures following detection of an infected lot bring along incidental costs in the year of detection and subsequent years. Potato lots in which brown rot is detected have to be destroyed.

Infections may be missed due to a limited sample size, so a negative outcome does not guarantee that the tested lot is not infected. Therefore, potato lots that were not found infected but have had (indirect) contact with the infected lot may still be classified as 'probably infected'. Such lots cannot be replanted anymore and have limited marketing possibilities. The owner farm of an infected lot and the field on which it was grown are placed under quarantine for a number of years. During this period, monitoring is increased and potato production possibilities on the farm are restricted, while the infested field cannot be used for potato cultivation at all.

Total incidental costs in a particular year depend on the number, size, and category (seed, ware, or starch) of detected lots, the number of farms involved, and the potato production characteristics of these farms. As these factors strongly vary per year, so do the incidental costs.

Export losses module

The export losses module quantifies the losses from reduced export of seed potatoes in response to the simulated *observed* brown rot incidence in the Dutch potato production chain. Ware potatoes are also exported in large quantities; however, as these potatoes are not replanted after export, they bring along a much smaller risk of introduction of brown rot in the potato production chain of the importing country. Therefore, we assume that export of ware potatoes is not affected by the presence of brown rot in the chain.

In a simulation run, export restrictions occur in a particular year if an extremely large number of infections are found in the respective year ('incidental outbreak') or if the number of detections in previous years ('historical level') was relatively high. Infected lots can be detected in the Netherlands, or – after export – abroad. The level of export restrictions in a year is determined by the so called critical values, which represent the minimum number of brown rot detections that will lead to a particular level of export restrictions. The critical values were estimated in consultation with experts (see section 4.3.3).

The effects of reduced demand on prices and traded volumes are quantified by means of partial equilibrium modelling, assuming that other markets remain unaffected by supply and demand shocks in the seed potato market. In partial equilibrium modelling usually a perfectly competitive market regime is assumed (Clarkson and Miller, 1982); however, this is not the case for the Dutch seed potato market. Approximately two-third of all seed potatoes produced in the Netherlands are monopoly-varieties, which are owned by a small number of trading companies. The trading companies control the supply of seed potatoes by contracting potato growers to grow a particular acreage with one or several monopoly varieties. At the end of the growing season, the trading companies set a price for their varieties on the basis of expected demand. Generally, one company acts as a price setter, after which other companies follow with similar prices. Due to weather variability, the average marketable yield per hectare varies between years. To avoid a situation where demand exceeds supply, trading companies normally contract a larger acreage than on average required to meet the demand. Consequently, in most years there is a surplus of seed potatoes. Instead of reducing the price of seed potatoes to a level where demand equals supply, trading companies maintain a high price and accept a surplus, which is sold as ware potatoes[1]. Market equilibrium is thus determined by the demand function of buyers and a price setting function of an intermediate party, i.e. the trading companies. A similar approach has been applied in the oligopolistic labour market; here, labour unions maintain wages at a higher level than would be the case if supply and demand of employment were in equilibrium, which results in a certain level of unemployment (Stacey and Downes, 1995)[2].

The structure of the seed potato market is graphically represented in Figure 4.2. D1 represents the total demand curve for a product in absence of a quarantine disease. The price-setting curve of the trading companies is C. This curve is upward sloping, but much less steep than the normal supply curve, due to the market power the trading companies have. The equilibrium market price for this product is (see intersection of demand with price-setting curve) equal to P1, which results in a traded quantity Q1. Total supply of seed potatoes by the contracted growers is given by the vertical supply curve S. The surplus in this equilibrium (Z1) is therefore equal to S minus Q1. Now, suppose that an outbreak of a quarantine disease leads to a reduction x in total demand, causing the demand curve to shift parallel to the left (from D1 to D2). As a result of the decrease in demand, a new equilibrium establishes at a lower price (P2) and smaller quantity (Q2), resulting in a larger surplus (Z2). From Figure 4.2 it becomes obvious that, if the equilibrium were determined by demand and actual supply, the reduction in price had been much larger. The reduction in demand resulting from the presence of brown rot or another quarantine disease in the Dutch potato production chain is considered to be temporary. The model assumes that trading companies prefer a temporary increase in surplus, rather than a downward adjustment of supply. This is because there is a time lag of 2 years between the decision to reduce supply and the actual reduction, as contracts on the produced acreage of potatoes grown in a particular season are made in the preceding fall.

[1] Since the surplus of seed potatoes is in any case only a marginal fraction of the total supply in the ware potato market this will hardly disturb the market equilibrium there.

[2] For a formal discussion of the wage-setting relationship see Layard, R., S. Nickell and R. Jackman (1991) in particular Chapters 2 and 4.

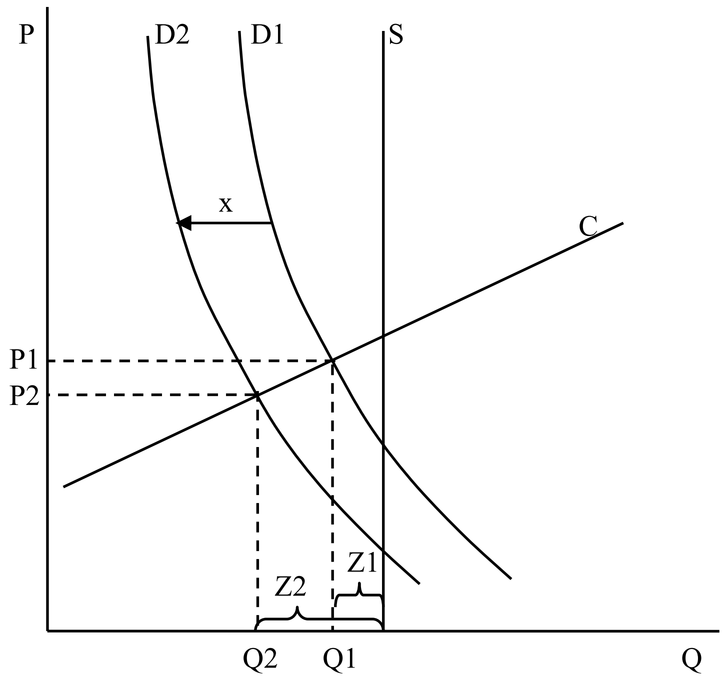

Figure 4.2. Effect of reduced export on the price and total quantity traded under imperfect market competition. D = demand curve, C = price setting curve, P = price, Q = quantity, S = supply, Z = surplus, x = decrease in total demand as a consequence of reduced export.

4.3 Parameterisation of economic modules

The following subsections describe the parameterisation of the three economic modules. Quantification of costs is based on average values of production volumes, potato prices, and costs and revenues per potato category (Appendix 4-I). In addition to 'regular' seed, ware, and starch potatoes, the Dutch potato sector distinguishes 'tbm' seed potatoes. Tbm seed potatoes are seed potatoes of a starch variety that can be grown under less strict regulations than regular seed potatoes, provided that they, or their offspring, are not transported off the farm until harvested as starch potatoes. Tbm seed potatoes are thus destined for on-farm replanting and cannot be marketed. They represent approximately 8% of the total seed potato acreage.

4.3.1 Quantification of structural costs

Monitoring costs comprise the costs of sampling potato lots and other sources. Sampling costs of potato lots are calculated by multiplying the average number of samples with the price per sample. The price per sample is currently €69.- in case of sampling per lot, and €64.- if sampling occurs per weight unit (normally 25 tonnes)[1]. To identify areas with contaminated surface water, the Dutch waterways are structurally sampled at a yearly cost of €125.000,-. The extent of the irrigation ban determines the total acreage of potatoes that suffers from drought stress. Yield and quality losses resulting from drought stress substantially vary across years and soil types. In a year with 'average' rainfall, drought stress leads to yield reduction of approximately 7.5% for seed potatoes, and 10% for ware and starch potatoes. Quality loss only applies to seed potatoes: minor quality loss causes a 10% discount in price, while serious quality loss results in downgrading to feed potatoes.

4.3.2 Quantification of incidental costs

Incidental costs are calculated through partial budgeting. Table 4.1 provides an overview of the incidental costs that may be incurred by farmers, specified per potato category (see Appendix 4-I for detailed information and data sources). Detected lots lead to complete loss of revenue and costs of destruction. Probably infected seed and ware lots can be marketed, but generally at a much lower price than their original value. Farms under quarantine restrictions may not be allowed to grow seed potatoes for one or more years, in which case the model assumes these farms will grow ware potatoes instead of regular seed potatoes and starch potatoes instead of tbm seed potatoes. Whereas regular seed potatoes and starch potatoes are normally largely grown from on-farm produced planting material, farms under quarantine have to purchase all planting material until seed potatoes can again be harvested on the farm. If the quarantine period of the field on which the detected lot was grown is longer than the applied crop rotation for potatoes, alternative land has to be rented in at least one year, assuming that the potato acreage on the farm remains the same. The minimum required crop rotation of potatoes in the Netherlands is 1:3, so a field quarantine period of three or more years will lead to extra costs.

The costs of additional samples taken on farms in their first year of quarantine are paid by the government. Seed and starch potato growers generally have contracts with a trading company or starch potato industry. If a potato lot is found infected, the company or industry loses the profit margin on this lot, which is approximately €1575.- / ha for seed potatoes and €170.- / ha for starch potatoes. The profit margin on a probably infected seed lot is €75.- / ha.

[1] These prices are excluding taxes; if the farmers are charged for the costs, the prices are increased with 19% V.A.T.

Table 4.1. Incidental costs for affected farms per potato category, in € per hectare.

Cost factor	Regular seed	Ware	Starch	Tbm seed
Detected lot				
Destruction of lot	1575	2250	1710	1125
Loss of total revenue	7770	4000	2280	4000
Probably infected lot				
Loss from marketing under restrictions	6895	3000	-	2500
Quarantine status of farm				
Prohibition on seed potato production	2935	-	-	930
Purchase of planting material	490	-	90	-
Quarantine status of field				
Rent of arable land	1500	1000	750	1250

4.3.3 Quantification of export losses

Quantification of export losses in relation to brown rot incidence is intricate. Available historical data on export volumes, seed potato prices, and brown rot incidence do not reveal any relationships. Export volumes fluctuate naturally over time, thereby masking potential small reductions in export due to brown rot outbreaks that have occurred in the past. Trading companies base their seed potato prices not only on (expected) demand, but also on the (expected) supply, which is assumed to be constant in the model but may vary substantially across years due to weather conditions. This latter effect biases the causal relationship between price and demand. Consequently, the export losses module is partly based on expert knowledge, and several assumptions and simplifications had to be made. In the remainder of this section, first a functional relationship between brown rot incidence and the level of export restrictions is defined. Next, the partial equilibrium model is developed, after which the economic consequences of a shift in export demand are quantified.

Relationship brown rot incidence – level of export restrictions

Export restrictions are categorized into four levels (L), which each correspond to a fractional reduction in export r. These levels are defined as 0 (no export losses, r=0), 1 (minor, r=0.05), 2 (major, r=0.20), and 3 (total export ban, r=1.0). The level of export consequences in a particular year is determined by the number of brown rot detections in Dutch potatoes in the Netherlands (DN_i) and abroad (DA_i), with i =0 indicating the number of detections in the current year and

i=1 the 'historical level' of detections. The historical level is calculated as the weighted average of the number of detections in the five years preceding the current year. It is presumed that the impact of detections on the level of export restrictions decreases with time, so the relative contribution of previous years to the average decreases with 50% per year.

Levels 1 to 3 of export restrictions are characterised by 'critical values' DN_{iL} and DA_{iL}. The critical value DN_{iL} (DA_{iL}) represents the *minimum* values of DN_i (DA_i) that result in level L with DA_i (DN_i) being zero. The two variables are non-additive, i.e. detections abroad have a larger impact on the level of export restrictions than detections in the Netherlands. This is because detections abroad imply that the Dutch monitoring system is not reliable. Furthermore, the relative importance of DN_i is large if DA_i is small and vice versa (see Figure 4.3). In other words, if DN_i is relatively low and DA_i is relatively high, the level of export restrictions is almost completely determined by DA_i, and DN_i has to increase a lot in order to let the level of export restrictions increase. Given this relationship between DN_i and DA_i, each level L of export restrictions can be described by an elliptic function:

$$\left(\frac{DN_i}{DN_{iL}}\right)^2 + \left(\frac{DA_i}{DA_{iL}}\right)^2 \geq 1 \qquad i = 0, 1 \tag{4.1}$$

We call this equation the export equation for level L. Each level has two export equations: one for the number of detections in the current year and one for the weighted number of detections in the previous 5 years. For each export equation, there are many combinations of DN_i and DA_i that cause the left hand side to equal 1. The curve on which these combinations are located is called an iso-consequence curve (Figure 4.3). For each year in a simulation, the actual values of DN_i and DA_i can be filled in the export equations of each level of export losses. The highest level L for which at least one of the two export equations equals one or higher is the level of export restrictions achieved in that year. After a reduction in export volume due to brown rot, the foreign demand will gradually recover over time. Therefore, export restrictions can decrease at maximum one level per year.

Countries differ in their risk perception with respect to brown rot. Dutch seed potatoes are exported to a large number of countries, and it is impossible to define critical values for each individual country. Therefore, importing countries of Dutch seed potatoes are divided into two regions: the European Union (*EU*), i.e. countries in which the same international brown rot regulations apply as in the Netherlands, and the rest of the world (*rest*). The two regions have different values for $DN_{i,L}$ and $DA_{i,L}$ (see Table 4.2), and the level of export restrictions in a year may differ per region.

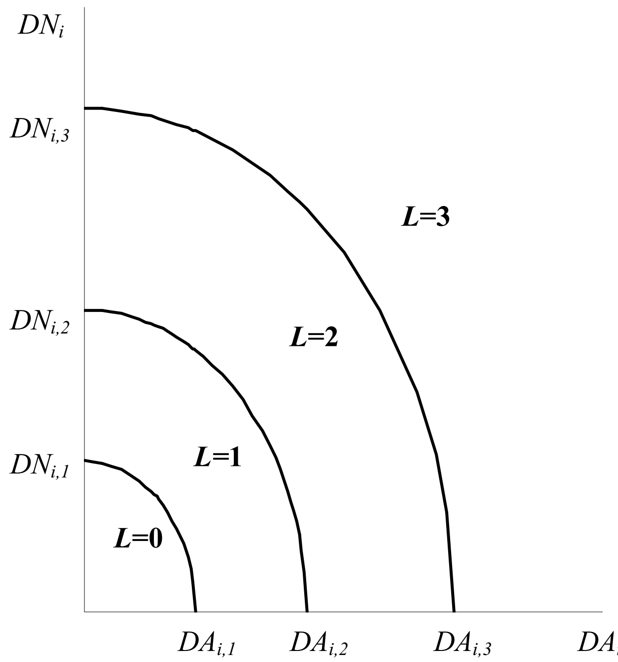

Figure 4.3. Graphical representation of the relation between the detection incidence in Dutch potato lots in the Netherlands (DN_i) and in other countries (DA_i), and the level of export losses (L). The iso-consequence curves determining the export level and the axes intersect in the critical values.

Development of the partial equilibrium model

Total quantity demanded (Q_{tot}) depends on price p and consists of domestic demand (Q_{NL}) and demand of the two export regions (Q_{EU} and Q_{rest}). Demand is presented by a simple constant elasticity functional form, viz. $Q_j = \alpha_j \cdot p^{\varepsilon_j}$, where ε_j is the import demand elasticity of region j. We assume that seed potatoes are a homogenous product, and that there is no price discrimination between the three markets. The seed potato price for export regions EU and $rest$ is therefore equal to the domestic seed potato price plus a fixed value representing transport and handling costs (τ_j). A reduction r_j in demand of export region j implies a constant relative decrease in demand over the whole range of p; the demand function is thus multiplied by 1-r_j. The domestic demand elasticity is assumed to equal zero; substitution possibilities for Dutch seed and ware potato growers are very small in the short run and Dutch growers are unlikely to buy potatoes from another country ($Q_{NL} = \overline{Q}_{NL}$). Consequently, domestic demand is not affected by a change in price. The resulting aggregated demand function is described by the following equation:

$$Q_{tot} = \overline{Q}_{NL} + (1 - r_{EU}) \cdot \alpha_{EU} \cdot (p + \tau_{EU})^{\varepsilon_{EU}} + (1 - r_{rest}) \cdot \alpha_{rest} \cdot (p + \tau_{rest})^{\varepsilon_{rest}} \tag{4.2}$$

where α_j, τ_j, ε_j, and $\overline{Q}_{NL}$ are constant and r_j follows from the previous step in the export module. The price setting curve of Dutch trading companies is assumed to be a linear function of demand:

$$p = w + \lambda \cdot Q_{tot} \tag{4.3}$$

where the slope λ reflects the change in p relative to a change in Q_{tot} and intercept w represents the opportunity costs of selling seed potatoes on the ware potato market. In most years the ware potato market is over-saturated; therefore, we assume a minimum ware potato price, which equals the feed potato price and is constant over time. Seed potatoes sold as ware potatoes do not need to be certified, which saves costs of certification. Thus, w equals the feed potato price plus certification costs. An analytical solution of equations 4.2 and 4.3 for endogenous variables p and Q_{tot} is not possible; however, the equilibrium values of p and Q_{tot} can be numerically determined for any level of export restrictions (r_{EU} and r_{rest}).

Quantification of economic consequences

A shift in equilibrium resulting from reduced demand results in a lower seed potato price and a larger surplus (Z), resulting in losses for seed potato growers. At the same time, the reduction in price causes benefits for 'consumers'; domestic seed and ware potato growers have lower costs of planting material. Part of the producer loss or consumer benefit may come at the account of trading companies; however, this will not affect the total losses and benefits. In the new equilibrium, producer loss (C) is calculated as:

$$C = (p_0 \cdot Q_{tot,0} + w \cdot Z_0) - (p_1 \cdot Q_{tot,1} + w \cdot Z_1) = Q_{tot,1} \cdot \Delta p + \Delta Q_{tot} \cdot (p_0 - w) \tag{4.4}$$

Where the prices and quantities in the original and new equilibrium have indices of respectively 0 and 1, Δp is the decrease in seed potato price, and ΔQ_{tot} is the decrease in demand, i.e. the increase in surplus. The benefits (B) for domestic seed and ware potato growers are:

$$B = \overline{Q}_{NL} \cdot \Delta p \tag{4.5}$$

Note that the planting material required per hectare is much smaller than the yield per hectare; the losses are thus much higher than the benefits. The net export losses equal the difference between C and B.

Table 4.2 provides descriptions and values of all parameters required for quantification of export losses, including their values. Most parameters are based on empirical data on production and export volume and price of seed potatoes; for information on data and sources, see Appendix 4-II. No data exist on critical values; these parameters were therefore estimated in consultation with six experts. Neither were import demand elasticities for seed potatoes available; instead, they were estimated on the basis of domestic demand elasticities for ware potatoes in the Netherlands and the UK (Bailey et al., 2000; Jongeneel, 2000) and import demand elasticities for other consumer goods (Erkel-Rousse and Mirza, 2002; Hong, 1999; Thomakos and Ulubasoglu, 2002). For simplicity, ε_{EU} and ε_{rest} were assumed to have the same value. The import demand elasticity can also be analytically derived from domestic supply and demand in importing countries, as is done in Appendix 4-II. The data used for this calculation were incomplete and subject to uncertainty. Nevertheless, the fact that the calculated value for ε is comparable to the estimated value supports confidence in the plausibility of the parameter value used. Because of the large uncertainty about critical values and import demand elasticity, a sensitivity analysis was performed to test the robustness of the model for these parameters (results are presented in section 4.4).

Table 4.2. Values and descriptions of parameters required by the export losses module of the economic model.

Parameter	Description	Unit	Value
Iso-consequence curves			
$DN_{0,L}$ (EU)	Critical values of DN_0 for the EU	-	20^1, 100^2, 200^3
$DN_{0,L}$ (rest)	Critical values of DN_0 for the rest of the world	-	50^1, 200^2, 1000^3
$DA_{0,L}$ (EU)	Critical values of DA_0 for the EU	-	10^1, 50^2, 100^3
$DA_{0,L}$ (rest)	Critical values of DA_0 for the rest of the world	-	20^1, 100^2, 200^3
$DN_{1,L}$ (EU)	Critical values of DN_1 for the EU	-	15^1, 25^2, 100^3
$DN_{1,L}$ (rest)	Critical values of DN_1 for the rest of the world	-	25^1, 50^2, 200^3
$DA_{1,L}$ (EU)	Critical values of DA_1 for the EU	-	5^1, 10^2, 50^3
$DA_{1,L}$ (rest)	Critical values of DA_1 for the rest of the world	-	10^1, 20^2, 100^3
Partial equilibrium model			
α_j	Coefficient of demand function for seed potatoes	-	264000^a, 14220600^b, 11000000^c
ε_j	Price elasticity of demand for seed potatoes	-	-0.0^a, -1.0^b. -1.0^c
τ_j	Price increase for exported potatoes	€ct/kg	4.1^b, 9.5^c
λ	Increase in market price of seed potatoes per tonne increase of demand	€ct·kg^{-1}/(kg·10^3)	$0.29 \cdot 10^{-4}$
w	Price of seed potatoes when sold as ware potatoes	€ct/kg	2.5
$\overline{Q}_{NL}$	Domestic demand for seed potatoes	kg·10^3	264000

Explanation of indices: a, b, c = Netherlands, EU, and rest of the world, respectively. Indices 1, 2, and 3 represent corresponding levels of export restrictions.

4.4 Model application

To illustrate the relevance of the bio-economic model in acquiring more insight into the economics of controlling quarantine diseases, we apply it to the current Dutch brown rot control policy (2006). Under this policy, a national ban on irrigation of seed potatoes with surface water applies, while irrigation of other potatoes with surface water is only allowed in regions where this water is free of brown rot bacteria. All regular seed lots, as well as tbm seed potatoes grown on farms that also produce regular seed potatoes, are sampled at a density of 1 sample per lot; ware and starch lots are tested at random. If a lot is found to be infected it is destroyed, and other lots that may have been in contact with the detected lot are traced back and tested at increased density. Lots grown on the farm on which an infected lot has been detected are – if they are not found to be infected – defined probably infected, as are lots of which at least two ‘sister’ lots (i.e. having the same parent) were found to be infected. The farm on which the infected lot was grown is put into quarantine for three years, during which sampling frequency and density is increased. Production of seed potatoes on this farm is prohibited in the first (and second, in case of tbm seed potatoes) year after detection. The field on which the detected lot has been grown is put into quarantine for at least four years, so the farmer will have to rent land in the third year after detection.

The benefits of the current control policy equal the reduction in export losses compared to a situation without brown rot control. Such situation is unthinkable as it will ultimately lead to a permanent export ban and collapse of the whole Dutch potato sector. Hence, we compare the current policy with a relaxed scenario, which differs from the base scenario in that only 10% of all seed lots are sampled. The two scenarios will further be referred to as the ‘default’ and ‘reduced monitoring’ scenario. Each simulation consists of 500 replications to ensure that results are representative for the simulated scenario. A replication covers a period 20 years and starts with a production chain that is free of brown rot. To allow the system to achieve a level of brown rot incidence that is in accordance with the simulated scenario, analysis of results is based on years 6 to 20 of the replications.

Table 4.3 shows the mean and the 5, 50 and 95 percentiles of average yearly costs for the default and reduced monitoring scenario, specified per cost category. The numbers of brown rot detections in subsequent years of a replication are correlated (see section 4.4.2), so the values represent average yearly costs per replication. According to the mean values for incidental costs in Table 4.3, in the reduced monitoring scenario the total costs of brown rot presence and control are 1.6 times higher than in the default scenario. The difference in total costs is mainly due to export losses, which increase almost tenfold when reducing the sampling frequency of potato lots. According to the percentiles, average yearly incidental costs and export losses strongly vary between replications. For both cost categories the means are higher than the medians, i.e.

their distributions are positively skewed. In the following subsections, the simulation results for the individual cost categories are discussed in more detail.

Table 4.3. Mean and 5, 50, and 95 percentile values of average yearly costs per replication in mln € per year, for the default and reduced monitoring scenario.

Cost category	Default scenario				Reduced monitoring scenario			
	mean	5%	50%	95%	mean	5%	50%	95%
Structural costs	6.1	6.1	6.1	6.1	3.6	3.6	3.6	3.6
Incidental costs	0.72	0.34	0.69	1.1	1.4	0.41	1.4	2.8
Export losses	0.81	0.0	0.0	3.2	7.5	0.0	6.5	18.6
Total costs	7.7	6.5	7.2	10.6	12.5	4.2	11.6	24.7

4.4.1 Structural costs

The costs of sampling potato lots are approximately 3 mln euros per year for the default scenario, as compared to 0.5 mln euros per year for the reduced monitoring scenario. Reducing the sampling frequency of seed lots thus causes a major reduction in structural costs. The economic consequences of the irrigation ban are the same for both strategies. Approximately 1000 ha of seed potatoes have reduced quality, of which 50 ha have serious quality loss. Another 3000 ha of seed potatoes and 300 ha of ware potatoes suffer from drought stress. The total losses from the irrigation ban equal 3 mln euros per year for both scenarios.

4.4.2 Incidental costs

Incidental costs are directly related to the number of detections. Figure 4.4 shows the cumulative frequency distribution of the yearly number of detections (a) and the average yearly number of detections per replication (b). Under the reduced monitoring scenario, infected seed lots are less likely to be detected than under the default scenario. Infected seed lots that are not detected or exported remain in the production chain, where they can cause an accumulation of infected lots over time. If eventually one lot is detected, tracing may lead to detection of many other infected lots. Consequently, the reduced monitoring scenario has a slightly higher frequency of zero detections and a wider distribution of the yearly number of detections than the default scenario (Figure 4a). Figure 4b shows that when yearly numbers of detections are averaged per replication, the curve corresponding to the reduced monitoring scenario lies completely to the right of that for the default scenario. Thus, over a period of 15 years, the 'advantage' of more years with no detections is more than offset by one or more years with a large number of detections.

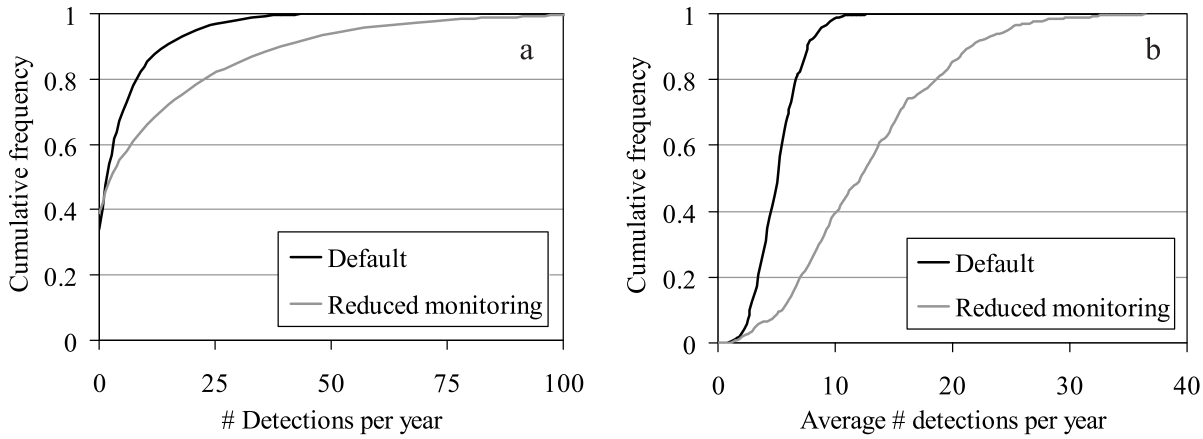

Figure 4.4. Cumulative frequency distributions of the yearly number of detections, as observed in individual years (a) and averaged per replication (b).

The cumulative frequency distributions of the yearly incidental costs and average yearly incidental costs per replication (Figure 4.5a and b) are consistent with Figure 4.4a and b, confirming the strong relation between the number of detections and incidental costs. When comparing individual years, the reduced monitoring scenario brings along lower or equal incidental costs than the default scenario in approximately 40 percent of all years. However, over an extended time period good years (i.e. years with low incidental costs) are always followed by one or more bad years, causing the default scenario to have the lowest average incidental costs in almost all replications. The difference between Figure 4.5a and b stresses the importance of taking into account year to year variation when determining the cost-effectiveness of a control policy.

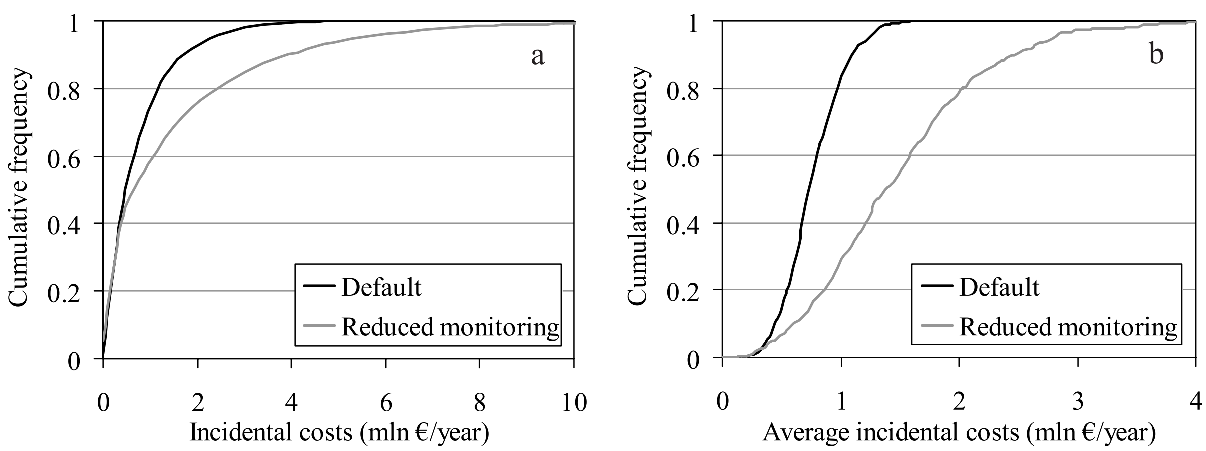

Figure 4.5. Cumulative frequency distributions of the yearly incidental costs, as observed in individual years (a) and averaged per replication (b).

Incidental costs are an enumeration of various cost factors related to detection of an infected lot. Table 4.4 shows the absolute and relative contribution of these factors to the total average incidental costs. This overview can be a starting-point for policy-makers in increasing the cost-effectiveness of a control strategy. It shows for instance that while downgrading of probably infected lots is considered a safety measure to exclude any risk of overlooking an infected lot, it accounts for roughly 60 percent of the total incidental costs. Increased sensitivity of the brown rot test would make this measure less necessary and thereby drastically reduce incidental costs. Furthermore, there is a trade-off between the structural costs and the costs of tracing; the higher the monitoring intensity, the more samples are taken regularly and the fewer samples have to be taken for tracing purposes.

Table 4.4. Absolute and relative contribution of different types of incidental costs to the total average yearly incidental costs.

Cost category	Default scenario		Reduced monitoring scenario	
	Absolute (€)	Relative (%)	Absolute (€)	Relative (%)
Destruction of detected lots[1]	70,361	10	165,497	12
Downgrading of probably infected lots[1]	440,847	61	851,248	59
Tracing of other lots	8,919	1	76,486	5
Increased sampling on quarantine farms	9,325	1	23,818	2
Consequential losses[2]	191,704	27	321,152	22
Total	721,155	100	1,438,201	100

[1] Including loss of profit margins for trading companies and industry.

[2] Consequential losses are all losses incurred by affected farmers as a result of restrictions to potato production in

4.4.3 Export losses

Equations 4.2 to 4.5 were used to calculate the yearly export losses for each combination of export restriction levels for the EU and rest of the world (Table 4.5). Given an average supply of 1.19 mln tonnes, losses in years with export restrictions range from 4.2 mln to 192 mln euros. As the critical values of brown rot detections are higher for the rest of the world than for the EU, price reductions at the right of the main diagonal are not observed in practice.

Table 4.5. Losses from reduced export of Dutch seed potatoes for each combination of export levels in the EU and the rest of the world, in mln euros per year.

		Level of export restrictions – rest of the world			
		0	1	2	3
Level of	0	0.0	4.2	17.0	82.3
export	1	6.4	10.6	23.3	88.4
restrictions	2	25.5	29.6	42.2	106.3
- EU	3	125.4	129.4	140.8	192.1

Export losses in a year are partly dependent on the historical level of detections, i.e. the number of detections in the preceding five years. The first historical level can be calculated over year six to ten of a replication, so export losses per replication are calculated for year 11 to 20. Figure 4.6 shows for both scenarios the cumulative distribution of average yearly export losses per replication. The curves are not completely smooth because the range of possible export losses is not continuous. The default scenario is dominant to the first order over the reduced monitoring scenario, which implies that with respect to average yearly export losses the default scenario is always more cost-effective than reduced monitoring scenario. Nevertheless, even under the default scenario export losses are observed in almost 50 percent of all replications.

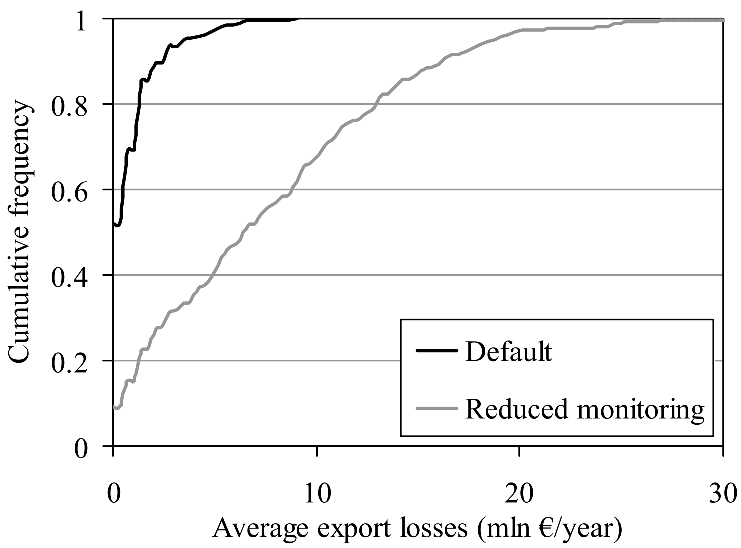

Figure 4.6. Cumulative frequency distributions of average yearly export losses per replication, for the default and reduced monitoring scenario.

A sensitivity analysis was performed on two types of parameters in the export losses module, i.e. the critical values ($DN_{i,L}$ and $DA_{i,L}$) and the import demand elasticities (ε_{EU} and ε_{rest}). We measured the effect of a 10% change in critical values and a 50% change in import demand elasticity on average yearly export losses and average total costs of brown rot (Table 4.6). The import demand elasticities were varied over a wider range than the critical values, because their default value is much lower than the default values of the critical values and a 10% change would have a minimal impact on their absolute value. Changes in parameter values lead to a considerable increase or decrease of average yearly export losses, varying from 13% to 37% compared to the default value. The impact of a change in parameter values on the total costs of brown rot is much smaller. The sensitivity of average yearly total costs to a change in parameter values is highest for the reduced monitoring scenario, because in this scenario export losses comprise a much larger part of the total costs than in the default scenario.

Given the range of 10%, respectively 50% over which the critical values and elasticities are changed, average yearly export losses are particularly sensitive to the critical values. These parameters determine the frequency of export losses, and even a small increase in the frequency of export restrictions has a considerable impact on the average yearly export losses. For instance, the occurrence of export restriction level 1 to the EU in one year of one replication causes a loss of 6.4 mln euros in that year, and increases the average yearly export losses over 500 replications with 1.3 thousand euros. A larger number of export levels would decrease the sensitivity as the difference in losses between subsequent levels would become smaller; on the other hand, a larger number of critical values would have to be estimated.

Table 4.6. Effect of a 10% change in critical values and a 50% change in import demand elasticity on average yearly export losses and average yearly total costs in mln euros in the default and reduced monitoring scenario. The relative change (%) compared to the default critical values is indicated between brackets.

Scenario	Default scenario		Reduced monitoring scenario	
	Average yearly export losses	Average yearly total costs	Average yearly export losses	Average yearly total costs
Default	0.81	7.7	7.5	12.5
Change in $DN_{i,L}$ and $DA_{i,L}$				
10% increase	0.59 (-28)	7.4 (-3)	6.6 (-13)	11.5 (-8)
10% decrease	1.1 (+37)	8.0 (+4)	8.9 (+18)	13.8 (+11)
Change in ε_{EU} and ε_{rest}				
50% increase	0.70 (-15)	7.5 (-2)	6.5 (-14)	11.5 (-8)
50% decrease	9.8 (+20)	7.8 (+2)	9.0 (+20)	14.0 (+12)

Although the average yearly export losses are rather sensitive to the critical values and import demand elasticities, the bio-economic model is robust with respect to the ranking of control strategies. Export losses, if they occur, are of considerable magnitude compared to the other categories of costs resulting from brown rot. Consequently, a control policy resulting in a low frequency of export losses will always be more cost-effective than a control policy that causes a high frequency of export losses.

4.5 Summary and conclusions

This chapter presents a bio-economic modelling concept for quantifying the costs and benefits of controlling quarantine diseases. The concept was implemented to evaluate strategies for brown rot control in the Dutch potato production chain for their cost-effectiveness. As the examples in this study show, short term gains by economising on monitoring and control could easily result in long term costs that more than outweigh the initial savings. Results also indicate that the time frame over which control strategies are evaluated affects calculated cost-effectiveness. Thus, export consequences and future costs should be accounted for when designing optimal control policies.

The quantification of export losses is delicate as it requires far-reaching simplifying assumptions on potentially variable and uncertain economic relationships. Results of the sensitivity analysis indicate that, although the export losses module is rather sensitive to a change in parameter values, the bio-economic model is robust with respect to ranking of scenarios for their cost-effectiveness. Export losses are of such magnitude that even a relatively large change in their values would not alter the conclusion on cost-effectiveness of the two scenarios that were compared. The export losses module only focuses on price effects; in practice, export restrictions have additional possible consequences on the potato sector. For instance, low revenues will invoke farms to produce more profitable crops instead, and even may force farms to quit seed potato production because their liquidity is too low. Also, as seed potato production and ware potato production are highly interrelated, it is likely that in case of severe or prolonged export losses also the ware potato sector is affected.

Scenario-studies, such as those presented in Figures 4.4 to 4.6, elucidate the short and long term costs and benefits of alternative brown rot control policies, and they may assist in policy development. Moreover, they objectify the economic importance of a control policy, which improves confidence of stakeholders in the authorities and support for – often costly – preventive measures. The approach for cost quantification is generic and suitable for application to other quarantine diseases and countries. Integration into a bio-economic model requires that the behaviour of the quarantine organism in the susceptible production chain and the effect of control measures on it are reasonably well-known. However, once such model is developed, a powerful tool is available for quarantine disease management.

Acknowledgements

We thank Dr. R. Jongeneel for his assistance in the development of the partial equilibrium model. We also thank the experts who were consulted for their cooperation in parameterisation of the export losses module. We acknowledge HZPC Holland B.V., the Dutch Potato Organisation (NAO), and the Dutch General Inspection Service for Agricultural Seed and Seed Potatoes (NAK) for providing the required data.

Appendix 4-I Justification of parameters in incidental costs module

Table 4-IA. Production characteristics of potatoes, per category.

	Regular seed	Ware	Starch	Tbm seed
Total Dutch acreage (ha)	39,000	70,500	45,000	3,500
Average lot size (ha)	1.40	2.47	3.15	0.73
Planting density (kg/ha)	5,000	2,500	2,300	3,500
Yield (kg/ha)	35,000	50,000	38,000	25,000

Table 4-IB. Prices of planting material and yield in eurocents per kg.

	Regular seed	Ware	Starch	Tbm seed	Feed[1]
Purchase of planting material	38	30	20	40	-
Sale of harvested potatoes	22	8	6	-	2
Value of on-farm replanted potatoes	24	-	-	16	-

[1] Feed potatoes are ware potatoes sold to the feed industry.

Data in Table 4-IA and 4-IB are used to calculate the economic data per hectare presented in Table 4-IC. Costs and revenues per hectare are based on the following assumptions:

1. On average 10% of the harvested seed potatoes is replanted as seed potatoes on the same farm in the next growing season. Correspondingly, 70% of the seed potato acreage is grown from on-farm propagated planting material.
2. All starch potatoes are grown from (on-farm produced) tbm seed potatoes.
3. Seed (including tbm) potatoes produced for on-farm multiplication purposes are included in the costs of planting material and revenue of harvested potatoes, at a value as indicated in Table 4-IB.
4. Probably infected seed and ware potatoes are assumed to be sold to the feed industry at 2 €ct/kg. Probably infected starch potatoes can be sold to the starch industry at the normal price; tbm potatoes are sold as starch potatoes.

Table 4-IC. Economic data on potato production in euros per hectare. Costs of planting material and revenue are based on tables 4-IA and 4-IB.

	Regular seed	Ware	Starch	Tbm seed
Costs of planting material	1410	750	370	1400
Additional production costs[1]	1600	1600	1250	1100
Costs of certification[2]	160	0	0	0
Revenue	7770	4000	2280	4000
Gross margin	4600	1650	660	1500
Revenue if probably infected	700	1000	2280	1400
Destruction costs[3]	1575	2250	1710	1125

[1] Additional production costs comprise fertilizer, crop protection costs, energy, etc.

[2] Seed potatoes have to be certified in order to be traded, the costs of which are paid by the farmer.

[3] Destruction costs are 45 euros per 1000 kg.

Sources: Statistics Netherlands (CBS, 2006), Dutch General Inspection Service for Agricultural Seed and Seed Potatoes (Toussaint, 2005), Applied Plant Research (Dekkers, 2001), HZPC Holland B.V. (Hoogenboom, 2005).

Appendix 4-II Justification of parameters in export losses module

Table 4-IIA. Average production and export volumes of Dutch seed potatoes.

Variable	Total	Netherlands	EU	Rest of the world
Supply (kg $\cdot 10^3$)[1]	1190000			
Demand (kg $\cdot 10^3$)	950000	264000	411000	275000
Market price of seed potatoes (€ct/kg)		30.5	34.6	40.0

[1] Excluding the amount of seed potatoes destined for on-farm multiplication. Supply exceeds total demand as trading companies accept a limited surplus of seed potatoes to avoid shortage of supply in years with low yields per hectare.

Calculation of import demand elasticity

The import demand elasticity can be quantified by the following equation:

$$\varepsilon_p^{imp} = \varepsilon_p^d \cdot \frac{D}{M} - \varepsilon_p^s \cdot \frac{S}{M}$$

Where ε_p^d is the domestic demand elasticity, ε_p^s is the domestic supply elasticity, D is demand, S is domestic supply, and M is the difference between supply and demand. Production, import, and export data of seed potatoes are only available for a number of countries within the EU. Therefore, we base the quantification of ε_p^{imp} on aggregated data of seven major importing countries of Dutch seed potatoes in the EU, i.e. France, Belgium, Germany, UK, Italy, Spain, and Portugal.

Total acreage of seed potatoes:		52,150 ha
Average marketable yield per hectare:		30 tonnes
Total gross supply:	(52150 · 30)	1564,000 tonnes
Export:		300,000 tonnes
Total net supply (S):	(1564 – 300)	1264,000 tonnes
Imports (M):		350,000 tonnes
Total demand (D):	(1264 + 350)	1614,000 tonnes

The values of the domestic price elasticities are unknown. Therefore, these elasticities are estimated on the basis of price elasticities for ware potatoes (Bailey, et al., 2000, Jongeneel, 2000). Elasticities for seed potatoes will be lower than elasticities for ware potatoes, because consumers of seed potatoes have fewer substitution possibilities and seed potatoes are produced by specialized farmers.

Demand elasticity: -0.1

Supply elasticity: 0.15

Using these data, the value of ε_p^{imp} is:

$$\varepsilon_p^{imp} = -0.1 \cdot \frac{1614}{350} - 0.15 \cdot \frac{1264}{350} = -1.003$$

Sources: Statistics Netherlands (CBS, 2006), United Nations (United Nations, 2006), Dutch General Inspection Service for Agricultural Seed and Seed potatoes (NAK, 2006), Dutch Potato Organisation (NAO, 2006), HZPC Holland B.V. (Hoogenboom, 2005).

CHAPTER 5

Options for cost-effective control of a quarantine disease: a quantitative exploration using 'Design Of Experiments' methodology and bio-economic modelling

This chapter has been submitted as: Breukers, A., W. van der Werf, J.P.C. Kleijnen, M. Mourits, and A. Oude Lansink.

Abstract

An integrated approach in control of quarantine diseases at the level of the plant production chain is complicated. The involved actors have different interests and the system is complex. Consequently, control policies may not be cost-effective. By means of a bio-economic model for brown rot in the Dutch potato production chain, the efficacy of different control options is quantitatively analysed. An impact analysis was performed using the methodology of 'Design of Experiments', to quantify the effect of factors in interaction on incidence and costs of brown rot. Factors can be grouped as policy, sector, economic, and exogenous factors. Results show that brown rot incidence and economic consequences are predominantly determined by policy and sector factors and to a lesser extent by economic and exogenous factors. Scenario studies were performed to elucidate how the government and sector can optimise the cost-effectiveness of brown rot control. Optimal cost-effectiveness of control requires cooperation of the sector and government, in which case brown rot incidence can be reduced by 75% and the costs of control can be reduced with at least 2 mln euros per year. This study quantitatively demonstrates the potential contribution of an integrated approach to cost-effective disease control at chain level.

5.1 Introduction

An integrated approach to the control of plant pests and diseases has long since been acknowledged as being important. In the second half of the twentieth century, the concept of Integrated Pest Management (IPM) gained wide acceptance. IPM is defined as 'a decision support system for the selection and use of pest control tactics, singly or harmoniously coordinated into a management strategy, based on cost/benefit analyses that take into account the interests of and impacts on producers, society, and the environment' (Kogan, 1998). IPM is mainly practiced at field scale, by individual farmers. By contrast, control of quarantine diseases generally focuses at the entire production chain. Unfortunately, at chain level, an integrated approach to the control of quarantine diseases is uncommon. Control policies are generally designed from a policy point of view, and consist of mainly regulatory measures imposed by the government (see e.g. Gottwald et al., 2001; Heikkila and Peltola, 2004).

One important reason for this is that a production chain consists of many actors with different, possibly conflicting interests. It is unclear how these different interests are weighed into the design of control policies, if at all. Moreover, enforcement of measures is often based on qualitative, rather than quantitative knowledge of their costs and effectiveness. Consequently, such policies may not be optimal from an epidemiological or economic point of view. An integrated approach at chain level would imply: taking into account the potential contributions and interests of the actors at different levels of the production chain. Development and scientific foundation of such approach requires quantitative knowledge of how actions of (groups of) actors affect cost-effectiveness of disease control at chain level.

From this follows another reason for the lack of integrated approaches at chain level: as disease prevalence and control take place at a larger scale, dispersal patterns of diseases and potential intervention points are less well understood (Irwin, 1999). Whereas numerous models have been developed to support disease control at field level (e.g. Holt et al., 1999; Brown et al., 2002; Jones, 2004; Willocquet et al., 2004), relatively few models focus on disease control at the level of the production chain (e.g. Stacey et al., 2004) – let alone models that account for the interests of different groups of actors in this chain. Disease dynamics at chain level have been modelled at fundamental level (e.g. Van den Bosch et al., 1999; Otten et al., 2003; Filipe and Maule, 2004). The resulting theoretical models, however, have limited applicability in the practical environment of disease control (Teng and Savary, 1992).

This chapter provides a quantitative analysis of the possibilities for increasing the cost-effectiveness of quarantine disease control by combining actions at different levels in the chain. An impact analysis and scenario studies are performed with a mechanistic and individual-based bio-economic model that simulates the epidemiological consequences and cost-effectiveness of controlling brown rot (caused by *Ralstonia solanacearum* race 3, biovar 2) in the Dutch potato production chain. Parameters of the model represent policy options, characteristics of actors in the potato production chain (e.g. farmers, trading companies), and socio-economic and environmental conditions. To date, it has been a matter of debate as to which factors are of crucial importance in determining the cost-effectiveness of control, and how a more cost-effective control of brown rot may be achieved.

By means of the impact analysis, the effects of factors on the incidence and costs of brown rot are quantified. Here, the techniques of Design of Experiments and regression metamodelling are applied, following Kleijnen and Sargent (2000). Scenario studies are performed to elucidate how different strategies of the government and the actors in the potato production chain affect the cost-effectiveness of brown rot control. These strategies are defined according to two objectives: minimising disease incidence and minimising costs. The results presented in this chapter quantitatively demonstrate how an integrated approach can contribute to cost-effective control of quarantine diseases at national scale.

5.2 Theory and approaches

5.2.1 The bio-economic model

The bio-economic model consists of a combined epidemiological and economic model. The epidemiological model simulates the spread of potato brown rot over potato farms and fields in the Netherlands during a sequence of years (Chapter 3). The smallest entity in the model, whose behaviour is modelled, is the potato lot. A lot is defined as a population of potato plants or tubers, of common descent, and being grown in one field under the same management, or being processed or stored as a single unit. Infections can arise via three possible pathways: primary infection, horizontal transmission, and vertical transmission. Primary infection occurs through irrigation of a potato lot with contaminated surface water. Brown rot bacteria can enter the surface water through infected plants of bittersweet (*Solanum dulcamara*), a host that is common along Dutch waterways. Horizontal transmission occurs through direct or indirect, machinery-mediated, contact between a healthy lot and an infected lot. Vertical transmission implies transmission of the disease as a result of clonal propagation of infected potato seed. The epidemiological model is spatially explicit, enabling spatial analysis of brown rot incidence and dispersal. It also contains stochastic elements to represent the irregularities characteristic for brown rot dynamics. Development and validation of this model have been described in Chapters 3 and 4. An extensive technical description of the model code is given by Breukers et al. (2006).

The economic model uses the output of the epidemiological model to quantify the corresponding annual costs of controlling brown rot as well as the losses resulting from its presence (Chapter 4). This model contains three cost categories: structural costs, incidental costs, and export losses. Structural costs are incurred as a consequence of preventive measures, such as monitoring. Incidental costs are related to reactive measures, such as destruction of an infected lot and quarantine measures on infected farms following a disease incident. Export losses occur if the observed level of brown rot incidence reaches a level that is unacceptable for countries importing Dutch potatoes. The economic model quantifies only those costs that are completely attributable to brown rot.

The stochastic nature of the epidemiological model allows the bio-economic model to present both average results and variation between years in brown rot incidence and economic consequences. To generate accurate simulation outcomes, the impact analysis is based on 500 replicates for each simulated scenario. Each simulation replicate covers a period of 20 years, the first five years of which are discarded to allow the system to 'settle in' from the initial conditions to the long term level and year to year variability. This period of 20 years is sufficient to allow for observation of potential long-term effects of the scenario on the modelled system (Chapter 3).

5.2.2 Impact analysis: DOE and metamodelling

The effects of model parameters on the simulated incidence and economic consequences of brown rot were estimated by means of metamodelling. A metamodel is a simple functional relationship between the simulation model's input variables (also called factors) and a specific output (response variable) (Kleijnen, 2005). This relationship can be estimated by means of regression analysis on the simulation inputs and output of a number of scenarios. The scenarios required for this estimation were selected through the techniques of Design of Experiments (DOE). DOE is an efficient method for performing an impact analysis, because it allows for estimation of factor effects on the basis of a minimum number of scenarios. Furthermore, DOE enables the estimation of interactions among inputs (Kleijnen and Van Groenendael, 1992).

The number of scenarios required for metamodelling depends on the number and type of effects that need to be estimated. In the current impact analysis, main effects and two-factor interactions were quantified. Higher-order effects were not estimated because they are difficult to interpret and often have negligible magnitudes (Kleijnen, 2005). Unbiased main effects, even when factors interact, were obtained by means of a so-called Resolution IV (R-4) design, while an R-5 design was used to estimate unbiased two-factor interactions (Banks, 1998). Both designs require only two levels for each factor (standardised to -1 and +1). Mathematically, a metamodel with main effects and two-factor interactions is represented by the following equation:

$$y_{i,j} = \beta_0 + \sum_{h=1}^{k} \beta_h x_{i,h} + \sum_{h=1}^{k-1} \sum_{h'=h+1}^{k} \beta_{h,h'} x_{i,h} x_{i,h'} + e_{i,j} \tag{4.1}$$

where $y_{i,j}$ represents the average simulation response of scenario i in replication j, $x_{i,h}$ the level of factor h in scenario i, β_0 the intercept (overall response), β_h the main effect of factor h, $\beta_{h,h'}$ the interaction between factors h and h' ($h = 1,\ldots, k$), and $e_{i,j}$ the fitting error of the regression model in replication j of factor combination i. Whereas the bio-economic model has numerous outputs, a univariate regression metamodel such as equation 4.1 has only one response variable. Therefore, a unique metamodel was estimated for each model output of interest.

Metamodels were fitted (calibrated) by means of Corrected Least Squares (CLS) (Kleijnen and Van Groenendael, 1992). A more common method is Ordinary Least Squares (OLS); however, this method assumes independent, normally distributed errors with zero expectation and constant variance. In the current application, the errors are heteroscedastic, and they are correlated across scenarios because the set of initial seeds used in the 500 replications is the same for each scenario. CLS corrects the variances of the β's for the observed variances and covariances in simulation outputs. Significance of the estimated effects was tested through a Student t statistic (Kleijnen and Van Groenendael, 1992).

5.2.3 Impact analysis: selection of factors and factor levels

Criteria for model parameters to be included in the R-4 design were: (1) they potentially affect the incidence or economic consequences of brown rot, (2) a change in their values within a time frame of five years is possible, and (3) the current structure of the Dutch potato production chain is preserved if their values are changed. Applying these criteria, a total of 33 factors were selected, divided into four categories: policy, sector, economic, and exogenous factors. Policy factors define control measures imposed by the government, such as sampling intensity of potatoes and quarantine measures imposed on affected farms. Sector factors represent structural and behavioural characteristics of actors in the potato production chain, such as the hygiene level, likelihood of disobeying brown rot regulations, and type of transport. Economic factors represent prices of inputs and products, and costs of preventive and reactive measures. Exogenous factors describe social and environmental characteristics that are relevant for brown rot presence and control (e.g. climate) and the brown rot situation abroad.

Table 5.1 (pg. 86-87) provides an overview of all factors and their acronyms, default levels, upper levels, and lower levels. The first letter of each acronym indicates the factor category (p = policy, s = sector, € = economic, e = exogenous factor). Default levels correspond to the factor level that is currently observed in practice. The upper and lower levels represent the maximum increase and decrease, respectively, that is realistic within a period of five years. Upper and lower levels are motivated in Appendix 5-I.

An R-4 design with 33 factors consists of 72 scenarios. An R-5 design for the same number of factors requires more than one thousand scenarios. Running this number of simulations would be very time-consuming; therefore, we estimated interactions per response variable for the five factors with the largest significant ($p<0.05$) main effects as demonstrated in the preceding R-4 design. This choice was based on the 'strong heredity' principle, which states that factors that do not have an important main effect do not have important interactions either (Wu and Hamada, 2000).

5.2.4 Impact analysis: selection of response variables

Response variables were selected using simulation results for the default scenario, which represents the brown rot policy and sector characteristics that currently (2006) apply in the Netherlands. Figure 5.1 shows the cumulative frequency distributions of the observed number of infections (a) and incidental costs (b) per year. Both outputs occasionally reach extremely high values, which cause the means to be higher than the medians. Factors determining brown rot incidence and incidental costs may do so by affecting the general level (e.g. mean or median) or the occurrence of extremes, or both. To distinguish between the two types of effects, two indicators are required for brown rot incidence and incidental costs. Since the distributions of these outputs are both right-skewed, the shape of each distribution is best represented by the median and the 90th percentile.

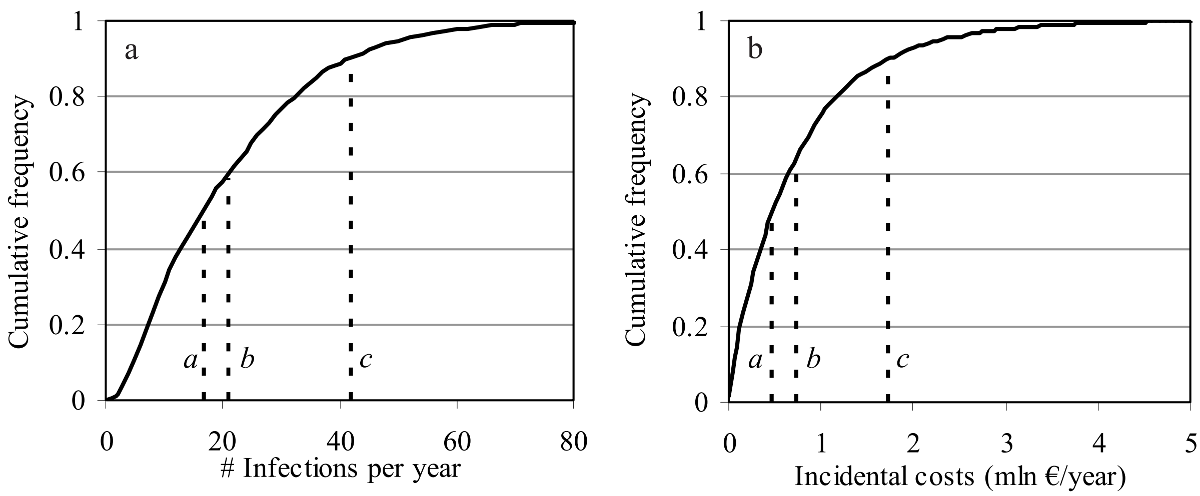

Figure 5.1. Cumulative frequency distribution of the number of infections (a) and incidental costs (b) per year in the default scenario, based on 500 replications. *a* = median, *b* = mean, *c* = 90th percentile.

Table 5.1. Factors and their levels in the impact analysis (factors levels that have more than one subdivision are given in Appendix 5-III).

Factor	Description	Acronym[1]	Subdivision	Default level	Lower level	Upper level
X1	Extent of surface water ban	p_swban	-	national	local	national
X2	Definition of undetected lots on detected farm as probably infected	p_probinf	-	true	false	true
X3	Sampling strategy	p_sampling	-	1 sample/lot	1 sample/farm	1 sample/25 tons
X4	Sampling strategy in case of tracing	p_density	-	1 sample/25 tons	1 sample/lot	1 sample/10 tons
X5	Minimum crop rotation	p_rotation	Potato category (seed, ware, starch, tbm)	3 / 3 / 3 / 3	3 / 3 / 3 / 3	4 / 4 / 4 / 4
X6	Minimum crop rotation in AM region[2]	p_amrot	-	2	2	3
X7	Field quarantine period	p_fieldq	-	5	4	5
X8	# Years seed potato production ban on detected farm	p_seedban	Potato category (seed, tbm)	1 / 2	0 / 1	2 / 2
X9	% Farms with closed production system	s_system	-	15	7.5	22.5
X10	% Farms with risk-seeking behavior	s_risk	Hygiene level (low, medium, high)	15 5 0	7.5 2.5 0	22.5 7.5 0
X11	Distribution of hygiene levels (low, medium, high) over farms	s_hygiene	Farm type (seed, ware, starch)	see Appendix 5-III table A	see Appendix 5-III table A	see Appendix 5-III table A
X12	Distribution of machinery use (private, shared, rent) over farms	s_machine	Potato acreage on farm (<10, …, >100)	see Appendix 5-III table B	see Appendix 5-III table B	see Appendix 5-III table B
X13	% Farms with bulk storage of seed potatoes	s_storage	Quality (well separated, poorly separated)	14.25 0.75	7.125 0.325	14.25 0.75
X14	P(field is illegally irrigated)	s_swuse	Summer type (normal, conducive)	0.01 0.02	0.005 0.01	0.015 0.03
X15	P(truck is disinfected before transport of seed potatoes)	s_protocol	Previous load (no seed potatoes, seed potatoes)	0.9 0.0	0.9 0.0	0.999 0.999
X16	% Seed potatoes transported in bulk	s_bulktrans	-	15	7.5	22.5
X17	% Seed potatoes transported in same trucks as ware potatoes	s_mixtrans	-	33	0.1	33
X18	% Seed potatoes cut or germinated before planting	s_cutseed	-	33	0.1	33
X20	P(conducive summer)	e_summer	-	0.3	0.2	0.4
X21	P(conducive fall)	e_fall	-	0.2	0.1	0.3
X19	Hygiene level on commercial stores	s_storehyg	-	high	low	high

Table 5.1 (continued)

Factor	Description	Acronym[1]	Subdivision	Default level	Lower level	Upper level
X22	P(exported infected lot is detected abroad)[3]	e_abroad	Potato category (seed, ware)	0.065 0.04	0.0325 0.02	0.0975 0.06
X23	Expected # imports of infected ware potatoes per year	e_import	-	2	0.001	10
X24	Potato prices (€ct/kg)	€_prices	Potato category (seed, ware, starch, tbm)	see Appendix 5-III table C	see Appendix 5-III table C	see Appendix 5-III table C
X25	Certification costs (€ct/kg)	€_certify	-	0.005	0.0045	0.0055
X26	Destruction costs (€ct/kg)	€_destroy	-	0.045	0.0405	0.0495
X27	Production costs (€/ha)	€_produce	Potato category (seed, ware, starch, tbm)	1600.- 1600.- 1250.- 1100.-	1440.- 1440.- 1125.- 990.-	1760.- 1760.- 1375.- 1210.-
X28	Costs of field rent (€/ha)	€_rent	Potato category (seed, ware, starch, tbm)	1500.- 1000.- 750.- 1250.-	1500.- 1000.- 750.- 1250.-	1875.- 1250.- 937.50 1562.50
X29	Sampling price (€/sample)	€_sample	Sampling method (per lot, per 25 tons)	69.- 64.-	62.10 57.60	75.90 70.40
X30	% Yield loss due to drought stress[4]	e_yloss	Potato category (seed, ware, starch, tbm)	0.075 0.10	0.0375 0.05	0.1125 0.15
X31	% Price reduction due to quality loss resulting from drought stress[4]	€_qloss	-	0.10	0.05	0.15
X32	# Ha yield loss due to drought stress;	e_yhectare				
	local ban		Potato category (seed, ware)	2000 300	2000 300	2200 330
	national ban			3000 300	3000 300	3300 330
X33	# Ha quality loss due to drought stress;	e_qhectare	-			
	local ban			500	500	550
	national ban			1000	1000	1100

[1] The first character of an acronym indicates its category: p = policy factor, s = sector factor, € = economic factor, e = exogenous factor.

[2] In a particular region of the Netherlands, a less strict minimum crop rotation applies to all potatoes except seed potatoes certified by the Dutch General Inspection Service for Agricultural Seed and Seed Potatoes (Nederlandse Algemene Keuringsdienst voor zaaizaad en pootgoed, NAK-Agro).

[3] Only seed and ware potatoes are exported.

[4] Starch and tbm potatoes are grown in regions of the Netherlands where either ground or surface water is available. Only seed potatoes can suffer from quality loss due to drought stress.

Structural costs remain constant over time at approximately 6 mln euros per year for the default scenario. Export restrictions are observed in 11.2% of the years. Export restrictions cause losses of at least several million euros, resulting in an average loss of 0.8 mln euros per year. As the occurrence of export losses is a catastrophe in itself, sector and policy representatives consider any level of export restrictions unacceptable and are rather concerned about the probability of export losses, than about their size.

In total, six response variables were selected for the impact analysis: median and 90th percentile of yearly number of infected lots, median of yearly structural costs, median and 90th percentile of yearly incidental costs, and frequency of years with export losses.

5.2.5 Impact analysis: metamodel validation

The objective of metamodelling was to quantify and rank the importance of factors and their interactions; the metamodels do not replace the bio-economic model. Therefore, a metamodel that provides a moderate level of explanation suffices (Kleijnen and Sargent, 2000). The R-square of the metamodels was calculated to determine the fraction of the variation explained by them. Next, a leave-one-out cross validation was performed. With leave-one-out cross validation, one factor combination at a time is eliminated from the regression analysis, after which the re-estimated regression model is used to predict the simulation output for the omitted combination. Scatter plots of predicted values against simulation outputs and Pearson's linear correlation coefficient ($\hat{\rho}$) were used to characterise the accuracy of the metamodel predictions.

R-5 designs for five factors are saturated; i.e., the number of effects to be estimated equals the number of factor combinations, leaving no degrees of freedom for validation (Law and Kelton, 1991). Therefore, the original R-5 designs were extended with five extra scenarios. These scenarios were also used in the estimation of the metamodels, because – provided that they are not outliers – increasing the number of scenarios improves the accuracy of estimated parameters.

5.2.6 Scenario studies

In controlling brown rot, the sector and government have two main objectives: (1) minimising brown rot incidence, and (2) minimising costs. As most measures that limit the incidence of brown rot cost money, there is a potential for trade-off between these objectives. Given the two objectives, three future strategies per group of actors are possible: (A) the importance of the objectives does not change (i.e. same as default), (B) the first objective gains greater importance, and (C) the second objective gains greater importance. Based on these strategies, nine scenarios were defined, representing all possible combinations of sector and government strategies (Table 5.2). Scenario codes indicate the sector and government strategy, respectively.

Factors and factor levels per scenario were selected according to the results of metamodelling. Only factors included in the top-five of important factors of at least one response variable were taken into account. It is assumed that the government can only affect policy factors, while actors in the sector can only affect sector factors. Brown rot incidence is minimised through factors that have a large impact on the yearly number of infections. The government can minimise costs of control by changing policy factors that have a large impact on structural or incidental costs. Actors in the sector can minimise costs through factors that affect yield or costs of production or labour. Here, individual actors in the sector are assumed to minimise primarily their own costs, rather than the costs of the sector as a whole.

Table 5.2. Scenarios for the government and the sector, with corresponding factors and their levels. The first letter of a scenario indicates the sector strategy; the second letter represents the government strategy. Explanations of factor acronyms are provided in Table 5.1.

Scenario	Sector objective	Adjusted factor levels	Government objective	Adjusted factor levels
AA	Default		Default	
BA	Minimizing brown rot incidence	s_risk = -1; s_hygiene = +1; s_swuse = -1	Default	
CA	Minimizing costs of control	s_system = -1; s_risk = +1	Default	
AB	Default		Minimizing brown rot incidence	p_sampling = +1
BB	Minimizing brown rot incidence	s_risk = -1; s_hygiene = +1; s_swuse = -1	Minimizing brown rot incidence	p_sampling = +1
CB	Minimizing costs of control	s_system = -1; s_risk = +1;	Minimizing brown rot incidence	p_sampling = +1
AC	Default		Minimizing costs of control	p_swban = -1; p_probinf = -1
BC	Minimizing brown rot incidence	s_risk = -1; s_hygiene = +1; s_swuse = -1	Minimizing costs of control	p_swban = -1; p_probinf = -1;
CC	Minimizing costs of control	s_system = -1; s_risk = +1	Minimizing costs of control	p_swban = -1; p_probinf = -1
C’B	Minimizing costs of control	s_system = -1; s_risk = +1; s_hygiene = -1; s_swuse = +1	Minimizing brown rot incidence	p_sampling = +1
BC’	Minimizing brown rot incidence	s_risk = -1; s_hygiene = +1; s_swuse = -1	Minimizing costs of control	p_swban = -1; p_probinf = -1; p_sampling = -1

Scenarios that increase the frequency of export losses, compared to the default situation, are unacceptable. Consequently, government and sector factors with a large impact on frequency of export losses cannot be simultaneously set at levels that increase the frequency of export losses. However, if the government and sector aim at contrasting objectives, the increased risk of export losses caused by modified government measures may be compensated for by the sector and vice versa. Therefore, two extra scenarios were included, which represent opposite objectives of the two groups of actors where frequency of export losses is not considered as a limiting condition (Table 5.2, scenarios BC' and C'B).

5.3 Results

Based on the results of the R-4 design, factors are ranked according to their impact on each response variable. Next, important interactions between factors are identified on the basis of the results of the R-5 design, after which the validity of the metamodels is discussed. Finally, the results of the scenario studies are analysed to evaluate how different sector and government objectives affect the cost-effectiveness of control.

5.3.1 Ranking of factors

Figure 5.2 shows the effects of the ten most important factors per response variable, based on the R-4 design. Factors with a positive sign for a particular response variable cause an increase in that variable, compared to the default situation, when set at their upper value and a decrease when set at their lower value; factors with a negative sign have opposite effects. Note that the default value of a factor is not necessarily located in the centre of the upper and lower level (i.e. at level '0'), and that factor effects presented in Figure 5.2 are the average effects measured over the entire hyperplane of response against explanatory variables. The estimated effects may thus be different from the observed change in simulation output when changing a factor from its default to its upper or lower value.

Four of the six response variables show a considerable difference in effect size between the highest-ranked factors and lower-ranked factors (Figure 5.2a, b, c, and f). These response variables are thus largely determined by a few (at maximum five) important factors. For five of the six response variables, the top-five of important factors is dominated by sector factors (Figure 5.2a, b, d, e, and f). These sector factors all affect the probability of primary infection through contaminated surface water. The observed importance of these factors is in agreement with an earlier observation that in the default scenario contaminated surface water is the most important infection source (Chapter 3). Below, factor effects are discussed for each response variable.

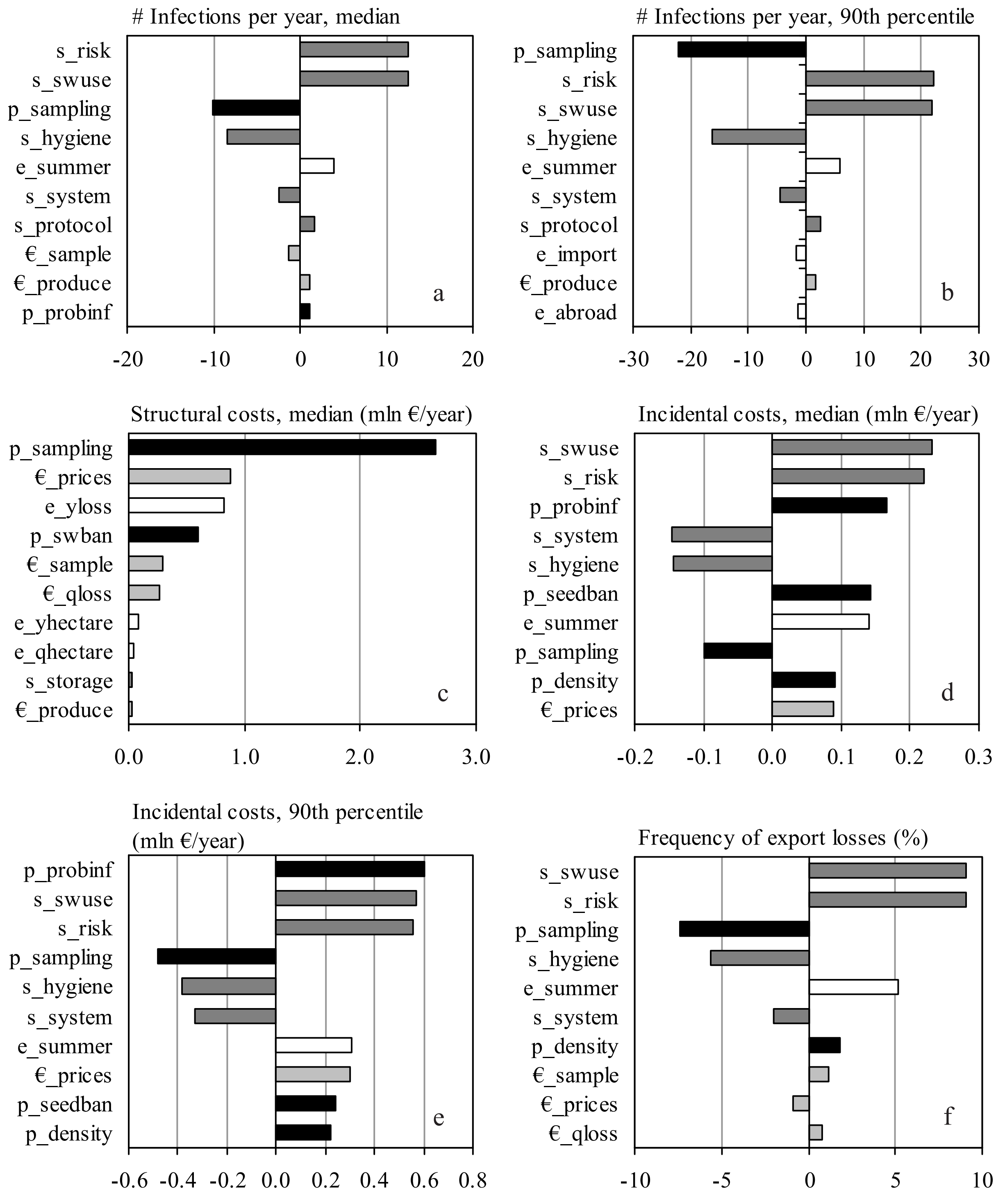

Figure 5.2. Main effects of the factors ranked from 1 to 10 per response variable, based on the R-4 design (all significant at p<0.05). Explanation of bar patterns: black = policy factor, dark grey = sector factor, light grey = economic factor, white = exogenous factor. Explanations of factor acronyms are provided in Table 5.1.

Yearly number of infections (Figure 5.2a and b). The median and 90th percentile have the same four dominant factors, implying that these factors affect the entire distribution of brown rot incidence. They change the median by approximately 10 infections per year and the 90th percentile by approximately 20 infections per year. In the default scenario, the two response variables have values of respectively 16 and 41 (Figure 5.1a); the impact of the highest-ranked factors on brown rot incidence is thus considerable.

Structural costs (Figure 5.2c). The median of structural costs constitutes the only response variable that is not dominated by sector factors and for which economic factors play a significant role. By far the most important factor for this response variable is the sampling strategy, with an effect of over 2.5 mln euros. This effect is completely attributable to a change in the number of samples, and thus sampling costs.

Incidental costs (Figure 5.2d and e). The difference in effect size between the first and 10th ranked factor is rather small, both for the median and the 90th percentile. Incidental costs are thus less strongly dominated by the highest-ranked factors. The effects range from over 0.1 mln euros per year to 0.2 mln euros per year for the median, and from 0.2 mln euros to 0.6 mln euros for the 90th percentile. Given the default values of respectively 0.5 and 1.7 mln euros for these response variables (Figure 5.1b), these impacts are modest. Incidental costs are thus affected substantially by a wider range of factors than other outputs of the model; however, the sensitivity to change is in relative terms smaller than for the other response variables.

Frequency of export losses (Figure 5.2f). The six highest-ranked factors are exactly the same as those for the median number of brown rot infections per year. This reflects the causal relationship between brown rot incidence and the occurrence of export losses. The most influential factors with respect to the frequency of export losses cause an increase or decrease of this frequency of between 5 and 10 percentage points; these effects are thus major compared to the default value of 11.2% for this response variable.

5.3.2 Identification of important interactions

Figure 5.3 shows the ten most important main effects and interactions, based on the R-5 design. For all response variables, at least three factors have main effects that are more important than any interaction. Furthermore, factors with high-ranked main effects generally have higher-ranked interactions than factors with less important main effects. These results corroborate the strong heredity assumption based on which factors with a rank below 5 were excluded from the R-5 design. Differences between the main effects estimated from the R-4 and R-5 design are small, showing that the restriction to the five most influential factors has not compromised the estimation of their effects.

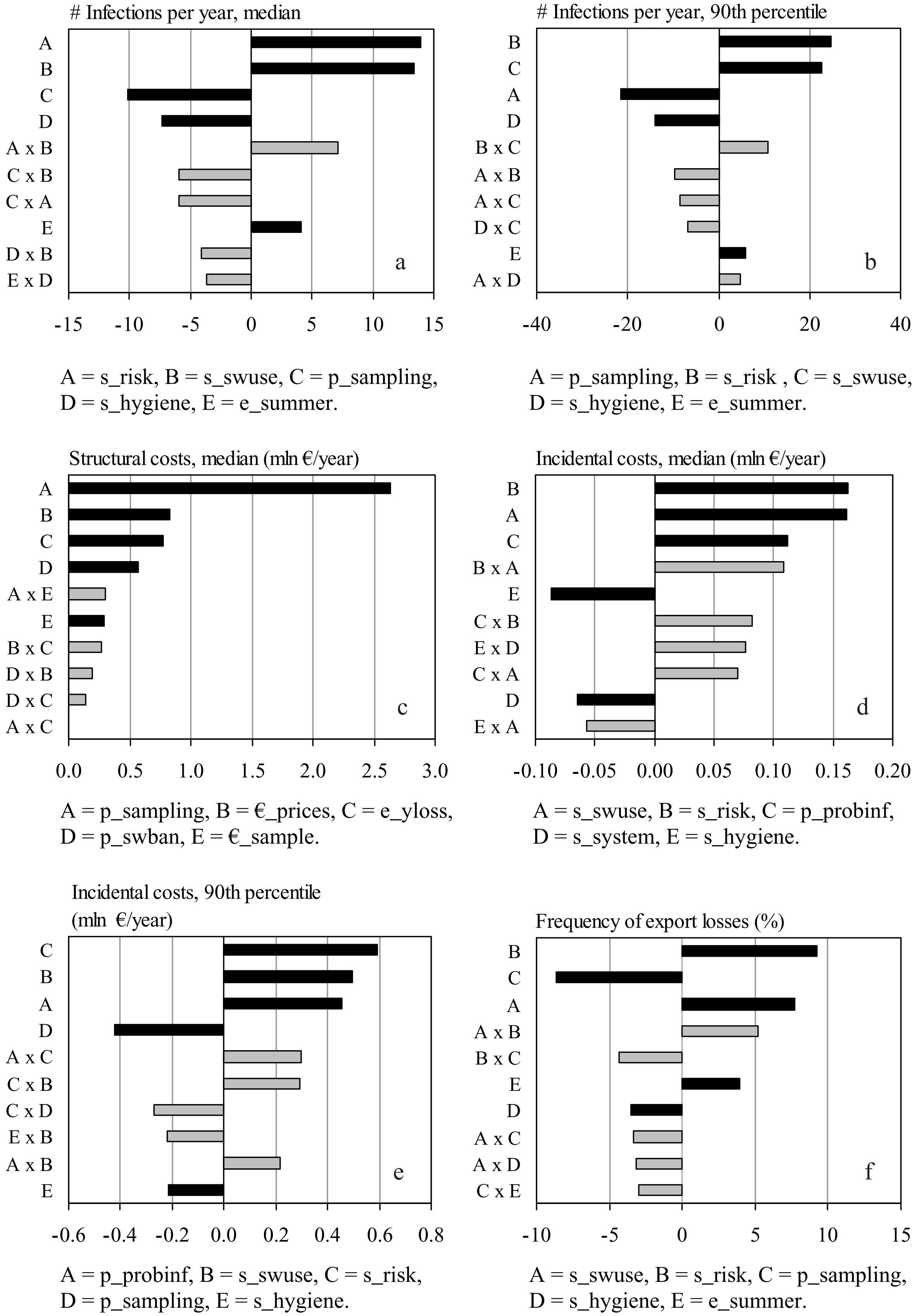

Figure 5.3. Ten highest ranked main effects and interactions per response variable, based on the R-5 design (all significant at p<0.05). Symbols A to E on the y-axes denote the top-five of factors in the R-4 design (A = highest ranked factor, etc.). Explanation of bar patterns: black = main effect, grey = interaction. Explanations of factor acronyms are provided in Table 5.1.

All positive interactions in Figure 5.3 involve factors whose effects have the same sign, while all negative interactions involve factors with opposite effect signs. This implies that all important interactions strengthen the main effects of the two factors involved, i.e. the two factors are more than additive. In practice, this means that in a scenario where several factors are set at levels that cause an increase (decrease) in cost-effectiveness, the total increase (decrease) in cost-effectiveness may be larger than expected on the basis of individual factor effects.

Many sector factors have important interactions with each other, which results from the fact that these factors have effects on the epidemiology of brown rot and are entangled with each other in the model. For instance, illegal irrigation is only possible at risk-seeking farms, because only these farms are assumed to disobey the law. Consequently, the factors representing probability of illegal irrigation at risk seeking farms and number of farms with risk-seeking behaviour interact. Important interactions are also observed between sector and policy factors. For instance, the policy factor determining sampling strategy (p_sampling) negatively interacts with sector factors that have a positive effect on brown rot incidence and vice versa. Thus, as the probability of brown rot infections increases, control measures become more important to curtail their further spread. The only response variable for which interactions do not play a significant role is the median of structural costs. Structural costs do not depend on brown rot incidence or the number of infections. They consist of two components, costs of monitoring and losses from restrictive regulations, which do not affect each other.

5.3.3 Validation of metamodels

The R-squares of the metamodels based on the R-4 design vary between 0.61 and 0.98 (Table 5.3), indicating that the main effects of factors explain a considerable fraction of the variation in simulation outputs. Metamodels based on the R-5 design, which include also two-factor interactions, explain almost 100% of the variation. Cross validation of all metamodels gives correlation coefficients ranging from 0.68 to 1.00 (Table 5.3), indicating a reasonable to excellent goodness of fit.

Scatter plots of the cross-validations of the metamodels based on the R-4 designs (Appendix 5-II) show that most metamodels underestimate extremes, while overestimating the middle range of simulation outputs. This is due to the fact that these metamodels only include main effects and do not account for higher-order effects. Moreover, the metamodels can give negative responses, while the simulation outputs have a minimum of zero. Including two-factor interactions causes the scatter plots to be more evenly distributed around the 1:1 line (Appendix 5-II) and thus increases the predictive value of the metamodels. We conclude that the R-4 and R-5 metamodels are valid for their intended application, which is identification of important factors and quantification of their main effects and interactions, respectively.

Table 5.3. R-squares of the metamodels of all response variables based on the R-4 and R-5 designs, and correlation coefficients ($\hat{\rho}$) resulting from cross validation of these models.

Response variables	Metamodels R-4 design		Metamodels R-5 design	
	R^2	$\hat{\rho}$	R^2	$\hat{\rho}$
Median of yearly # infections/year	0.73	0.86	0.98	0.78
90th percentile of # infections/year	0.79	0.89	0.99	0.88
Median of structural costs/year	0.98	0.99	1.00	1.00
Median of incidental costs/year	0.61	0.78	0.98	0.68
90th percentile of incidental costs/year	0.65	0.80	1.00	0.93
Frequency of export losses	0.74	0.86	0.99	0.94

5.3.4 Scenario studies

According to the results of scenarios, the costs of control are almost completely determined by the government, while the average number of detections per year is largely determined by the sector (Figure 5.4a). Confirming the results of the impact analysis, the average yearly number of infections and frequency of export losses in the scenarios are strongly correlated (Figure 5.4b).

Minimisation of costs by the sector (strategy C) results in a large average yearly number of infections and a high frequency of export losses. This is primarily a result of greater use of surface water for irrigation, which increases the chance of primary infection. For a given strategy of the sector, minimisation of brown rot incidence by the government (strategy B) leads to the smallest yearly number of infections and lowest frequency of export losses, which is largely due to the high sampling frequency in this strategy. However, the impact of this strategy on yearly number of infections and frequency of export losses decreases as the sector attaches more importance to minimising brown rot incidence. Moreover, brown rot minimisation by the government increases the costs of control with 2 mln euros per year. Thus, the cost-effectiveness of brown rot control by the government strongly depends on the strategy of the sector.

The extra scenarios BC' and C'B give 'extreme' results (Figure 5.4). In BC', the government prioritises cost minimisation regardless of the consequences for the risk of export losses while the sector minimises brown rot incidence; in scenario C'B, the opposite occurs. The results indicate that a government aiming at minimising brown rot incidence cannot compensate for the negative consequences of a sector that aims at minimising (private) costs of control. In contrast, a control policy aiming at cost minimisation is acceptable as long as the sector's main objective is to minimise brown rot incidence. Thus, the sector can compensate for a reduction in brown rot control efforts by the government, but the reverse is not true.

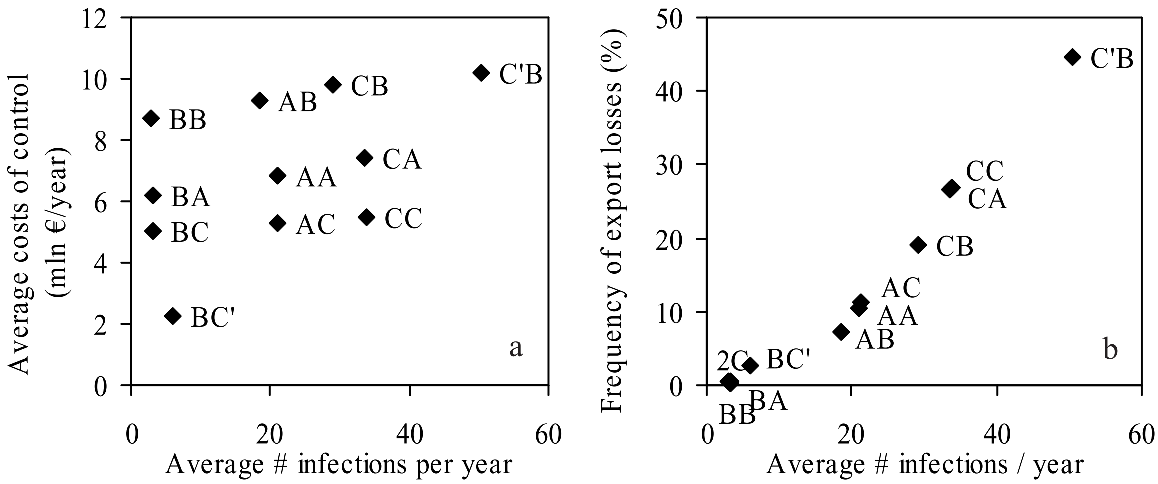

Figure 5.4. Effects of scenarios on average yearly number of infections vs. frequency of export losses (a), and on average yearly number of infections vs. average yearly costs of control (b). Scenarios are explained in Table 5.2.

According to Figure 5.4, the cost-effectiveness of control compared to the default scenario (AA) can be increased by a shift in the strategy of the government towards the minimisation of costs (AC), a shift in the strategy of the sector towards the minimisation of brown rot incidence (BA), or a combination of these two strategies (BC and BC'). A shift in the strategy of the sector can reduce the average yearly number of infections by approximately 75%. A shift in the strategy of the government can reduce average costs of control by approximately 2 mln euros per year. If both groups change their strategy, a reduction in costs of more than 4 mln euros per year to the current situation can be achieved (2C'). Scenarios 2C and 2C' together comprise the cost-efficient set of scenarios. A scenario belongs to the efficient set if no alternative scenario leads to the same level of brown rot incidence with fewer costs (Mas-Colell et al., 1995). Thus, the two most cost-effective scenarios are those in which the sector minimises brown rot incidence and the government minimises costs.

5.4 Discussion

The aim of this chapter was to quantitatively analyse the possibilities for increasing the cost-effectiveness of controlling quarantine diseases at the level of the production chain, using brown rot in the Dutch potato production chain as a case study. The impact analysis showed that the cost-effectiveness of brown rot control is predominantly determined by government and sector factors, although some exogenous and economic factors can cause subtle differences in cost-effectiveness. Interactions between policy and sector factors indicated a dependency between these two groups in the cost-effectiveness of control, which was confirmed by the scenario studies. Compared to the default scenario, the sector can reduce brown rot incidence by more than 50% while the government can reduce the costs of control with at least 2 mln euros per year. The largest increase in cost-effectiveness can be achieved if the sector recognises its responsibility for avoiding introduction of brown rot (and other diseases) into the potato production chain; in this situation, policy measures can be relaxed to a large degree. However, if actors in the sector aim at minimising costs by actions that increase the risk of brown rot introduction, then even an intensive, costly sampling strategy cannot prevent a high level of brown rot incidence and frequency of export losses.

A caveat in the analysis is that sector changes that lead to reduced brown rot incidence are not costed. Adjustments such as improving hygiene and switching to a closed production system certainly bring along costs (e.g. costs of investment, labour). These costs, however, are not solely attributable to brown rot and therefore not included in the simulation model. Likewise, changes in certain policy measures, such as a national irrigation ban and defining lots grown on the same farm as a detected lot 'probably infected', do not seem to affect brown rot incidence. In practice, these measures are imposed as a precaution to cover potential but yet unidentified risks, which are not included in the model. These limitations of the bio-economic model should be kept in mind when interpreting simulated scenarios with respect to their cost-effectiveness.

The impact analysis presented in this chapter should not be interpreted as a sensitivity analysis. In a sensitivity analysis, all factors are changed over the same relative range, which enables a more objective comparison of factors effects. In contrast, the purpose of the impact analysis was to quantify the change in the incidence and costs of brown rot that may be caused by a realistic degree of change in factor levels. Thus, the measured impacts depend on the sensitivity of model outputs to the factors as well as the magnitudes of their ranges. Consequently, a factor with a small range may be declared unimportant, even though the simulation model is sensitive to changes in this factor. Nevertheless, for most response variables, the differences between effects of high and low ranked factors are such that increasing the range of low ranked factors would not cause their effects to become as large as those of important factors.

The metamodels support the identification of potential cost-effective scenarios, but they cannot replace the bio-economic model. One reason is that the effect of a factor on a response variable may be nonlinear, in which case the value of factor level 0 is not located exactly in the centre of values of the upper and lower levels. Furthermore, the upper and lower levels of the factors included in the impact analysis were standardised to +1 and -1, but factor values that lie between the values of the upper and lower level may be difficult to standardise to a level between -1 and +1. This is the case for categorical factors such as sampling strategy, in which case a scaling of levels between -1 and +1 is not possible at all. Consequently, the metamodels cannot quantify the cost-effectiveness of scenarios containing other than those that are characterised by factor levels included in the experimental designs.

The results of the impact analysis show the strengths of using DOE and metamodelling as compared to simpler approaches. A commonly applied alternative is one-at-a-time (OAT) sensitivity analysis, in which one factor per scenario is increased or decreased. However, this approach does not take into account possible interactions between factors. As shown in this chapter, identification of interactions can provide relevant information for policy-makers. For instance, as many sector and policy factors amplify each other's effects, the impact of a highly cost- or brown rot minimising strategy on the cost-effectiveness of control will be larger than expected on the basis of main factor effects. Another strength of DOE is that it measures average factor effects over the entire hyperplane of response against explanatory variables, whereas OAT only measures the local effect of factors.

This chapter illustrates how impact analysis and scenario studies can complement each other. An impact analysis reveals which factors are important and how these factors interact, but it does not provide insight in the over-all effects of factors on the cost-effectiveness of control. Important insights from the scenario studies, such as the conclusion that the most cost-effective control is achieved if the sector minimises brown rot incidence and the government minimises costs, could not have been obtained on the basis of the impact analysis alone. On the other hand, in absence of the impact analysis, it would be difficult to define a small set of scenarios that provides insight into the relationship between sector and government behaviour and cost-effectiveness of control, and it would remain uncertain if the most influential variables were included in the scenarios. The impact analysis allows for a preselection of factors to include in the scenario studies, and provides a starting-point for policy-makers for defining other, possibly cost-effective scenarios.

The current study has shown how bio-economic modelling can support the efficient design of optimal control strategies against quarantine diseases. By quantifying the effect of factors on disease incidence and economic consequences, factors that play a dominant role in determining the cost-effectiveness of control can be identified. Moreover, results from the analysis in this chapter clearly show the interdependency between sector and government in reaching an optimal cost-effective approach towards controlling brown rot in the potato production chain. This quantitative evidence can be used to enhance private-public partnership towards ecologically and economically sound brown rot management.

Acknowledgements

We thank the Dutch Plant Protection Service and the members of the brown rot response group for providing us with data and valuable feedback.

Appendix 5-I Motivation of factor levels

Policy factors: Most policy-related factors are categorical, and the extreme levels chosen represent likely alternatives when tightening or relaxing a measure. Where possible, these alternatives are based on past or proposed adjustments of measures. Some factors are binary, in which case either the upper or lower level equals the default level. Due to the threat of other potato diseases than brown rot, minimum crop rotation schedule for potatoes is unlikely to be shortened.

Sector factors: Factors representing farm or sector characteristics were assumed to increase or decrease maximally by 50%, which is in accordance with objectives and effectiveness of other recently implemented policies, such as the Dutch crop protection policy (Schroën et al., 2000; LNV, 2004). Machinery is in practice a quasi-fixed asset; the corresponding factors are therefore assumed to vary over a range of at maximum 10%. Disinfection of trucks may in theory occur at a frequency of almost 100%, but in practice there will always be a few exceptions; therefore the upper level of the corresponding factor is set at 0.999.

Economic factors: Levels for potato prices were based on observed fluctuations of historical data on costs and prices (Dekkers, 2001; Hoogenboom, 2005; CBS, 2006). Levels for land rent prices were based on the observed general trend in Dutch land rent prices (CBS, 2006). Certification, destruction, and production costs are in practice semi-fixed and therefore assumed to increase or decrease at maximum 10%. Price reduction due to quality loss is determined by trading companies and assumed to be increased or decreased at maximum 50%, depending on future quality requirements of buyers.

Exogenous factors: The frequency of a conducive summer or fall is assumed to increase or decrease with at maximum one per ten years. The potato acreage that suffers from drought stress is unlikely to decrease as long as the ban on surface water is in force. The probability of importing an infected lot can be minimised, but one cannot guarantee that this event will never occur; therefore, the lower level of this factor is set at 0.001. The probability that an exported infected lot is detected abroad depends on monitoring intensity of importing countries. Given the large variety of countries to which Dutch potatoes are exported, it is assumed that this probability increases or decreases at maximum 50%.

Appendix 5-II Scatter plots resulting from cross validations

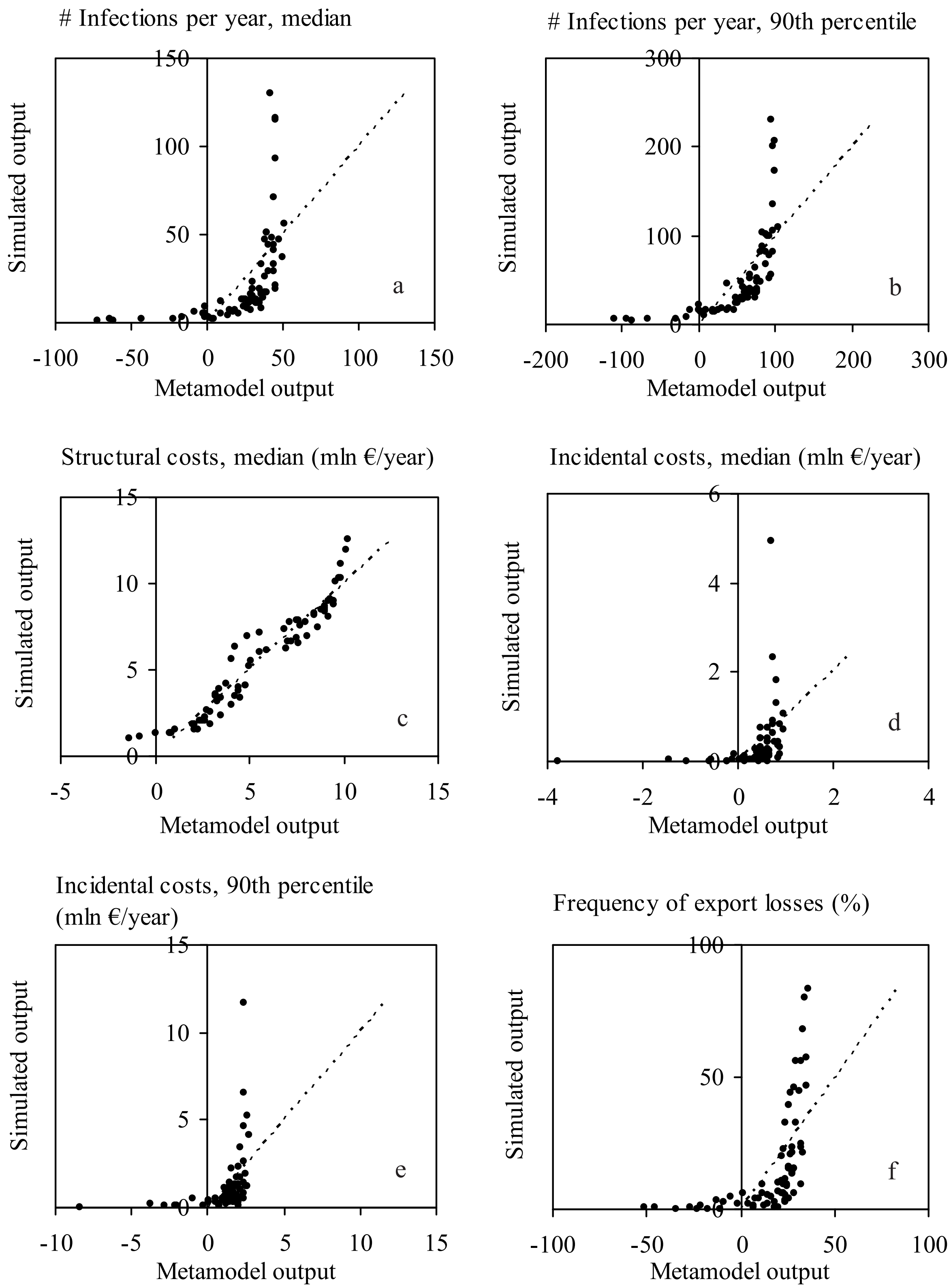

Figure 5-IIA. Scatter plots of metamodel prediction and simulation realisation, based on cross-validation results of the metamodels estimated from the scenarios in the R-4 design. The dashed line represents the 1:1 line.

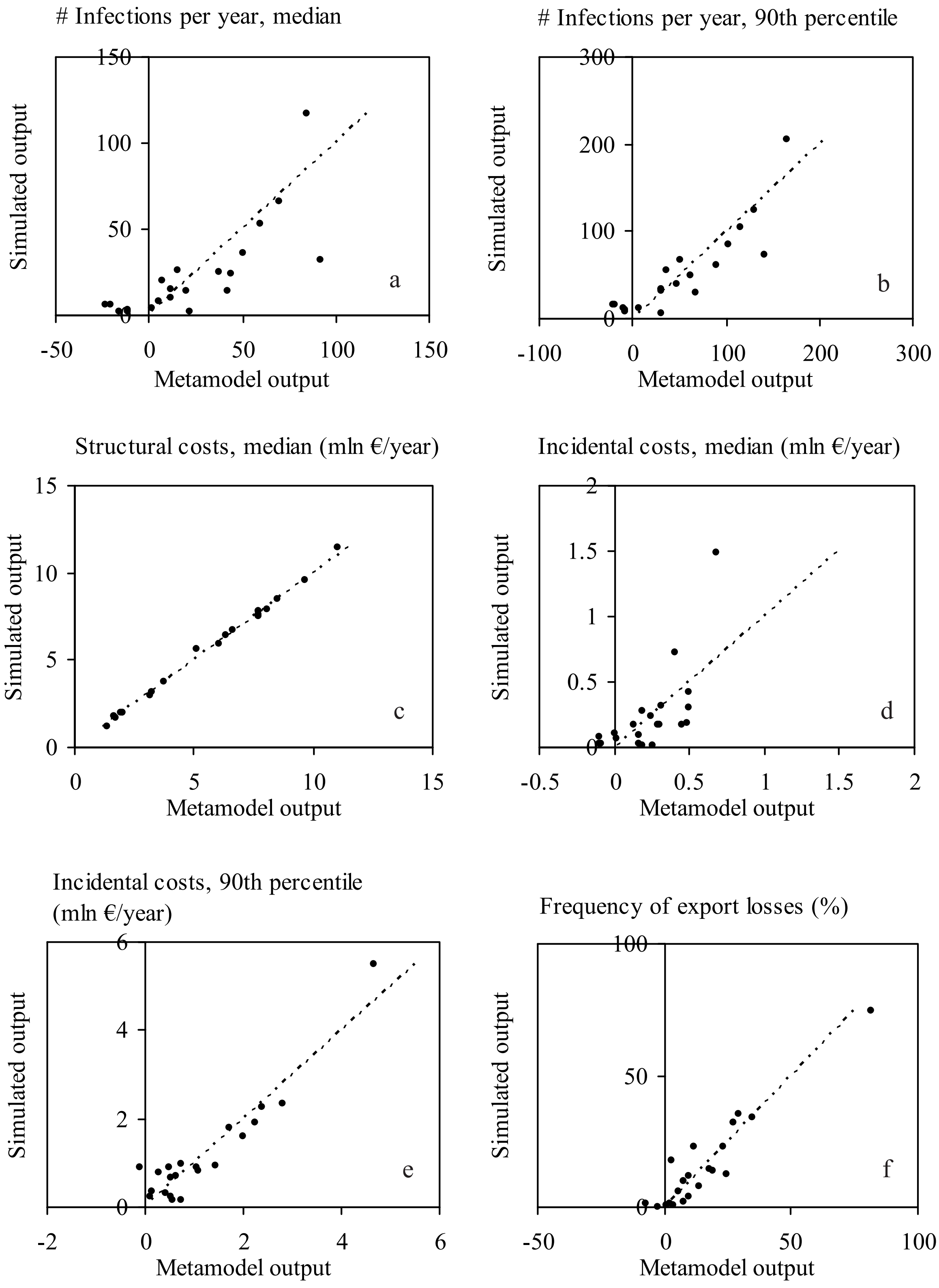

Figure 5-IIB. Scatter plots of metamodel prediction and simulation realisation, based on cross-validation results of the metamodels estimated from the scenarios in the R-5 design. The dashed line represents the 1:1 line.

Appendix 5-III Levels of factors containing more than one subdivision

Table 5-IIIA. Default, lower, and upper factor levels for the distribution of hygiene levels over potato growing farms.

Category of potatoes grown on farm	Default level			Lower level			Upper level		
	low	medium	high	low	medium	high	low	medium	high
Only seed potatoes	0.25	0.65	0.10	0.375	0.575	0.05	0.125	0.725	0.15
Ware (and seed) potatoes	0.35	0.60	0.05	0.525	0.45	0.025	0.175	0.75	0.075
Starch (and seed/ware) potatoes	0.45	0.55	0.00	0.675	0.325	0.00	0.225	0.775	0.00

Table 5-IIIB. Default, lower, and upper factor levels for the distribution of type of machinery used by potato growing farms.

Farm category	Default level			Lower level			Upper level		
	private	shared	rent	private	shared	rent	private	shared	rent
Closed production system	0.8	0.2	0.0	0.72	0.26	0.0	0.88	0.12	0.0
< 10 ha potatoes	0.39	0.23	0.38	0.351	0.231	0.418	0.429	0.229	0.342
10-25 ha potatoes	0.49	0.25	0.26	0.441	0.273	0.286	0.539	0.227	0.234
25-50 ha potatoes	0.61	0.27	0.12	0.549	0.319	0.132	0.671	0.221	0.108
50-75 ha potatoes	0.70	0.21	0.09	0.63	0.271	0.099	0.77	0.149	0.081
75-100 ha potatoes	0.75	0.20	0.05	0.675	0.27	0.055	0.825	0.13	0.045
> 100 ha potatoes	1.0	0.0	0.0	0.90	0.10	0.0	1.0	0.0	0.0

Table 5-IIIC. Default, lower, and upper factor levels for prices of planted and harvested potatoes.

Price category	Default level				Lower level				Upper level			
	seed	ware	starch	tbm	seed	ware	starch	tbm	seed	ware	starch	tbm
Normal farmer price	0.22	0.08	0.06	0.0	0.143	0.052	0.039	0.0	0.297	0.108	0.081	0.0
Price if probably infected	0.02	0.02	0.06	0.06	0.013	0.013	0.039	0.039	0.027	0.027	0.081	0.081
Value of potatoes kept on farm	0.24	0.0	0.0	0.16	0.156	0.0	0.0	0.104	0.324	0.0	0.0	0.216
Value of on-farm produced planting material	0.24	0.24	0.16	0.24	0.156	0.156	0.104	0.156	0.324	0.324	0.216	0.324
Purchase price of planting material	0.38	0.30	0.20	0.40	0.323	0.255	0.17	0.34	0.437	0.345	0.23	0.46
Profit starch industry			0.0045				0.002925				0.006075	

CHAPTER 6

General discussion

6.1 Introduction

The aim of the research described in this thesis was to develop a bio-economic model that can be used to evaluate the effect of control strategies on the incidence and costs of brown rot in the Dutch potato production chain, and thus support the design of cost-effective control policies. The objective was pursued in four different steps, which were described in Chapters two to five. Chapter 2 deals with the development of a modelling concept that is appropriate for simulating brown rot epidemics in the Dutch potato production chain. In Chapter 3, this concept is elaborated to a functional epidemiological model. In Chapter 4, the epidemiological model is coupled to an economic model, resulting in the intended bio-economic model. In the fifth chapter, the bio-economic model is used to conduct an impact analysis and scenario studies, the results of which can help in directing the design of cost-effective control strategies.

This chapter starts with a brief review of the main insights obtained from the bio-economic model. Next, the major strengths and weaknesses of the approach and the scope and validity of the model are addressed. Where relevant, possibilities for further progress are discussed. The chapter ends with an outlook to the possible contribution of the bio-economic model to the cost-effective control of brown rot and other quarantine diseases.

6.2 Insights obtained from analyses of the bio-economic model

The results presented in this thesis illustrate how epidemiological and economic modelling can enhance knowledge of the epidemics and economics of brown rot. Applications of the epidemiological model presented in Chapter 3 improve insight into the behaviour of brown rot within the potato production chain. Under the default scenario, which resembles the current situation, average simulated brown rot incidence is in dynamic equilibrium at approximately 15 infections per year, although large fluctuations are observed between individual years[1]. Because the distribution of brown rot incidence is right-skewed, this equilibrium lies higher than the median. Under the default scenario, primary infection through surface water is the major infection source; reducing the sampling frequency of seed potatoes increases the relative importance of vertical transmission. However, even at a sampling frequency of 10%, vertical transmission and horizontal transmission rates are too low to cause an increase in average brown rot incidence over time.

[1] Results presented in Chapters 3, 4, and 5 are based on different model versions. Also, due to a change in the brown rot policy in 2005, the default scenario in Chapter 3 was based on a sampling density of 1 sample per 25 tonnes, while results in subsequent chapters are based on the current (2006) sampling density of one sample per lot. Consequently, simulation results of similar scenarios may differ between chapters; however, general conclusions are consistent.

The integrated bio-economic model enables the quantification of costs and benefits, allowing for a quantitative comparison of control strategies with respect to their cost-effectiveness. Comparison of two scenarios (Chapter 4) indicates that a reduction in sampling frequency to 10% reduces the structural costs by 2.5 million euros compared to the default sampling frequency. However, this reduction in structural costs is more than offset by an increase in export losses of 6.7 million euros on average. This demonstrates the importance of taking into account export losses when determining the cost-effectiveness of control policy. Furthermore, the response time of brown rot incidence in the production chain – and thus of the economic consequences – to a particular control policy may cover several years; conclusions on the cost-effectiveness of control strategies thus strongly depend on the period over which costs are quantified.

The impact analysis performed in Chapter 5 revealed that particularly policy and sector parameters have a major impact on the incidence and economic consequences of brown rot, while most economic and exogenous parameters are of lesser importance. Scenario studies showed that involving the sector in control of brown rot can greatly increase the cost-effectiveness of control. If the sector minimizes the risk of brown rot introduction into the production chain, brown rot incidence may be reduced by more than 50%. In that case, policy measures may be relaxed, resulting in an average cost reduction of four million euros per year. Results of the impact analysis and scenario studies provide a basis for formulating recommendations for future control of brown rot, as will be done elsewhere in this chapter.

6.3 Choice of epidemiological modelling approach

Comparison of two conceptual models (Chapter 2) revealed that the choice of modelling technique for describing disease dynamics very much depends on the context in which a model will eventually be used. An individual-based modelling approach (IBM) was preferred over a state variable model (SVM) because (1) results of an IBM are more ready-to-use for subsequent economic analysis due to the concreteness of the in- and outputs, (2) an IBM is better capable of representing different control policies because it includes management relevant details, and (3) an IBM can be easily combined with a geographical information system (GIS), which enables the analysis of spatial patterns and increases the appeal and practical interpretability and value of the model.

Without doubt IBMs have their shortcomings. One often mentioned drawback of complex models like IBMs is the large number of parameters that have to be estimated, which could potentially increase uncertainty of the model (Van Nes and Scheffer, 2005). Indeed, the IBM developed in this study contains many parameters, whereas a classical model, for instance an SVM, might be built with fewer parameters, e.g. ‘horizontal transmission rate’ or ‘frequency of primary infection'. However, these parameters are in fact an aggregation of many probabilities and conditions and, hence, are very difficult to estimate. In the IBM, these parameters are cut into pieces; sector characteristics are explicitly included and each epidemiological parameter is conditional, i.e. represents the probability of one particular event to occur, given the local circumstances at the respective location and moment. Such parameters may be estimated with less uncertainty than the abstract parameters of an SVM and they are more easily understood by users, stakeholders, and experts.

Another potential drawback of IBMs is lack of transparency, which makes them difficult to communicate and increases uncertainty about the correctness of the model. Moreover, the complex structure can hinder updating or further development (Van Nes and Scheffer, 2005). This is also true for the IBM developed in this project. At the start of the project, little was known about the impact of specific characteristics and events in the potato production chain on brown rot incidence, so many details were included. The currently available model can be used to evaluate whether certain details are redundant for obtaining representative and robust results. A next step may be to develop a model that has a more generic structure and is more broadly applicable. To support the application and timely updating of the current model, a technical documentation was written, in which the structure and processes of the model are described in detail (Breukers et al., 2006).

IBMs usually have a practical application, i.e. they are used to make predictions, as was the main purpose in this research. Nevertheless, IBMs can contribute to general knowledge and theory as well, but only if modellers take time to explore the model and obtain a general understanding of its behaviour (Grimm, 1999; Van Nes and Scheffer, 2005), as was done in Chapter 3 of this thesis. Furthermore, the results of an IBM can be used to help parameterise abstract, analytical models such as the one presented in Chapter 2. For example, the frequency of primary infection and the relative growth rate of existing infections can be estimated from simulated average brown rot incidence and importance of different infection pathways. These data may lead to more realistic and plausible parameters than the ones in Chapter 2, which were derived from a limited set of empirical data on *observed* infections (i.e. detections), before the IBM was completed.

6.4 Quantification of economic consequences

6.4.1 Structural and incidental costs

Structural costs and incidental costs together comprise the total costs of control. The economic model only quantifies costs of measures that are directly attributable to brown rot; costs of measures that improve product quality in general are not included. For instance, increasing hygiene level reduces the probability of horizontal transmission, but the corresponding costs of increased labour are not accounted for. Another example is the on-farm storage of potatoes, which reduces the risk of brown rot dispersal between farms, but requires a large investment. Although such measures may contribute considerably to the total structural costs, they serve a much wider aim than reducing the introduction or dispersal probabilities of brown rot, and it is not realistic to put them at the account of brown rot control. Nevertheless, these costs should be kept in mind when interpreting results on the cost-effectiveness of scenarios, as was illustrated by the scenario studies of Chapter 5.

Farm level information on potato production is restricted to the categories and respective acreages on each farm. Consequently, calculated incidental costs for an affected farm are only dependent on the potato categories and respective acreages grown on the farm. In practice, other farm characteristics affect the incidental costs as well; for instance, the classes of seed potatoes grown, and the fraction of potatoes that is grown from on-farm produced planting material. Including such details would have gone at the cost of transparency of the model, as differences in incidental costs can be less clearly attributed to differences in the categories of potatoes grown. Therefore, the model uses average production data and prices per potato category. As a consequence, it underestimates the variance in incidental costs incurred by affected farms; however, total incidental costs calculated for a particular control policy are representative for the Dutch potato production chain.

One important aspect that has not been included in the model yet is the possibility of Dutch farmers to insure their potatoes against the losses resulting from a detection of brown rot (Potatopol, 2004). The yearly premium of this insurance can be categorised as structural costs. Insured farmers may have to pay an after-premium as well, which is dependent on the number of detections and thus contributes to incidental costs. The insurance serves as a safety net for farms that are affected by brown rot, as it avoids extreme losses for single farmers. At the national scale, the insurance causes a small increase in structural costs, because part of the premium is used to finance the insurance company.

6.4.2 Quantification of export losses

Formulation of a relationship between brown rot incidence and subsequent export restrictions was an intricate undertaking. Empirical data were very limited, so experts were asked to estimate the minimum number of detected lots that would lead to certain levels of export restrictions. Experts found these estimations very difficult because they had to visualise extreme situations with which they have little or no familiarity. In practice, EU regulations require extra measures to be taken in case of a large outbreak (European Union, 1998; European Union, 2000), and also the sector itself will do anything to avoid export restrictions. By contrast, the aim of the model is to quantify export losses that would occur if a control policy were maintained for an extended period of time. Consequently, the estimated critical values for the occurrence of export restrictions are subject to a large degree of uncertainty. Moreover, the economic model is rather sensitive to these parameters (Chapter 5). Nevertheless, the method leads to robust ranking of scenarios. The export module may be further refined, for instance by distinguishing more than three levels of export restrictions. It may also be worthwhile to elicit information from experts in countries that are major importers of Dutch seed potatoes, as these are not biased by the Dutch legal system and do not have the urge to protect the Dutch export status.

Quantification of losses in case of export restrictions was done by means of partial equilibrium modelling. This approach studies the market of only one good, while leaving other markets out of consideration (Mas-Colell et al., 1995). Studies that do take into account effects of export bans on other sectors of the economy are, for instance, those of Wittwer et al. (2005) and Mahul and Durand (2000), which respectively use general equilibrium modelling and input-output analysis. These methods, however, require much more data than a partial equilibrium approach. Besides, a shift in equilibrium of the seed potato market is not likely to affect other markets. The seed potato market has no other suppliers than seed potato growers, and the only 'consumers' of seed potatoes are other seed potato growers (i.e. the same market) and ware potato growers. For most potato varieties, the price of seed potatoes is rather insensitive to demand (see Chapter 5). Furthermore, ware potato growers cannot replace seed potatoes by other planting material, unless they choose another crop. Consequently, the impact of a shift in the demand for seed potatoes on the ware potato market will be minimal, which justifies the simplification made by a partial equilibrium model.

As explained in Chapter 5, the Dutch seed potato market consists of free varieties and monopoly varieties. Because monopoly varieties comprise the majority of all seed potatoes, the partial equilibrium model was based on these varieties, and the relation between supply and price was represented by a reaction curve instead of a supply curve. The calibrated reaction curve was rather flat, i.e. trading companies will adjust the production volume rather than decrease the price in case of reduced demand. In contrast, a supply curve that represents the relation between price and supply of free varieties would be very steep. Seed potato growers cannot easily switch to cultivation of other crops, so they will be reluctant to reduce their acreage, even if prices are low. In other words, the price elasticity of supply of free seed potato varieties is very low (Arsenault, 2004). Thus, if free varieties were explicitly included in the partial equilibrium model, the effect of export restrictions on average seed potato price would be larger, resulting in a smaller decrease in demand.

The most important threat of brown rot according to many stakeholders in the Dutch potato sector is permanent damage to the reputation of Dutch (seed) potatoes. In this respect, stakeholders are often primarily concerned about the frequency of export losses, rather then their magnitude if they occur. If the level of brown rot incidence frequently leads to export restrictions, other countries may loose confidence in the Dutch control policy, resulting in a decrease of the critical number of detections required for export restrictions to occur. Another potential consequence is that the relaxation time of export restrictions increases; in the worst case, demand may not recover to the level prior to the occurrence of export restrictions. Such consequences are very difficult to quantify and go beyond the scope of this thesis.

6.5 Verification and validation of the bio-economic model

Model verification and validation are often considered indispensable processes in model development, but their criteria are highly dependent on the intended use of the model (Balci, 1995; Kleijnen, 1995). The objective of the bio-economic model was to support the design of cost-effective brown rot control policies. Performance criteria of the model were therefore that (1) it should be a realistic representation of the Dutch potato production chain, (2) simulated incidence and economic consequences of brown rot should be credible and in line with current knowledge, and (3) simulation results should enable robust ranking of scenarios with respect to their cost-effectiveness. Verification and validation can be divided into the following steps: conceptual validation, model verification, data validation, and operational validation (Sargent, 1988; Rykiel, 1996). This section discusses how these steps were dealt with in this research.

Conceptual validation implies determining whether the structure of the real system and underlying theories and assumptions are correctly represented by the conceptual model, within the context of its intended use. The structure of the conceptual model closely resembles that of the real system, and the simplifications and assumptions that were made were thoroughly discussed with experts. This creates confidence in the correctness of the conceptual model.

Model verification means ensuring that the computerised simulation model performs as intended by the conceptual model. The bio-economic model was verified throughout its development by means of dynamic testing, which implies executing the model under different conditions (Sargent, 1988). Correctness of the model was verified by performing traces, i.e. monitoring model entities to check whether the model's logic is correct. In all phases of the verification, the model performed as intended. Another often used method for model verification is input-output analysis, as was done for instance in Chapter 5. This analysis, however, was performed for different purposes, and its results should not be interpreted within the context of model verification.

Data validation implies certifying that the data are of sufficient quality to achieve the intended level of accuracy within the model. The bio-economic model is quite data-intensive: it requires input on farm, field, and sector characteristics, epidemiological parameters, and a large set of economic data, such as potato prices and production costs. Some of these data were readily available, while other data could be estimated with adequate accuracy from literature or other sources. Almost no data were available on infection probabilities (e.g. probability of transmission through contaminated machinery, probability of infection through irrigation with contaminated surface water) and the effect of brown rot incidence on export volume, so the corresponding parameters had to be estimated on the basis of expert elicitation. A disadvantage of using expert knowledge is that the correctness of resulting parameters cannot be verified; the accuracy of the data depends on how well the experts know the system. Therefore, sensitivity analyses were performed on parameters that were estimated through expert elicitation.

Operational validation addresses the question whether model output meets the performance standards required for the intended application of the model. Operational validity of the model could not be measured by comparison of simulated and real data, because the system is for a large part unobservable; e.g. we cannot measure true brown rot incidence or the height of export losses. Moreover, the Dutch brown rot control policy has been adjusted several times during the last decade, so available data are not based on the same policy. Consequently, the model could only be validated by exploring model behaviour, which was done in Chapters 3 and 5. Obtained model results were consistent with existing knowledge of the real system. Results were also communicated with experts and sector representatives. These people found the results plausible, which enhances confidence in the representativeness of model output.

Given the current knowledge, the accuracy of the bio-economic model is at the maximum achievable level. The limiting factor at this moment is the (lack of) availability of data. If more detailed, objective information becomes available, model performance may be further improved.

6.6 Implications for future control of brown rot

Model applications in this thesis have shown that the model is suitable for the evaluation of control strategies for their cost-effectiveness. Thereby, it can serve as an instrument for scenario analyses, to support the design of cost-effective control policies. However, applications presented in this thesis have shown that the model is more than just an instrument. The applications have led to a better understanding of the trade-off between costs and effectiveness of controlling brown rot. It is quantitatively demonstrated that the cost-effectiveness of control should always be determined on the basis of multi-year perspectives, taking into account potential future consequences. The bio-economic model has shown that the consequences of export restrictions are indeed catastrophic, and that an intensive control policy is economically justified. It has also been shown, however, that the cost-effectiveness of control can be greatly increased if introductions of brown rot through contaminated surface water are reduced. The risk of primary infection is primarily determined by activities of stakeholders in the sector; highly cost-effective control of brown rot thus requires cooperation of the government and sector. The advice to involve the sector in control of brown rot fits within the objective of the Dutch government to hand over a large part of their responsibility to the sector (Veerman, 2005).

In the control or eradication of quarantine diseases, education is generally acknowledged as an important factor of success (Myers et al., 1998). Control of a quarantine disease is more effective if all stakeholders involved acknowledge the necessity of controlling that disease. Moreover, stakeholders in the affected sector are probably more likely to voluntarily cooperate in a control program if this is in their own interest. An institutional analysis of brown rot control in the Netherlands showed that the private interest in controlling brown rot may differ between (groups of) stakeholders (Janssens et al., 2006). Also, whereas stakeholders are directly confronted with the costs of control measures, the indirect benefits from avoiding export losses are much less obvious. The bio-economic model can play a significant role in achieving support from the sector, by enabling objective communication on the costs and benefits of measures and providing quantitative evidence of the potential value of the sector's participation in control.

An equitable distribution of costs and benefits increases the support of stakeholders for the control of brown rot (Belli et al., 2001). Although not shown in this thesis, the bio-economic model can provide insight into the distribution of costs and benefits among different stakeholders. For instance, the model can show how a reduction in monitoring would reduce the structural costs to seed potato growers, but increase incidental costs at farms involved in an outbreak. If the costs and benefits turn out to be unequally distributed, e.g. a large fraction of the structural costs is paid by actors who experience only minor benefits from reduction in brown rot incidence, there are several instruments for the government and sector to intervene. One example, which has already been mentioned in this chapter, is insurance. Indemnity payments are conditional upon compliance with regulations concerning the control of brown rot, so the effect of insurance is twofold. Insurances against losses from plant quarantine diseases are still rather uncommon; the only other one we know of is the Corn Rootworm IPM Policy in the US, which intends to reduce pesticide use by coupling compensation for incurred losses from the disease with binding advice on pesticide treatment (Van Asseldonk et al., 2001). Another possibility, which is common in the control of contagious animal diseases, is public-private co-financing (Van Asseldonk et al., 2005). Within this system, the government finances the costs of an outbreak of a disease, but is (partly) repaid by a fund that exists of compulsory yearly levies of benefiting stakeholders.

It is questionable whether complete eradication of brown rot from the Dutch potato production chain will ever be achieved. The presence of brown rot bacteria in the Dutch surface water serves as a permanent external reservoir. Consequently, even if all stakeholders comply with preventive measures such as the ban on surface water and disinfection of transport, there are small, but identifiable risks of introduction of brown rot in the potato production chain. For instance, a potato field may be flooded with contaminated surface water. Or, dispersal of brown rot bacteria to surface water outside prohibition areas may remain unnoticed for one or more seasons, which could lead to infections in ware or starch potatoes. Within a few years, it will probably be possible to disinfect surface water prior to its use for irrigation. This development can lead to a large reduction in the structural costs resulting from drought stress, which comprise a considerable part of the current structural costs. However, it cannot eliminate all of the above-mentioned risks. The large outbreak in 1998, when 105 infections were traced back to three starch seed potato growing farms, is a perfect example of how one (un)intentional introduction of brown rot can cause a catastrophe if it is not detected in time. It will therefore be more realistic to aim at 'functional eradication', which implies that occasional reoccurrence and intermediate action is accepted (Janse and Wenneker, 2002). The bio-economic model can support the development of a control policy by which this aim is achieved at minimum costs.

6.7 Applicability of the model for control of other (quarantine) diseases

The bio-economic model has specifically been developed for the case of brown rot in the Dutch potato production chain. Whether it is applicable to brown rot in other countries depends on the similarity of the potato production system and climatic conditions and the availability of a detailed dataset on farms and fields in that country. In any case, economic parameters would have to be adjusted, as these are very specific for the Dutch potato production chain. A different climate from that in the Netherlands only requires adjusting the epidemiological parameters; a different structure of the chain would also have implications for the structure of the individual-based model.

Application of the model to other diseases in the same potato production chain can be achieved with minor adjustments as long as the infection pathways and legal system are comparable to those of brown rot. An example of a disease that qualifies for this is ring rot, caused by *Clavibacter michiganensis* ssp. *sepedonicus*. The same applies to extension of the model with other diseases than brown rot. One advantage of including other diseases in the model is that the cost-effectiveness of their combined control can be evaluated. For instance, in the case of brown rot and ring rot, only one sample is required to test a potato lot for the presence of both diseases; the relative cost-effectiveness of sampling thus increases. Another advantage of developing a model for more than one disease is that possible interactions between diseases can be accounted for. For instance, pathogens may compete with each other (e.g. biotrophic vs. necrotrophic pathogens) or display spatial co-occurrence (e.g. viruses that have the same vector) (Savary et al., 2006).

Although the possibilities for using the bio-economic model for other diseases or other countries are rather limited, the insights to which it has led, and which have been discussed earlier in this chapter, are widely applicable. For instance, an integrated approach in the control of quarantine diseases can increase its cost-effectiveness, although the potential contribution of the sector is disease-specific. Also, conclusions on the cost-effectiveness of a control policy should be based on expected consequences over a period that is in line with the response time of the affected system; i.e. the period of observation (or simulation) should be sufficiently long for the system to reveal potential long-term consequences of a policy. The length of the response time depends on spatio-temporal dynamics of the disease within this system. The individual-based modelling approach has proven to be a useful tool for modelling disease epidemics at the level of the production chain. It would be interesting, but challenging, to evaluate the possibility for developing a generic individual-based conceptual framework for modelling various production chains and diseases. Furthermore, to date we have found no other models that describe the correlation between plant disease incidence and subsequent export restrictions. The method developed in this project can serve as a starting point for future developments.

Much work has been done on modelling the effectiveness and economics of control of animal disease epidemics (e.g. Vonk Noordegraaf et al., 1998; Mahul and Durand, 2000; Van der Gaag, 2004), while similar research in the field of plant health is lagging behind. The work presented in this thesis comprises a valuable contribution to the field of economics of controlling plant diseases and is a good example of integrating plant disease epidemics with the economics of their control.

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Summary

Potatoes comprise a major cash crop in the Netherlands. Since 1995, the Dutch potato production chain has been hit by several outbreaks of brown rot, a quarantine disease caused by *Ralstonia solanacearum* race 3, biovar 2. The risk of establishment of brown rot as an endemic disease in the Netherlands threatens the Dutch export of seed potatoes. To avoid economic losses from reduced export, the Dutch government has implemented an intensive and costly control policy. Yet, it is unknown whether this policy is optimal from a cost-effective point of view. Design of a cost-effective control policy requires quantitative knowledge of the effect of control strategies on brown rot incidence and economic consequences. This thesis describes the development of a bio-economic model that can be used to evaluate the cost-effectiveness of brown rot control strategies in the Netherlands.

To determine which modelling approach is most suitable for modelling brown rot epidemics within the potato production chain, two conceptual epidemiological models, i.e. a state-variable model and an individual-based model (IBM), have been developed (Chapter 2). The state variable model can be used to provide insight into the basic principles of brown rot dispersal. It shows that a single difference equation for the dynamics of the fraction of infected seed lots in the total potato lot population can elucidate key aspects of brown rot epidemics. However, this model is unable to reflect the large fluctuation in yearly number of infections that is inherent to brown rot epidemics, and its parameters are hard to estimate. The IBM provides a more detailed and realistic representation of brown rot incidence in the potato production chain. A drawback of the IBM is that, due to its complexity, it provides less insight into the fundamental characteristics of brown rot dynamics. Nevertheless, the IBM is believed to be more suitable for application in this project, because (1) results of an IBM are more ready-to-use for subsequent economic analysis due to the concreteness of the in- and outputs, (2) an IBM is better capable of representing different control strategies because it includes management relevant details, and (3) an IBM can be easily combined with a geographical information system (GIS), which enables the analysis of spatial patterns and increases the appeal and practical interpretability and value of model results.

The IBM has been further developed into a functional epidemiological model (Chapter 3). The epidemiological model simulates the dynamics of brown rot over potato growing farms and arable fields in the Netherlands during a sequence of years; the smallest entity in the model, whose behavior is modeled, is the potato lot. A lot is defined as a group of potato tubers or plants of the same variety and quality class, which are grown together on the same field and treated as one unit. The epidemiological model is spatially explicit, enabling spatial analysis of brown rot incidence and dispersal. It also contains stochastic elements to represent the irregularities characteristic for brown rot dynamics. Infections can arise in the model via

three possible pathways: primary infection, horizontal transmission, and vertical transmission. Primary infection can occur through irrigation of a potato field with contaminated surface water. Brown rot bacteria can enter the surface water through infected plants of bittersweet (*Solanum dulcamara*), a wild host that is common along Dutch waterways. Horizontal transmission occurs through direct or indirect, machinery-mediated, contact between a healthy lot and an infected lot. Vertical transmission implies transmission of the disease as a result of clonal propagation of infected potato seed. Model applications show that in the default scenario (i.e. Dutch brown rot policy of 2003) average simulated brown rot incidence is in dynamic equilibrium at approximately 15 infections per year, although large fluctuations are observed between individual years. In this scenario, primary infection accounts for approximately 60% of all infections; vertical transmission is responsible for roughly 20% of the infected lots, while the remaining horizontal transmissions are mainly caused by harvesting and grading. Decreasing the testing frequency of seed potatoes increases the relative importance of vertical transmission at the costs of the importance of primary infection.

In Chapter 4, the epidemiological model is integrated with an economic model into a bio-economic model, which quantifies the costs and benefits of a control strategy on the basis of its effect on brown rot incidence in the potato production chain. The economic model distinguishes three cost categories: structural costs, incidental costs, and export losses. Structural costs are incurred as a consequence of preventive measures, such as monitoring. Incidental costs are related to reactive measures that follow detection of an infected lot, such as destruction of the infected lot and quarantine measures on affected farms. Export losses occur if observed brown rot incidence reaches a level that is unacceptable for countries importing Dutch potatoes. According to results of the bio-economic model, the costs of brown rot under the current Dutch control policy (2006) are 7.7 mln euros per year. Reducing the sampling frequency of seed potatoes from 100% to 10% of all lots reduces the structural costs by 2.5 mln euros. However, this reduction in structural costs is more than offset by an increase in export losses of over 6.5 mln euros on average. It is also shown that the response time of brown rot incidence in the production chain – and thus of the economic consequences – to a particular control policy may cover several years; conclusions on the cost-effectiveness of control strategies thus strongly depend on the period over which costs are quantified.

Chapter 5 explores how the cost-effectiveness of brown rot control can be increased. An impact analysis is performed to quantify the effect of many factors on the incidence and economic consequences of brown rot, and identify important interactions between these factors. Factors represent policy options, characteristics of actors in the potato production chain, economic factors, and social and environmental circumstances (i.e. exogenous factors). The impact analysis is performed according to the techniques of Design of Experiments and regression metamodeling. Results of this analysis are used to conduct scenario studies, to further elucidate how the government and actors in the potato production chain can affect the cost-effectiveness of brown rot control. It appears that policy and sector factors in particular have a large impact on the cost-effectiveness of control, while exogenous and economic factors are of lesser importance. According to the scenario studies, policy measures may be relaxed to a large degree if the sector recognizes its responsibility for avoiding introduction of brown rot. Thereby, a reduction in brown rot incidence of more than 50% and a reduction in costs of control of more than 4 mln euros per year can be achieved. Thus, accounting for potential contributions of other stakeholders than the government can improve the cost-effectiveness of brown rot control.

The results of the research described in this thesis, as well as its strengths and weaknesses, and implications for the future control of brown rot and other quarantine diseases are discussed in Chapter 6. It is concluded that the bio-economic model can facilitate the design of optimal brown rot control policies, by providing more insight into the effect of different factors on the incidence and economic consequences of brown rot in the Dutch potato production chain, and by enabling the *ex ante* evaluation of control strategies for their cost-effectiveness. Moreover, the bio-economic model can play an active role in achieving support from the sector, by enabling objective communication on the costs and benefits of measures, and by providing quantitative evidence of the potential value of the sector's participation in control. The approach used in this research and the general insights to which the bio-economic model has led are applicable to other quarantine diseases as well.

Samenvatting

Aardappelen vormen een belangrijk akkerbouwgewas in Nederland. Sinds 1995 is de Nederlandse aardappelketen getroffen door diverse uitbraken van bruinrot, een quarantaineziekte die veroorzaakt wordt door *Ralstonia solanacearum* race 3, biovar 2. Het risico dat bruinrot zich vestigt als endemische ziekte in Nederland vormt een bedreiging voor de Nederlandse export van pootaardappelen. Om economische schade als gevolg van verminderde export te voorkomen heeft de Nederlandse overheid een intensief en kostbaar beleid ter beheersing van bruinrot geïmplementeerd. Tot nu toe is het is niet bekend of dit beleid optimaal is vanuit het oogpunt van kosteneffectiviteit. Het ontwerp van een kosteneffectief beleid vereist kwantitatieve kennis van het effect van beheersstrategieën op de incidentie en economische gevolgen van bruinrot. Dit proefschrift beschrijft de ontwikkeling van een bio-economisch model dat gebruikt kan worden om de kosteneffectiviteit van beleidsopties ter beheersing van bruinrot in Nederland te evalueren.

Om te bepalen wat voor methode van modellering het meest geschikt is voor het modelleren van de epidemiologie van bruinrot in de aardappelproductieketen zijn twee conceptuele modellen ontwikkeld (Hoofdstuk 2). Deze modellen betreffen een toestandsvariabele model (state-variable model) en een individu-gebaseerd model (individual-based model, IBM). Het toestandsvariabele model kan gebruikt worden om inzicht te verkrijgen in de basisprincipes van bruinrot verspreiding. Het laat zien dat één enkele differentievergelijking ter beschrijving van de dynamica van geïnfecteerde pootaardappelpartijen in de totale populatie van aardappelpartijen de voornaamste karakteristieken van de epidemiologie van bruinrot kan verhelderen. Het model is echter niet in staat om de voor bruinrot typerende grote fluctuaties in het jaarlijks aantal infecties weer te geven. Bovendien zijn de benodigde parameters van dit model moeilijk te schatten. Het IBM daarentegen geeft een gedetailleerdere en realistische weergave van bruinrot incidentie in de Nederlande aardappelproductieketen. Een nadeel van het IBM is dat het, vanwege haar complexiteit, minder inzicht biedt in de fundamentele eigenschappen van bruinrot dynamica. Desondanks is het IBM meer geschikt voor toepassing binnen dit project, om de volgende redenen: (1) de resultaten van een IBM laten zich beter lenen voor een vervolgens uit te voeren economische analyse (2) een IBM is beter in staat om verschillende beleidsopties uit te beelden omdat het details bevat die gerelateerd zijn aan management aspecten, en (3) een IBM kan eenvoudig gecombineerd worden met een geografisch informatie systeem (GIS), waarmee analyse van ruimtelijke patronen mogelijk wordt. Combinatie met GIS maakt model resultaten bovendien toegankelijker en vergroot de praktische interpretatie en waarde ervan.

Het IBM is verder ontwikkeld tot een functioneel epidemiologisch model dat de bruinrot dynamica over alle aardappeltelende bedrijven en akkerbouwpercelen in Nederland simuleert over een periode van meerdere jaren (Hoofdstuk 3). De kleinste eenheid in het model waarvan het gedrag gemodelleerd wordt is de aardappelpartij. Een aardappelpartij is gedefinieerd als een groep aardappelknollen of -planten van hetzelfde ras en dezelfde kwaliteitsklasse, die op hetzelfde perceel geteeld worden en behandeld worden als één eenheid. Het epidemiologisch model is ruimtelijk expliciet, waardoor ruimtelijke analyse van bruinrot incidentie en verspreiding mogelijk is. Daarnaast bevat het model stochastische elementen om onregelmatigheden die karakteristiek zijn voor bruinrot dynamica te kunnen weerspiegelen. Het model onderscheidt drie verschillende infectieroutes: primaire infectie, horizontale transmissie en verticale transmissie. Primaire infectie kan ontstaan via beregening van een aardappelpartij met besmet oppervlaktewater. Bruinrot bacteriën kunnen in het oppervlaktewater terechtkomen via besmette planten van de soort bitterzoet (*Solanum dulcamara*), een wilde waardplant die veel voorkomt langs de Nederlandse waterwegen. Horizontale transmissie ontstaat als gevolg van direct of indirect (via machines) contact tussen een gezonde partij en een geïnfecteerde partij. Verticale transmissie betekent overdracht van bruinrot als gevolg van klonale vermeerdering van besmet pootgoed. Toepassingen van het model laten zien dat de gemiddelde gesimuleerde bruinrot incidentie in het standaard scenario (het Nederlandse bruinrot beleid anno 2003) rond de 15 infecties per jaar ligt, hoewel de aantallen infecties in afzonderlijke jaren sterk kunnen fluctueren. In dit scenario wordt 60% van alle infecties veroorzaakt door primaire infectie en 20% door verticale transmissie. De overige infecties worden veroorzaakt door horizontale transmissie, die met name optreedt tijdens rooien en het daaropvolgende proces van inschuring. Bij verlaging van de bemonsteringsfrequentie van pootaardappelen neemt het relatieve aandeel van verticale transmissie toe, ten koste van het aandeel primaire infectie.

In Hoofstuk 4 wordt het epidemiologisch model geïntegreerd met een economisch model tot een bio-economisch model. Dit model kwantificeert de kosten en baten van een beheersstrategie op grond van het effect van deze strategie op bruinrot incidentie in de aardappelproductieketen. Het economisch model onderscheidt drie kostencategorieën: structurele kosten, incidentele kosten en export verliezen. Structurele kosten treden op als gevolg van preventieve maatregelen, zoals monitoring. Incidentele kosten zijn gerelateerd aan reactieve maatregelen die gelden in geval van detectie van een besmette partij, zoals vernietiging van de besmette partij en quarantaine maatregelen op betrokken bedrijven. Export verliezen treden op als de waargenomen bruinrot incidentie een voor importerende landen van Nederlands pootgoed een onacceptabel niveau bereikt. Volgens de resultaten van het bio-economisch model zijn de kosten van bruinrot in het huidige Nederlandse beheersbeleid (2006) 7,7 miljoen euro per jaar. Het verminderen van de bemonsteringsfrequentie van pootaardappelen van 100% naar 10% van alle partijen leidt tot een daling in structurele kosten van 2,5 miljoen euro. Echter, deze daling wordt ruimschoots overtroffen door een toename in export verliezen van gemiddeld meer dan 6,5 miljoen euro. Ook blijkt dat de reactietijd van bruinrot incidentie in de productieketen – en daardoor ook die van economische gevolgen – onder een gegeven beleid verschillende jaren kan omvatten.

Conclusies over de kosteneffectiviteit van beheersstrategieën zijn dus sterk afhankelijk van de periode waarover het systeem geobserveerd wordt.

Hoofdstuk 5 verkent de mogelijkheden tot verhoging van de kosteneffectiviteit van beheersing van bruinrot. Middels een impact analyse worden de effecten van een groot aantal factoren op de incidentie en economische gevolgen gekwantificeerd. Ook worden belangrijke interacties tussen deze factoren geïdentificeerd. Factoren vertegenwoordigen beleidsopties, eigenschappen van actoren in de aardappelproductieketen, economische factoren, en sociale en omgevingseigenschappen (exogene factoren). De impact analyse is uitgevoerd volgens de technieken van Design of Experiments en regressie metamodellering. Resultaten van de analyse zijn gebruikt om scenario studies uit te voeren, om verder te ontrafelen hoe de overheid en actoren in de keten de kosteneffectiviteit van beheersing van bruinrot kunnen beïnvloeden. Het blijkt dat voornamelijk beleids- en sectorfactoren een grote invloed hebben op de kosteneffectieviteit van bruinrot beheersing, terwijl exogene en economische factoren minder belangrijk zijn. Uit de scenario studies blijkt dat beleidsmaatregelen sterk gereduceerd kunnen worden als de sector haar verantwoordelijkheid voor het voorkómen van bruinrot introducties onderkent. Daarmee kan een reductie in bruinrot incidentie van 50% behaald worden, terwijl de kosten van maatregelen met gemiddeld 4 miljoen euro per jaar verlaagd kunnen worden. Door rekening te houden met de potentiële bijdrage van andere actoren dan de overheid kan de kosteneffectiviteit van het bruinrot beleid dus verbeterd worden.

De resultaten van het beschreven onderzoek, alsmede de sterke en zwakke punten ervan en mogelijke implicaties voor toekomstige beheersing van bruinrot en andere quarantaine ziekten, worden bediscussieerd in Hoofdstuk 6. Geconcludeerd wordt dat het bio-economisch model het ontwerp van optimale bruinrot beleidsopties kan vergemakkelijken. Het biedt inzicht in het effect van verschillende factoren op de incidentie en economische gevolgen van bruinrot in de Nederlandse aardappelketen, en maakt *ex ante* evaluatie van de kosteneffectiviteit van beheersstrategieën mogelijk. Bovendien kan het model een actieve rol spelen in het creëren van draagvlak in de sector. Het model biedt de mogelijkheid tot objectieve communicatie over de kosten en baten van maatregelen en levert kwantitatief bewijs voor de potentiële waarde van een bijdrage van de sector in bruinrot beheersing. De gehanteerde methodiek en de algemene inzichten die verkregen zijn met behulp van het bio-economisch model zijn ook toepasbaar voor andere quarantaineziekten.

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Curriculum vitae

Maria Louisa Henrica (Annemarie) Breukers werd op 24 september 1979 geboren in Ell. In 1997 behaalde zij haar VWO diploma aan de Philips van Horne scholengemeenschap te Weert. In datzelfde jaar begon zij met de opleiding Biologie aan de toenmalige Landbouw Universiteit te Wageningen. Tijdens deze studie deed ze twee afstudeervakken, in de richtingen Fytopathologie en Agrarische Bedrijfseconomie. Dat laatste afstudeervak werd uitgevoerd aan de University of Guelph, Canada. Daarnaast liep ze stage bij BASF Nederland (divisie Agro) en de Plantenziektenkundige Dienst. In september 2002 studeerde ze af in de specialisatie Plantenbiologie. Van september 2002 tot en met september 2006 werkte zij als Assistent in Opleiding (AIO) bij de leerstoelgroep Bedrijfseconomie van Wageningen Universiteit. Het onderzoek dat zij daar uitvoerde werd in september 2006 afgerond en staat beschreven in dit proefschrift. Sinds november 2006 is zij als wetenschappelijk onderzoeker werkzaam bij de afdeling Plant van het Landbouw-Economisch Instituut.

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With the educational activities listed below the PhD candidate has complied with the educational requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 22 credits (= 32 ECTS = 22 weeks of activities)

Review of Literature (4 credits)

- Bio-economic modelling of potato brown rot in the Netherlands (2002)

Writing of Project Proposal (4 credits)

- Bio-economic modelling of potato brown rot in the Netherlands (2002)

Post-Graduate Courses (5.5 credits)

- Bayesian Statistics (2003)
- Food safety risk analysis (2003)
- The art of modelling (2004)

Deficiency, Refresh, Brush-up and General Courses (5 credits)

- Research Methodology (2002)
- Advanced Statistics (2003)
- Scientific Writing (2003)
- Hoorcollege geven (2005)

PhD Discussion Groups (4 credits)

- PhD meetings / department meetings Business Economics Group (2002-2006)

PE&RC Annual Meetings, Seminars and Introduction Days (1.5 credits)

- Epidemiology and economics of *E. coli* 157 (2002)
- Workshop economie en bestuur van plantgezondheid (2003)
- Interactiedag gewasbescherming (2003)

- PE&RC annual meeting: ‘Biological disasters’ (2004)
- KNPV najaarsvergadering (2005)

International Symposia, Workshops and Conferences (5.25 credits)

- EPPO conference on computer aids for plant protection (2002)
- Symposium ringrot (2003)
- Alcalá 2nd international conference on mathematical ecology (2004)
- Economics of plant health, workshop (2005)
- Introduction and spread of invasive species (2005)
- International bacterial wilt symposium (2006)

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