Agricultural production with change and uncertainty: a temporal case study simulation of Colorado potato beetle

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AGRICULTURAL PRODUCTION WITH CHANGE AND UNCERTAINTY: A TEMPORAL CASE STUDY SIMULATION OF COLORADO POTATO BEETLE

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Abstract

Changes in climatic and policy environments combined with uncertainty related to stochastic environmental fluctuations make design of invasive pest policy challenging. These external changes are often exacerbated by changes in the species characteristics. We discuss facing local change and uncertainty when deciding ex ante on a specific policy strategy. Our empirical case deals with an invasive agricultural pest, Colorado potato beetle, and agricultural production in Finland. Invasions are modelled as temporally random events and stochasticity in key variables is built into the analysis. The viability of two specific policy options is evaluated given uncertainty and local change.

Keywords: Colorado potato beetle, protected zone, zone protégée, invasive alien species.
JEL classification codes: Q1, Q28, Q58

Introduction

Uncertainty and change are facts of life, and should not come to anyone by surprise. However, to a greater extent we can take them into account in our actions, the better ground we are on. This applies not just to our personal behaviour, but also, and perhaps more importantly, to the various policies we choose to design and implement. We discuss agricultural production and policy when there is change and uncertainty regarding a specific environmental phenomenon: invasive pest species. The case we use for the empirical assessment deals with an invasive agricultural pest, Colorado potato beetle (*Leptinotarsa decemlineata*) (CPB) and potato production in Finland.

Changes in local climatic conditions and agricultural policies and uncertainty related to stochastic environmental fluctuations make invasive pest policy relatively challenging to design and implement. These changes are often exacerbated by dynamic changes in the species characteristics. It is therefore no wonder that threats to animal and plant health by invading organisms are on the increase. About a quarter of all agricultural output is lost annually due to damages imposed by invasive pests or costs of their control (Schmitz and Simberloff, 1997). Globally, agricultural losses to introduced species are estimated at US$ 55-248 billion annually (Bright, 1999). In the case of Finland such changes affecting crop production seem significant in the near future.

First, Finland's membership in the European Union has opened borders and increased trade and movement of goods and people. Although pests such as the CPB may be carried by stormy winds, more unpredictable invasion pathways include transport with traded goods. Invasion pressure from this source has considerably increased with the increased Russian timber imports.

Secondly, potential warming of temperatures may be changing environmental conditions in Finland (e.g. Jylhä et al., 2004). Temperature changes are larger close to polar areas and growing conditions both to plants and to their pests may be rapidly changing with the warming temperatures. The CPB seems to suffer somewhat from cold winters and especially from cold and short summers. However, with the changing weather, the threat from both increasing invasion pressure and permanent establishment of the CPB in Finland increase.

Finally, agricultural practices and modifications in those practices in surrounding countries may also increase the invasion pressure. Large-scale use of pesticides in Russia and Poland initiate and speed up development of resistance to common pesticides. Also structural changes in Russia and Estonia have caused large number of private people to start subsistence potato production on small domestic plots, which may also affect the pests' living conditions.

Resulting from all this, the CPB invasion pressure is increasing in Finland. This increasing pressure must be accounted for when designing policy tools against the pest. This paper deals with ex-ante assessment of possible costs of an invasion by the CPB into the Finnish agricultural network. Invasions are modelled as temporally random events and stochasticity in key variables is built into the analysis. Further, our analysis includes three trends that represent changes in climatic conditions and pest traits. In other words, uncertainty and local change are integral factors in the analysis.

The main purpose of the current study is to evaluate the viability of two specific policy options when facing local and global change. The rest of the paper is organised as follows. The next section provides the basic background to the question by discussing uncertainty and change. The section after that constructs a theory-based economic simulation model of certain policy options, followed by a numerical evaluation. The final section draws some conclusions.

Uncertainty and change

We categorise existing uncertainty into three broad categories according to Heal and Kriström (2002), namely scientific, impact and policy uncertainty. We suffice ourselves here to highlighting the relationship of the CPB case study to uncertainty and change – the specifics of the case study are discussed later. We discuss each type of uncertainty in turn.

First, we are uncertain of the invasion process and its pre-determinants in the points of origin in Russia. Certain weather patterns, including particular wind corridors, can be related to invasions, but the exact relationships of the various components are unknown. This can be seen as *scientific uncertainty*, which arises when a certain physical relationship is not known.

Secondly, it is unknown how the continued invasions would affect the production patterns in Finland. Production may be regionally rearranged and new more tolerant plant varieties may be introduced. In the shorter term, also the impact of the beetle on potato yield is somewhat uncertain depending for instance on timing of the invasion, weather conditions and producer counter-measures. These can be seen as *impact uncertainty*, where the impacts of natural phenomena on the various components of human societies are uncertain, even if the physical science behind them is known.

Finally, there is a third type of uncertainty, which can be categorised as *policy uncertainty*. It is related to questions such as: What type of policy should we undertake, and what are the conditions that determine the optimal policy? Does the optimal choice change over time and are there irreversibilities involved? In such questions, we may know the physical structure of problems, and how those affect the human societies, but we are still uncertain about the impacts of our own corrective actions. For instance, there is uncertainty related to which policies are needed to address the problems, how those policies impact on the issue in question and what are the costs of undertaking the policy. We answer some of these questions in our case study. However, the analysis is naturally restricted by how we choose to tackle scientific and impact uncertainty.

Additionally, when modelling particular relationships involving naturally varying processes there may exist *stochastic uncertainty*, which is not amenable to learning. We solve this primarily by allowing for stochastic variability in key parameters, and undertaking the analysis with sufficient amount of iterations to accommodate various parameter combinations.

Finally, there is imperfect knowledge about some (deterministic) key relationships or parameters. This so called *parametric uncertainty* is handled by using expert opinions in building the probability distributions for the parameters used in the analysis. We also undertake sensitivity analysis. Additionally, for discount rate and certain other model variables that are subject to *value uncertainty*, we try different values, as there do not exist commonly agreed values.

Our policy problem has a temporal nature as it includes interactions between actions taken today and the impacts of those actions experienced in the future in light of uncertainty. Therefore, the temporality must be taken into account in the modelling exercise. The variables used in such models can be divided as follows (Kann and Weyant, 1999):

1. Set of physical state variables (economic and climatic indicators) [P]
2. Set of control variables (describing the policies) [C]
3. Set of information variables (in models that include learning) [I]

In our model the physical [P] characteristics are updated at every period, whereas information [I] and control [C] variables are updated only at a limited number of periods – in our case solely in the first period. Thus our model can be considered to be a kind of Single-Period Decision Analysis model as categorised by Kann and Weyant (1999). In our case, instead of evaluating all (infinite) states of the world, we try to evaluate a large number of states for the two discrete policy alternatives. Furthermore, we analyse the reliability of the model through the following procedures:

1. Sensitivity analysis of key variables and their impact on results;
2. Sensitivity analysis on which variables affect the outcome most;
3. Discussion on which inputs we know least of.

In addition to uncertainty, the analysis is further complicated by slowly incurring changes due to modified agricultural practices in surrounding countries, changes in temperatures and the generally increased trade and movement of goods. Due to change the factors which may already be uncertain to start with may further change over time, and these change parameters themselves are uncertain.

We account for such local changes through three separate trends, where the mean value of the variable changes linearly. Changes analysed materialise in winter survival, invasion frequency and magnitude, and pesticide resistance of the pest. These represent on one hand changing climatic conditions and agricultural practices and on the other dynamic development of the pest population. All the trends are analysed at three different levels: i) no change; ii) slow change; and iii) rapid change.

The model

The model deployed is based on a pollution model by Barrett and Segerson (1997). The assumptions of the model are as follows: i) two alternative strategies are available; ii) control is only damage reducing; iii) strategies have no external costs or benefits; iv) producers are price-taking profit maximisers; v) price transfers may be imperfect, i.e. prices are allowed to vary due to the invasion; vi) the society is a risk neutral cost minimiser; and vii) the pest is host-specific and causes no ecological or food safety damage.

Private objective

The producer objective function for a representative producer in hectare *i* is (the time subscript *t* has been dropped in this section for clarity):

$$\begin{aligned} &\max\ \pi_i = p_S q_i(x_i)\left[1 - D(N_i)\right] - \left[x_i + p_z z_i(p_z, N_{0i})\right] \\ &\text{s.t } N_i = N_{0i} - \eta z_i(p_z, N_{0i}) \end{aligned} \tag{1}$$

Production revenue is represented by $p_S q_i(x_i)$, i.e. the state-dependent producer price of the agricultural product (p_S) multiplied by the quantity produced (q_i) which depends on inputs (x_i) (with $\partial q_i/\partial x_i>0$). The properties of $q_i(x_i)$ have no practical relevance for the model as long as they remain unaffected by the presence of the pest. The price depends on the magnitude of the invasion and the damage that has occurred (see equation 5 later).

The pest damage function is $D(N_i)$. The magnitude of damage (D) depends on the density of pest individuals in the production area (N_i, with $\partial D/\partial N_i>0$). N_i follows $N_i = N_{0i} - \eta z_i(p_z, N_{0i})$, where N_{0i} is the number of pest individuals invading the i^th^ hectare, η is a parameter measuring the effectiveness of control inputs and z_i is the per hectare quantity of control inputs, such as pesticides. Together ηz_i measure the magnitude of pest individuals eradicated by the producer (reactive control) (with $\eta, z_i \geq 0$, $\partial D/\partial \eta<0$, $\partial D/\partial z_i<0$). The amount of control applied is dependent on the price of control p_z and on the pre-control number of pest individuals in the production area. The resulting damage is proportional to the quantity produced in the absence of the pest, and is a figure between 0 and 1.

Production costs are represented by $x_i + p_z z_i(p_z, N_{0i})$. The first term denotes the production costs in the absence of the pest. These non-control inputs (x_i) are assumed to be a numeraire input, with price equal to unity. Note that any production subsidies are ignored. The second term is the magnitude of reactive control (z_i) multiplied by its unit price (p_z).

Social objective

In this setting, the society has to make a choice between the following two policy alternatives.

$$\text{Pre-emptive control: } E(TC_1)=\sum_{t=1}^{T}\frac{C_F + C_{Vt}(A_t, I_t) + \omega_{t-1} w_{t-1}\theta_{t-1} C_{Vt-1}(A_{t-1}, I_{t-1})}{(1+r)^t} \tag{2}$$

Due to uncertainty regarding the magnitude of the pest invasion, it is appropriate to talk about expected total costs (*E(TC)*). These consist of the fixed costs of pre-emptive control (C_F) and the variable costs of pre-emptive control (C_{Vt}). The latter depend on the area invaded (A_t), which is measured by the production hectares affected, and on the inspection visits I_t that are needed for control and surveillance ($\partial C_{Vt}/\partial A_t>0,\ \partial C_{Vt}/\partial I_t>0$).

It is also possible that the protection system has failed in the previous year, and some proportion of the area in the previous year is still invaded. The failure probability of the protection system is ω_t, the proportion of the area remaining infected w_t, and the winter survival of the beetle population θ_t. The annual costs are discounted at discount rate r and summed up over the years $t = 1$ to T.

$$\text{Reactive control: } E(TC_2)=\sum_{t=1}^{T}\frac{\Delta PS_t + \Delta CS_t}{(1+r)^t} \tag{3}$$

The expected total costs consist of the expected change in producer surplus (ΔPS_t) plus the expected change in consumer surplus (ΔCS_t). Expected change in consumer surplus, due to the shift of the supply curve, is estimated by

$$\Delta CS_t = \Delta p_t q\left[\left(A_{TOT} - D_t A_t\right) + \left(\frac{D_t A_t}{2}\right)\right] \tag{4}$$

In equation (4) A_{TOT} represents the total production area in the country. Equation (4) represents the losses experienced by the consumers due to invasion induced commodity price increase and reduced supply. The equation assumes that the demand curve is linear over the price range considered. The price change above is

$$\Delta p_t = -p\varepsilon D_t \frac{A_t}{A_{TOT}} \tag{5}$$

In other words, there is a base price p, which is then modified by the magnitude of the invasion and the damages $D_t \frac{A_t}{A_{TOT}}$ (i.e., by how much supply is reduced), and the yield effect on price ε.

The change in producer surplus is estimated through two different effects on the producer objective function, and considering the ensuing aggregate change in profit as the impact of the invasion on producers. In other words, the annual impact is (from the private objective function)

$$\Delta PS_t = \Pi_t^{NOINV} - \Pi_t^{INV} \tag{6}$$

$$\Delta PS_t = \sum_{i=1}^{A_{TOT}}\left[pq_i(x_{it}) - x_{it}\right] - \left\{\sum_{i=1}^{A_{TOT}-A_t}\left[p_t q_i(x_{it}) - x_{it}\right] + \sum_{i=A_{TOT}-A_t}^{A_{TOT}}\left[A_t\left\{p_t q_i(x_{it})(1-D_t) - \left[x_{it} + p_z z_{it}\right]\right\}\right]\right\} \tag{7}$$

This can be simplified into two effects as follows. The first effect is the damage and additional control costs inflicted on those producers whose farm is invaded. In other words,

$$(qpD_t + p_z z_{it})A_t \tag{8}$$

The second effect is the subsequent price increase enjoyed by all producers, regardless of whether they have been subject to the invasion or not,

$$- q\Delta p_t \left[(A_{TOT} - A_t) + A_t (1 - D_t) \right] \quad (9)$$

Given these policies, the degree of risk aversion is a factor that can potentially affect the policy choice and evaluation. Risk attitude is likely to be culture specific, and thus in case of a worldwide problem such as climatic change this factor may be important. For instance, the US is characterised as being an impatient society with high discount rate and high risk tolerance, whereas Europe and Japan are seen to be at the other end of the spectrum (Heal and Kriström 2002). In our case study we assume the society to be a risk neutral welfare maximiser (or, in fact, a cost minimiser). The problem of the risk neutral and welfare maximising society is thus to choose min $\{E(TC_1), E(TC_2)\}$.

The simulation study

Background to simulation

Invasive alien species affect the environment, natural resources and resource-based production in Finland as elsewhere. In agricultural production, Colorado potato beetle is one of the potentially most important pests. Traditionally the situation concerning invasive pests has been quite preferable, partly due to Finland's isolated geographical location. However, as discussed earlier this situation is changing. This makes it important to analyse how possible protection policies function under uncertain and changing conditions.

Protected zones are a voluntary black-list instrument for the member countries of the European Union (EU) to use if they wish to protect their production environment against specified invasive plant pests. This protection naturally carries a cost. The actions required include surveillance for the presence of the pest, labelling and import restrictions for plant products associated with the pest, eradication, disinfection and post-monitoring in the case of an invasion, and so forth. Often the benefits of not having the pest around outweigh these costs, but this is by no means inevitable (European Commission, 2000; EU, 2002; Mumford, 2002; MacLeod et al., 2005).

In this study we evaluate the economic viability of the Finnish Colorado potato beetle protection system under uncertain and changing conditions. Alternatively, resources could be devoted to reactive control of the invading organism in order to reduce the impact of the invasion. Our framework consists of two possible actions, the currently used pre-emptive policy and reactive control as an alternative. These lead to two potential strategies that we evaluate: i) invest in pre-emptive control; or ii) allow invasion if it so happens and invest in reactive control.

Pre-emptive control through the protection system involves reducing the likelihood of establishment through surveillance and co-ordinated eradication. The emphasis is on preventing establishment rather than the wind-borne invasion events per se. Reactive control is understood as producer application of control in the event of an invasion. Reactive control measures are not perfectly effective in that crop losses may still result.

The economic costs in the strategies are as follows. In the case of pre-emptive control the economic cost consists of the fixed and variable costs of the protection system. The fixed costs consist of maintaining the appropriate infrastructure in order to swing into action when needed, as well as regular checks at the borders and on the fields to monitor the pest status. The variable costs are dependent on the invasion magnitude and consist of authority driven eradication of the pest and financial compensation for the producers. It is also possible that the protection system partially fails, and not all pests can be eradicated in any one year. In such a case those hectares are in the simulations added to the invaded area in the following year.

In the case of reactive control two types of costs are considered. First, there are changes in producer surplus due to price changes, pest control costs and the value of lost production, caused by imperfect control or interim damage occurring before control application. Second, there may be changes in consumer surplus if product prices increase due to reduced supply. External damage to ecosystems or human health is ignored, as the beetle does not display such impacts.

The cost data

The planning horizon in the simulation is 50 years, during which time invasion events are assumed to take place randomly. The length of the analysed period is chosen to demonstrate the impact of changes, giving them sufficient time to materialise. At the end we also discuss the implications of the planning horizon actually chosen in policy making.

In problems that deal with change the time horizon is often long or very long, implying the importance of the discount rate. Weitzman (2001) reports of a survey of 1,720 economists, who were asked which discount rate should be used in problems related to global warming. The median of their answers was 2% and the mean was 4% ± 3%. In our study we have chosen to use the 2% discount rate as the basis for evaluations, although we also test the significance of higher and lower discount rates.

The cost estimates used in the analysis are presented in Table 1.

Table 1. The cost estimates used in the analysis.

Cost	***Estimate (€)***	***Source and notes***
PROTECTED ZONE (PRE-EMPTIVE CONTROL):		
KTTK fixed costs:	37,827 € / year	Plant Production Inspection Centre (KTTK), based on costs in years 1999, 2000 and 2001.
KTTK variable costs:		
i) inspection	256 € / visit	KTTK. Estimated from costs in years 1999-2004.
ii) control substances	20 € / ha	KTTK. Estimated from costs in years 1999-2004.
iii) compensation and eradication	610 € / ha	KTTK. Estimated from costs in years 1999-2004.
NO PROTECTED ZONE (REACTIVE CONTROL)		
i) production losses	10% of yield in infected areas	Elsewhere (USA, Russia) crop losses of 15-20% have been reported. A lower figure is used due to temperature dependent feeding and the current low level of resistance.
ii) control costs	100 € / ha	Estimate, includes costs of control substances and labour costs. In the USA, costs of up to 300 €/ha exist.
iii) consumer effects	calculated	Invasion induced price increases are assumed. Yield effect on price is taken to be -2 (10% yield reduction causes 20% price increase). The shock is assumed to stay for the duration of that year (Jalonoja and Pietola 2001).
iv) trade effects	assumed zero	Finnish potato trade is at present very small scale activity.
v) environmental costs	assumed zero	There are no direct environmental impacts. Impacts of control substances are not accounted for here.
vi) health costs	assumed zero	If control substances are used in accordance with regulations there will be no health implications.

Change in the case study simulation

As discussed earlier, three trends are included in the analysis to account for local change. The first trend is increasing winter survival of the pest. Through local climatic change and changes in the beetle's winter tolerance it is possible that the winter survival of the beetle population is getting better. In the simulation the change materialises through increases in the percentage of those who survive the winter. The winter survival variable is created for each time period as follows

$$\theta_t = \theta\_mean(1 + (t-1)\theta\_trend) \qquad (10)$$

In equation (10) *θ_mean* denotes the baseline winter survival and *θ _trend* is the trend variable that depends on the trend strength. We assume that in slow change, the winter survival increases in 50 years from an average of about 30% to about 45%. In rapid change, the change is from 30% to about 60%. Note that the mean follows the deterministic path, while stochastic annual variation is allowed around this mean.

The second trend is increasing invasion pressure. Due to local and regional climatic change and advancement of the permanent beetle population towards north it is to be expected that invasions will become more frequent. In the simulations, the probability of an invasion increases through time. Also the average size of an invasion increases over time.

$$A_{INITt} = A_{INIT}\_mean(1+(t-1)A_{INIT}\_trend) \tag{11}$$

$$\gamma_t = \gamma\_mean(1+(t-1)\gamma\_trend) \tag{12}$$

The interpretation of (11) and (12) is similar to that of (10). A_{INITt} is the initial invaded area and γ_t the invasion probability. We assume that with slow change, the average size of an invasion increases from about 400 ha to about 600 ha. The annual invasion probability increases from about 33% to about 50%. With rapid change, the average size of an invasion increases to about 800 ha. The annual invasion probability increases to 65%.

The third trend is increasing pesticide resistance. The beetle is good at developing resistance towards different pesticides. Due to this the effectiveness of pesticides decreases and the costs increase. We show the impact of increasing pesticide resistance only through increasing costs of control, although in reality a larger share of beetle population would be likely to survive and hence spread the following year. Thus in the simulation the protected zone variable costs per hectare and the reactive control costs per hectare both increase.

$$C_{Vt} = C_V\_mean(1+(t-1)C_V\_trend) \tag{13}$$

$$p_z z_{it} = p_z z_i\_mean(1+(t-1)p_z z_i\_trend) \tag{14}$$

In (13) and (14), C_{Vt} is the variable cost of protection and $p_z z_{it}$ the reactive control cost. We assume that with slow change, the variable costs of protection increase in 50 years from 20 e/ha to about 40 e/ha. In reactive control the costs increase from about 100 e/ha to about 200 e/ha. With rapid change, the variable costs of protection increase in 50 years from 20 e/ha to about 50 e/ha. In reactive control the costs increase from about 100 e/ha to about 250 e/ha.

In addition, in the case of all the trends, the increasing pressure also materialises through increase in the failure probability ω_t of the protection system, and increase in the area in which protection fails w_t. The failure probability increases from 30% to 100% in about 47 years, and the invaded area in which protection fails from 20% to about 70%.

Applying the formulae

The initial invasion magnitude is expected to be on average similar to the invasion in 2002, i.e. within the total production area of 29100 ha: i) about 1600 ha is inspected (5.5%); and ii) about 400 ha is controlled (1.4%). These magnitudes are, however, allowed to vary stochastically, as well as incorporate change through changing mean values.

To calculate the total expected costs in different scenarios we use the equations developed in the theoretical section. The formulae used in the calculations become as follows.

Pre-emptive control costs: $$E(TC_1) = \sum_{t=1}^{50}\left(\frac{F_1 + F_2 + V_1 I_t + (V_{2t} + V_3)A_t}{(1+r)^t}\right) \tag{15}$$

s.t. $A_t = \gamma_t A_{INITt} + \omega_{t-1} w_{t-1} A_{t-1} \theta_{t-1}$

In the simulations, it is the area invaded, not the pest population, which grows. In the protected zone strategy, it is assumed that the pest can be prevented from establishing, albeit a certain proportion of the population may survive to the next year.

The probability of invasion γ_t is modelled in the simulation such that in any given year there either is an invasion or there is not. The probability then affects the *frequency* of invasions. For instance, if the probability is 0.33, *on average* there is an invasion every third year.

The controlled area and inspection visits depend on the invasion magnitude in the present year A_{INITt} (i.e. how large is the invasion coming from outside the system) as well as on the area of the protection system that is being carried over from previous years $\omega_{t-1}\, w_{t-1}\, \theta_{t-1}\, A_{t-1}$. The inspection visits depend multiplicatively on the area controlled.

The cost of pre-emptive control is thus affected by the invasion magnitude, the frequency of invasion years, and the extent of a possible failure in the previous year's protection. The invasion frequency has an impact in two ways: first, by dictating whether there is an invasion or not in a particular year (direct effect), and second, by the fact that there may be remnants of previous invasions still existing in the network (indirect effect). The cost of the protection system thus varies in time depending on how often and to what extent preventative actions are needed.

In the case of reactive control, two pest spread scenarios are analysed. Scenario 1 assumes logistic spread and Scenario 2 linear spread. As a special case we discuss the situation in which there is no winter survival. In addition to spread of the existing population, new random invasions are allowed just like in the case of pre-emptive control. The difference equation for the development of the infected area in Scenario 1 is as follows

$$A_t^1 = \gamma_t s_{INITt} A_{INITt}\left(1-\frac{A_{t-1}^1\theta_{t-1}}{A_{TOT}}\right)+\frac{A_{t-1}^1 s_{t-1}\theta_{t-1}}{\left(1+\dfrac{(s_{t-1}-1)A_{t-1}^1\theta_{t-1}}{A_{TOT}}\right)} \tag{16}$$

Change in the area comprises of possible new invasions plus spread of the existing population. The term s_{INITt} accounts for the fact that the pest spreads already in the first year in the case of reactive control. This is because it is foreseeable that without authority enforced control, the beetle manages to spread into a wider area already in the initial year of invasion. In the case of pre-emptive control, this first year spread is not taken into account, as it is assumed that the coordinated and timely control measures can curb any spread. Hence, the initial year invaded area is always somewhat larger in the case of reactive control.

The term $1-\dfrac{A_{t-1}^1\theta_{t-1}}{A_{TOT}}$ accounts for the fact that if the existing size of the invasion is already large, it is less likely that any new invasion would add to the infected area. Hence the size of the new invasion is weighted by the proportion of available unaffected area. Finally, note that only a given proportion of the population (θ_t) survives the winter and is able to continue spreading.

In Scenario 2 the spread equation is as follows

$$A_t^2 = \gamma_t s_{INITt} A_{INITt}\left(1-\frac{A_{t-1}^2\theta_{t-1}}{A_{TOT}}\right)+\left(A_{t-1}^2+s_{t-1}^{lin}\right)\theta_{t-1} \tag{17}$$

$$\text{s.t. } A_t^2 \le A_{TOT}$$

In equation (17), s_t^{lin} is the additive spread variable, i.e. the hectarage added each year due to spread. In the special case with no winter survival, the difference equation is simply

$$A_t^{SC} = \gamma_t s_{INIT\,t} A_{INITt} \tag{18}$$

Reactive control costs in Scenarios 1 and 2 are thus: $E(TC_2) = \sum_{t=1}^{50}\left(\frac{\Delta PS_t + \Delta CS_t}{(1+r)^t}\right) =$

$$E(TC_2) = \sum_{t=1}^{50}\left(q \frac{\left[(pD_t + p_z z_{it})A_t\right] - \Delta p_t\left[(A_{TOT} - A_t) + A_t(1-D_t)\right] + \Delta p_t\left[(A_{TOT} - D_t A_t) + \left(\frac{D_t A_t}{2}\right)\right]}{(1+r)^t} \right) \quad (19)$$

Reactive control costs consist of changes in producer and consumer surpluses. Producer surplus change consists of damages and control costs incurred (first term in the numerator) and the additional income due to invasion induced price increase (second term). The loss of consumer surplus is due to the price increase (third term). Note that some of the terms in (19) cancel out. We have maintained the division between consumer and producer effects in order to analyse the division of policy costs.

In the simulations stochastic variation is allowed in invasion events (on/off), production losses, annual control and inspection magnitudes, spread rates, winter survival, and protection system success. The variable values used are presented in Table 2.

Table 2. Parameter and variable values and the symbols used.

Parameters and Variables	Symbol	(Mean) Value	Variance
Production losses (%)	D_t	0.10	0.005
Reactive control costs per hectare (€)	$p_z z_{it}$	100	-
Pre-invasion producer price (€)	p	0.20	-
Yield effect on price	ε	-2	-
Base production quantity per hectare (kg)	q	24400	-
Discount rate (%)	r	0.02	-
Fixed costs of the protection system (€)	F_1	36222	-
Miscellaneous fixed costs (€)	F_2	1605	-
Inspection cost per visit (€)	V_1	256	-
Pre-emptive control substance costs per ha (€)	V_{2t}	20	-
Eradication and compensation per ha (€)	V_3	610	-
Total hectarage (ha)	A_{TOT}	29100	-
Initial control magnitude (ha)	A_{INITt}	400	20000
Annual hectarage controlled (ha)	A_t	varies	> 0
Inspection multiplier	g	4	-
Annual inspection visits (visits)	I_t	$g * A_t$	> 0
Invasion induced price increase (€)	dp_t	$-D*p*\varepsilon*A_t/A_{TOT}$	> 0
Invasion probability (%)	γ_t	0.33	-
Spread multiplier in first year	s_{INITt}	1.5	0.05
Spread multiplier in nonlinear spread	s_t	1.8	0.4
Spread area in linear spread (ha)	s_t^{lin}	400	10000
Proportion of population that survives winter (%)	θ_t	0.3	0.02
Failure probability of protection system	ω_t	0.3	-
Failure area of protection system	w_t	0.2	-
Trend multiplier in invasion magnitude (low/high)	A_{INIT}_trend	1.01/1.02	-
Trend multiplier in invasion probability (low/high)	γ_trend	1.01/1.02	-
Trend multiplier in winter survival (low/high)	θ_trend	1.01/1.02	-
Trend multiplier in V_2 (low/high)	C_V_trend	1.10/1.20	-
Trend multiplier in $p_z z_i$ (low/high)	$p_z z_i\_trend$	1.02/1.04	-
Trend multiplier in failure probability	ω_trend	1.05	-
Trend multiplier in failure area	w_trend	1.05	-

Basic results

The analysis was conducted for 300,000 iterations in order to have a sufficient representation of various parameter combinations. The results are reported below. We will first discuss the number of cases preferring each strategy, followed by discussion on mean, minimum and maximum costs involved. We then conclude the results section by discussing benefit cost ratios (BCRs) before moving to sensitivity analysis. Finally, we discuss briefly intertemporal and intratemporal division of the costs.

Table 3. Cases (%) where the strategy has a lower cost than the other strategy.

Cases %	***Scenario***	***Pre-emptive control***	***Reactive control***
No trend	Scenario 1	13.0%	87.0%
	Scenario 2	6.5%	93.5%
Slow trend	Scenario 1	85.8%	14.2%
	Scenario 2	31.0%	69.0%
Rapid trend	Scenario 1	100.0%	0.0%
	Scenario 2	80.9%	19.1%

Table 3 depicts the number of iterations (cases) in which one of the strategies imposes lower costs than the other. For instance, in the case of all trends set at 'slow', in 85.8% of the iterations, pre-emptive control imposes lower costs than reactive control. In other words, on average in 85.8% of different realisations of future, pre-emptive control is the more economical choice.

As is evident, whenever there is winter survival of the pest and some anticipated change, pre-emptive control is the cost minimising strategy in 31-100% of the cases. The trends thus enhance the profitability of protection. On the other hand, if we assume that there will be no changes in the future, or that the pests die for certain over the winter (results not shown in the table), it seems that it would be economically sensible to abandon the protection system. However, in the presence of uncertainty, these results have to be supplemented by looking at the mean, median, minimum and maximum costs of the strategies, as depicted in Table 4.

Table 4. The discounted present value costs in each strategy and scenario.

Costs		***Pre-emptive control***	***Reactive Control***		
			Scenario 1	***Scenario 2***	***No winter survival***
No trend	Mean (€)	9,878,500	8,241,800	8,260,200	3,822,400
	Median (€)	9,826,300	8,016,200	8,185,500	3,760,500
	Min (€)	3,586,700	581,660	1,510,900	284,870
	Max (€)	17,898,000	29,159,000	18,518,000	9,731,700
Slow trend	Mean (€)	14,383,000	18,385,000	13,707,000	6,067,400
	Median (€)	14,339,000	17,717,000	13,617,000	6,011,300
	Min (€)	6,435,200	3,466,600	4,718,300	876,250
	Max (€)	23,627,000	95,834,000	26,245,000	13,692,000
Rapid trend	Mean (€)	20,127,000	51,275,000	21,975,000	8,923,400
	Median (€)	20,104,000	47,051,00	21,850,000	8,873,100
	Min (€)	11,099,000	11,172,000	10,652,000	2,488,900
	Max (€)	30,084,000	236,710,000	37,753,000	17,276,000

The trends unambiguously increase the costs of both strategies, but increase the costs of reactive control relatively more. This is also evident from looking at the number of cases where pre-emptive control is cheaper in Table 3. This is because, given the trends, the pest is able to spread to larger areas, survive the winters better and hence result in larger costs in reactive control.

Further, the differences in mean cost estimates are not very large in the context of 'no change' and to some extent in 'slow change'. In the case of rapid change, the differences become larger. Finally, if there is no winter survival, costs are unambiguously lower with reactive control than with pre-emptive control (but note that the two figures in the table cannot be directly compared, because the pre-emptive control costs include some winter survival). The mean costs are depicted in Figure 1.

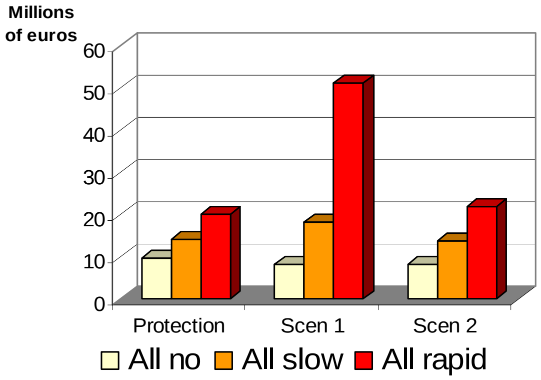
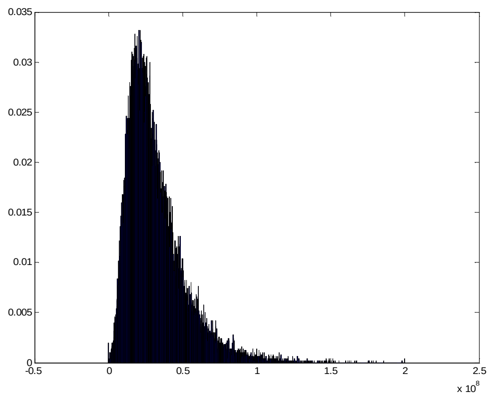


Figure 1. Mean costs of protection and reactive control (two scenarios) at different levels of change.

As for the variability of the cost estimates, it is remarkable how the costs vary from the minimum cost of Scenario 1 under 'no change' of less than 600,000 euro (or less than 300,000 euro in the case of no winter survival) to the maximum cost of Scenario 1 under 'rapid change' of nearly 240 million euro over the 50 year period. This would be unfortunate if we had no way of knowing which state is likely to materialise.

However, it is possible to look at the distribution of costs and make subjective evaluations as to how that impacts on policy considerations. Figure 2 depicts the probability density functions of net benefits of protection under the two scenarios (i.e. costs of reactive control minus the costs of pre-emptive control) under slow change. The x-axis measures the net benefits (in euros) and the y-axis the probability of those net benefits materialising.

Note the relatively long tail on the RHS of Scenario 1, indicating that high net benefits (which can also be interpreted as risks of giving up protection) are rare but possible. In the case of Scenario 2 the net benefits are more evenly distributed, with relatively many iterations producing negative net benefits, implying that in those cases it would be profitable to give up protection.



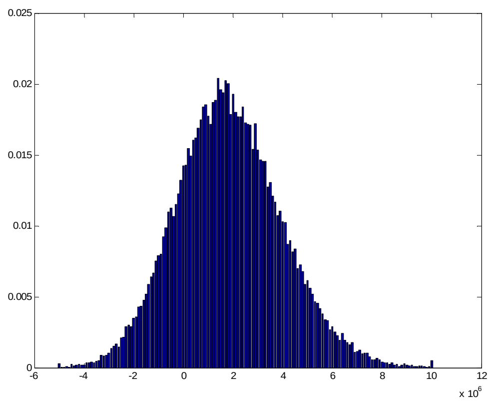


Figure 2. Distribution of net benefits of protection under Scenario 1 (left) and Scenario 2 (right)

Another way to look at the results is to compute the benefit cost ratios. Here the figures are BCRs for pre-emptive control. Thus the ratio is produced by dividing the benefits of the protection system (i.e. avoided reactive control costs) by the costs of the protection system. It measures *by how much* one of the strategies is more economical than the other. For instance, the mean ratio of 1.27 for 'slow change' means that giving up pre-emptive control would be on average 1.27 times more expensive than continuing with it. BCR less than one hence implies that protection is not economical. These calculations are presented in Table 5, where the ratios are displayed for each scenario and trend. The mean ratios under different levels of change are also presented in Figure 3.

Table 5. The benefit cost ratios of each strategy and scenario.

B:C RATIOS		***Scenario 1***	***Scenario 2***
NO CHANGE	Mean	0.82	0.84
	Minimum	0.16	0.29
	Maximum	2.48	1.48
SLOW CHANGE	Mean	1.27	0.95
	Minimum	0.47	0.48
	Maximum	6.38	1.52
RAPID CHANGE	Mean	2.54	1.09
	Minimum	0.86	0.71
	Maximum	11.41	1.60

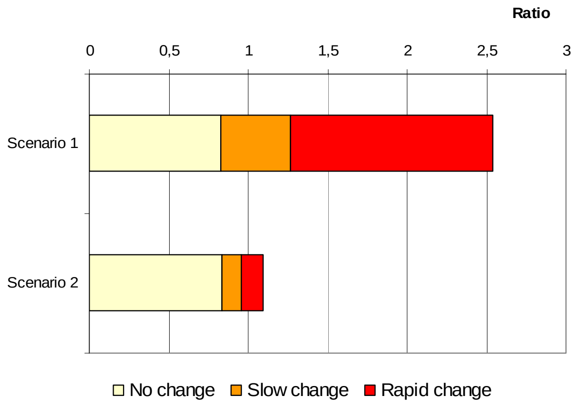


Figure 3. Benefit cost ratios of the two scenarios at different levels of change.

Again it can be seen that the trends strengthen the viability of the protection system. The results can also be compared to those of Mumford et al. (2000), who estimated a BCR of about 7.5 for the British CPB protected zone. At the extreme the protection system is about 6 times more expensive than reactive control (minimum BCR in Scenario 1 under no change). At the other extreme reactive control is about 11 times more expensive than protection (maximum BCR in Scenario 1 under rapid change). However, again most of the results support the protected zone, provided that there is or will be some change and some winter survival.

Sensitivity and uncertainty analysis

Sensitivity analysis was conducted for a wide range of values. The results revealed that the variables that were fairly insignificant include the reactive control cost and the fixed costs of the protection system. The variables that were significant include winter survival, logistic spread rate and the variable cost of protection. Some results are presented in Table 6.

Table 6. The sensitivity analysis 'elasticity' values.

Scenario	Damage	Winter survival	Invasion magnitude	Spread	Reactive control cost	Variable protection cost
Mean cost						
Protection	0.00	0.19-0.20	0.91-0.92	0.00	0.00	0.92
Scenario 1	0.64-0.72	1.44-3.31	0.99-1.01	1.26-2.92	0.23	0.00
Scenario 2	0.64-0.72	0.80-1.00	0.68	0.00	0.23	0.00
BC -ratio						
Scenario 1	0.64-0.72	1.30-2.99	0.07-0.16	1.26-2.91	0.23-0.24	-0.63-1.69
Scenario 2	0.64-0.72	0.63-0.77	-0.16-0.42	0.00	0.23	-0.63-1.68

The figures in Table 6 are 'elasticities' indicating by how much the mean costs (first row) or BCR (second row) will change given a change in the column variable. For instance, a figure of 1.44 means that a 1% increase in winter survival would increase the mean costs by 1.44%. The range of values given is due to different outcomes arising from changes of different sizes in the column variable.

To illustrate the impact of one variable that is important also in terms of possible future change, Figure 4 depicts the impact of different levels of winter survival on the mean BCRs. It should be noted that allowing, for instance, 100% winter survival would imply that the BCR would be ca. 27 in Scenario 1 and ca. 12 in Scenario 2, suggesting very high costs for giving up the protection system.

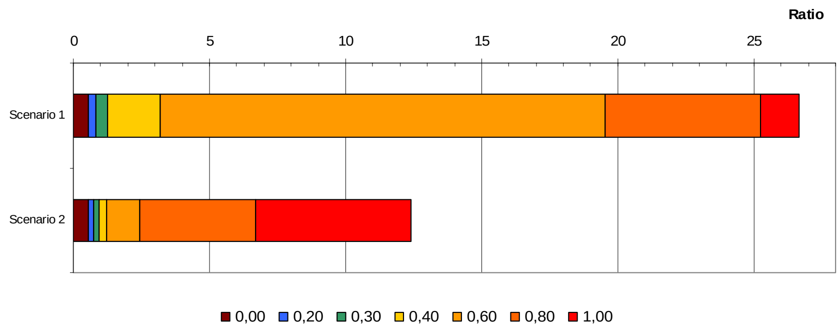


Figure 4. Benefit cost ratios with different levels of winter survival.

Intertemporal and intratemporal issues

Intertemporal issues include questions such as how costs are distributed among years, what is the impact of the discount rate, and whether we should be concerned about large initial investment or large costs later on. Real option values clearly matter in the analysis of policy measures. There are two types of option value impacts with contradictory implications. First, by waiting and not acting now, we could learn information about the true impacts of local change, for instance that they might be smaller than initially expected. Thus we could formulate better policy later on, instead of currently having to invest in expensive abatement. Second, by acting now in a precautionary way and preserving the current conditions we may avoid the irreversibilities that are associated with change in the future, for instance if it is possible that impacts can be greater than initially expected. (Heal and Kriström 2002)

Intertemporal costs can be analysed by looking at the annual costs of the strategies, either discounted or not discounted. In the current version of the paper, we show in Figure 5 the annual net benefits of protection (cost of reactive control less the cost of protection) discounted at 2% and given slow change. From the diagram it can be seen that the protected zone can be seen as an investment that may produce negative net benefits in the early years, but given change the discounted net benefits may increase rapidly over time. This is because the benefit of protection, i.e. preventing the spread of the pest, results in greater cost savings in the future.

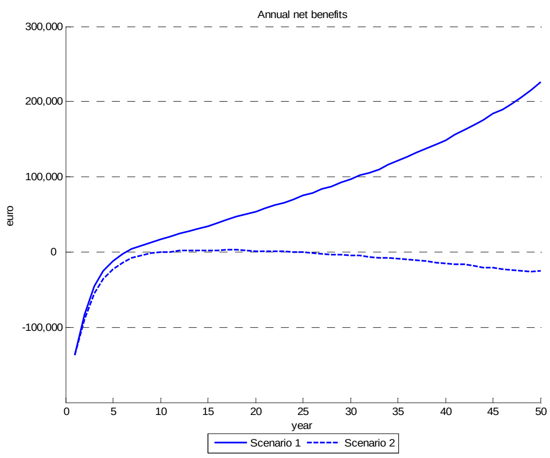


Figure 5. Annual net benefits of protection with slow change.

The strategy choice also has distributional (intratemporal) effects. Given imperfect potato markets, possible invasion induced price increases unambiguously lead to losses in consumer surplus. An invasion would also affect the distribution of profits within the producers. Hence in the case of reactive control, the distributional effects depend on the area invaded (and hence crop lost) and on how the price responds to the invasion.

The pre-emptive strategy too has to be funded by some means. If it is the taxpayers that end up paying the bill, they in essence are subsidising the producers. Further division is between those producers that have been subjected to the invasion and those who have not. Those unaffected may even benefit from the presence of the pest, if the prices increase. However, this benefit may be short-sighted, as the risk of the invasion to also these production areas naturally increases.

Figure 6 displays the division of mean costs under different levels of change to producers and consumers/taxpayers. The cost to consumers is displayed to the right of zero point on the horizontal axis, and the cost to producers to the left of the zero point. The costs to producers vary from zero to about minus 20 million euro. In other words, the producers on aggregate will benefit from the invasion due to prices increasing more than the costs of reactive control and crop losses. Note, however, that the cost to consumers is always larger than any possible benefit to producers, making the total impact of the invasion negative as expected.

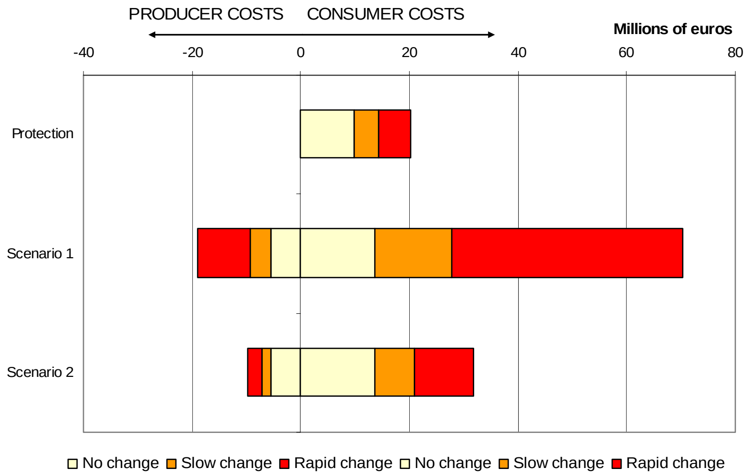


Figure 6. The intratemporal division of policy costs.

It should be observed that any assumptions regarding the price response to the invasion do not affect the costs of the two policies – they only impact on the division of those costs. Hence in an analysis of mere aggregate costs the price response assumption is trivial.

If distribution of costs matters, the overall strategy choice depends on the relative magnitudes of the consumer and producer effects, and how these are weighted. We have assumed similar weights for both groups, but in reality the case may be that one of the groups is given more weight in decision making. We have assumed the consumers/taxpayers to carry the full costs of the protection system. It can naturally be the case that the producers are made to contribute towards these costs. A clear conclusion nonetheless is that in real-life policy environment it is important to consider how the market environment responds to the shock and how any counter-measures are to be financed.

Discussion

In the only other economic analysis of the CPB protection system that we are aware of, Mumford et al. (2000) analyse the case of England. They argue that in Britain early potatoes are not at risk, hence no crop losses will result but extra management activities need to be undertaken. The costs they analyse comprise of monitoring and chemical treatment. They come up with a BCR of 7.5. Our results give somewhat smaller ratios – even less than one in some cases. The difference in results is largely due to different assumptions used. For instance, the area to which Mumford et al. (2000) assume the pest to spread within England is fairly small, and it would not also result in any crop losses, which we according to our current understanding find to be a somewhat arguable assumption. Further differences are in assumptions regarding winter survival, uncertainty and change. However, even given these key differences, the estimates are reasonably close to each other.

The establishment of an invasive pest is to a large extent an irreversible event, as subsequent eradication is – if not impossible – at least prohibitively expensive. The real option values enter the problem in two ways: as a ‘precautionary principle’, suggesting we should avoid potentially irreversible environmental changes until we know more about their impacts, and as an ‘inverse precautionary principle’, suggesting we should avoid undertaking expensive policies with irreversible investments until we know more about what is needed (Heal and Kriström 2002). However, irreversibility as well as related option value of non-invaded area will be left for later study.

In many occasions preventative actions are a good choice of strategy. Even if the protection system might not succeed in keeping the pest out of the country, it could still reduce the impact of the invasion or postpone the moment that we have to give it up. However, no strategy is automatically preferred in all circumstances. Pre-emptive control seems to be sub-optimal in cases where there are high costs of pre-emptive control compared to its benefits. This is especially so if there is an exogenous factor (temperature) automatically eradicating the population at regular intervals.

The current version of the paper presents work that is still ongoing. Hence the analysis here is unfinished and the paper is undergoing constant revision.

References

Barrett, J. and Segerson, K. (1997). Prevention and treatment in environmental policy design. Journal of Environmental Economics and Management 33: 196-213.

Bright, C. (1999). Invasive species: pathogens of globalization. Foreign Policy 116: 50-64.

EU (2000). EU Council Directive 2000/29/EC of 8 May 2000 on protective measures against the introduction into the Community of organisms harmful to plants or plant products and against their spread within the Community.

EU (2002). EU Commission Directive 2002/28/EC of 19 March 2002 amending certain annexes to Council Directive 2000/29/EC on protective measures against the introduction into the Community of organisms harmful to plants or plant products and against their spread within the Community.

European Commission (2000). Health and consumer protection directorate-general. Report on a mission carried out in Denmark from 4 to 8 September 2000 in order to audit the plant health system in the potato sector.

Heal, G. and Kriström, B. (2002). Uncertainty and climate change. Environmental and Resource Economics 22: 3-39.

Jalonoja, K. and Pietola, K. (2001). Whole sales market for fresh potatoes in Finland. Agricultural and Food Science in Finland 10: 69-80.

Jylhä, K., Tuomenvirta, H. and Ruosteenoja, K. (2004). Climate change projections for Finland during the 21st century. Boreal Environment Research 9: 127-152.

Kann, A. and Weyant, J. P. (2000). Approaches for performing uncertainty analysis in large-scale energy/economic policy models. Environmental Modeling and Assessment 5: 29-46

MacLeod A., Baker R.H.A. and Cannon R.J.C. (2005). Costs and benefits of European Community (EC) measures against invasive alien species – current and future impacts of *Diabrotica virgifera virgifera* in England & Wales. A paper prepared for symposium on Introduction and Spread of Invasive Species, 9-11 June 2005, Berlin, Germany.

Mumford, J.D. (2002). Economic issues related to quarantine in international trade. European Review of Agricultural Economics 29: 329-348.

Mumford, J.D., Temple, M.L., Quinlan, M.M., Gladders P., Blood-Smyth, J.A., Mourato, S.M, Makuch, Z. and Crabb, R.J. (2000). Economic policy evaluation of MAFF’s Plant Health Programme. Report to Ministry of Agriculture Fisheries and Food, London, United Kingdom. Available on the Internet: http://www.defra.gov.uk/esg/economics/econeval/planth/

Schmitz D.C. and Simberloff D. (1997). Biological invasions: a growing threat. Issues in Science and Technology Online. Summer 1997. Available at http://www.nap.edu/issues/13.4/schmit.htm

Weitzman, M. (2001). Gamma discounting. The American Economic Review 91: 260-271.