The effects of variation in management objectives on responses to invading diseases under uncertainty: Forest Pathogens

Abstract

The real options approach provides a powerful tool for determining the optimal time at which to adopt disease control measures given uncertainty about the future spread of an invading pest/pathogen. We consider the management of disease invasions in the natural environment typified by woodlands. Previous studies considered the timing of control from the point of view of a central planner, for example a governmental decision making body. However, decisions regarding the deployment of control measures in the landscape are typically taken by individual land managers. Woodlands provide both marketable benefits, such as timber, and non-marketable benefits, for example biodiversity. The relative importance placed on these types of benefit depends on the land purpose, which is determined by a managers' objectives. We investigate how management objectives influence the optimal timing of control adoption. Our results show that differences in objectives lead managers to exercise the option to control at different times, and potentially never adopt disease control. Since infection can spread from one region to another, managers who do not adopt control therefore transfer the risk of infection to other managers within the landscape. For landscapes composed of managers with divergent objectives, this creates conflict due to the transferable externality (the disease). We show targeted subsidies can reduce differences in the timing of control adoption between managers with divergent objectives. Both lump-sum subsidies and annual subsidies bring forward the adoption of control strategies, causing them to be implemented over a wider range of infection proportions in an individual woodland. However, the two types of subsidy have opposite effects on the decision to suspend control. Annual subsidies delay suspension and extend the region over which control continues to be implemented. In contrast, lump-sum subsidies slightly reduce the region over which control continues to be implemented. For high proportions of infection, this implies that a lump-sum subsidy can induce a value-maximising manager to suspend control earlier: the opposite effect to that presumably intended. Our results have important implications for national decision making bodies and suggest that incentives may need to be targeted at specific groups to ensure a coherent response to disease control.

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1. Introduction

In the face of an invasive pest or pathogen within the natural environment, such as woodland, a key choice facing decision makers is whether or not to adopt control measures to reduce the spread of the pest or pathogen (Cunniffe et al. 2015). Initiating control measures, such as movement bans or the spraying of chemical treatments, involves costs that cannot be fully recovered at a later date (sunk costs), for example the cost of purchasing equipment (Saphores 2000; Dixit and Pindyck 1994). Furthermore, there is uncertainty surrounding the potential gains from controlling, namely the reduction in losses to benefits provided by the natural environment, due to the unpredictability of pest/pathogen spread. The irreversible nature of the control initiation costs, combined with the uncertainty in the future returns from control means that it can be beneficial to wait before adopting control, even if the expected future pest/pathogen damage outweighs the cost of control (Saphores 2000; Sims and Finnoff 2012; Sims and Finnoff 2013; Ndeffo Mbah et al. 2010; Marten and Moore 2011). The question facing decision makers is therefore when is it optimal to adopt measures to control pest/pathogen spread given the uncertainty about the future course of an epidemic or pest infestation?

This question of when, if ever, to adopt control has previously been studied using a real options approach, which provides a powerful tool to analyse the effects of uncertainty, in the context of irrecoverable adoption costs (Dixit and Pindyck 1994; Saphores 2004). Disease control is considered as an *option* that can be exercised to reduce damage caused by a pest/pathogen. The real options approach provides a threshold in the proportion of infected area at which it is optimal to deploy control immediately (Saphores 2000; Ndeffo Mbah et al. 2010; Sims and Finnoff 2013; Sims, Finnoff, and Shogren 2016). The greater the uncertainty in the spread of the pest/pathogen, the larger the infected area must be for it to be optimal to adopt control and so essentially the longer a decision maker would wait before undertaking control measures (Saphores 2000). If, however, the control measure can be cancelled in the future and some of the costs recouped (i.e. the initial costs of control are not entirely irreversible), this reduces the threshold in infected area for control and so control is adopted sooner (Sims and Finnoff 2013). Typically in real options the future uncertainty in infected area is described by an unbounded process, typically geometric Brownian motion (GBM) (Saphores 2000; Dixit and Pindyck 1994). However, the potential area that can be infected by a pathogen/pest is limited. Inclusion of this upper boundary also leads to control being adopted earlier (Dangerfield et al. 2017; Sims and Finnoff 2012).

Previous studies consider the timing of control from the point of view of a central planner, for example governmental decision making bodies such as Defra in the UK (Sims and Finnoff 2013; Sims and Finnoff 2012; Marten and Moore 2011). However, for many diseases in the natural environment, decisions regarding the deployment of control measures are typically taken by individual land managers responsible for specified regions. In this paper we consider the timing of control from the perspective of an individual manager. We motivate the problem for the control of woodland pathogens/pests in a landscape but the results have broader applicability to other systems in which there are multiple ecosystem services with differing associated benefits from controlling disease.

Woodland provides marketable benefits, such as timber, and non-marketable benefits, for example in supporting biodiversity. The key difference between these two types is that non-marketable benefits accrue over time, while marketable benefits provide a financial return at discrete time points, for example at the end of a rotation in forestry or season in crop production. The relative importance placed on the two benefits depends on land managers objectives (Urquhart and Courtney 2011). In this paper we investigate how diverging objectives affect the waiting time before adopting control.

We use the issue of invasive pests and pathogens within UK forestry as a motivating example. Pests and pathogens can cause significant reductions in the marketable and non-marketable benefits provided by forests (Pimentel, Zuniga, and Morrison 2005). For a number of current invasive species threats within the UK, such as Dothistroma needle blight[1] or *Heterobasidion annosum*[2], the decision of whether or not to adopt control measures is taken at the level of the land manager. At the landscape scale, there is significant variation in the objectives of different UK forest managers (Urquhart and Courtney 2011; Urquhart, Courtney, and Slee 2010), where privately owned forests account for 70% of forested area. Urquhart and Courtney (2011) identify six distinct groups of forest manager, based on the relative importance they place on marketable and non-marketable benefits. The groups in Urquhart and Courtney (2011) include 'investors' who only seek to obtain marketable benefits from the forest, such as timber production and 'conservationists' who seek to maximise the non-marketable benefits such as biodiversity and disregard the marketable benefits (Urquhart and Courtney 2011). Due to the differences in the timing at which marketable and non-marketable benefits are obtained, variations in the implicit or explicit weightings placed on these two types of benefits by each forest manager are likely to affect how they respond to a particular pest or pathogen risk.

Using a real options approach to incorporate uncertainty into the decision process, we explore how varying the function that describes the value of the forest (the owner's objective function) influences the threshold at which control should be adopted immediately. This provides insight into how variations in the different benefits obtained from a forest affect the optimal timing of control for individual owners. These benefits could reflect the value which a forest owner gets

[1] https://www.forestry.gov.uk/dothistromaneedleblight
[2] https://www.forestry.gov.uk/fr/rootandbuttrot

from both timber and non-timber attributes, and/or a Payment for Ecosystem Services that they receive for producing public good-type benefits along with the financial benefits of timber production. We model the forest manager as taking decisions over control measures in his/her forest independently of other managers, in the sense that expectations over the actions of others do not enter into the decision-making process.

Our results suggest there can be significant variation in the optimal timing of pest or pathogen control measures between forests managed under different management objectives. Since disease can spread from one region of land to another, a manager who does not adopt control therefore transfers the risk of infection to other managers within the landscape. When the landscape is composed of managers with divergent objectives, this creates conflict due to the transferable externality (the disease). We thus further investigate the impact of subsidies on control strategies and the extent to which targeted subsidies can reduce the divergence in the timing of control adoption between forests managed with different objectives. We consider two different types of subsidy: the first reduces the upfront costs of initiating control while the second reduces the ongoing costs of control. The dynamic nature of our epidemiologically-based real options modelling framework allows analysis of both adoption and cancellation of control measures as the impact of pests or pathogens varies over time. In particular it allows us to analyse the impact of the different types of subsidy on both the timing of control adoption and cancellation.

Our results identify the combinations of disease characteristics for which the timing of control adoption is likely to differ significantly for forests managed according to different objectives. Furthermore the results indicate how subsidies affect these disease control strategies and hence suggest which form of subsidies (lump-sum or ongoing) are more likely to be effective in increasing the long-term incidence of disease control. The results of this paper have important implications for local and national decision making bodies, such as the UK Government

Department for Environment Food and Rural Affairs (Defra), the Forestry Commission in England and Scotland and Natural Resources Wales, which seek to achieve reductions in pest or pathogen spread at a larger spatial scale than an individual forest. The structure of the remainder of the paper is as follows. Section 2 introduces the model, Section 3 presents the results, and Section 4 concludes.

2. Method

In this article, we use terminology typically associated with an invasive pathogen rather than pest, and so we refer to trees as being infected or diseased, rather than invaded. This is for ease of writing, but we note that the model frameworks described here apply equally well to invasive pests, such as oak processionary moth[3] and oriental gall wasp[4], two pests that have been found in England in recent years.

2.1 Value of the Forest in the Absence of Disease

Consider an area of even-aged forest composed of a single species that is of size L hectares. We assume the value generated by the forest over a fixed period of time, T years, is composed of two parts: a single payment that is received at the final time T, which represents the net return from selling the timber, $M(L)$, and an annual payment that characterises the value obtained from a flow of non-timber benefits, $S(L)$. We assume that T is an exogenous time, such as the length of a pre-determined rotation period. Non-timber benefits include amenity, recreation or biodiversity values, for which the owner either derives utility or receives a payment from a third party, such as the government. Therefore, the present value of benefits from the forest, in the absence of disease, is given by the following,

[3] https://www.forestry.gov.uk/oakprocessionarymoth#Further information

[4] https://www.forestry.gov.uk/gallwasp

$$M(L)e^{-rT} + \int_t^T S(L)\, e^{-r(s-t)} ds, \tag{1}$$

where r is the discount rate.

We assume that functions $M(L)$ and $S(L)$ take the following forms,

$$M(L) = pL \tag{2}$$

$$S(L) = bL, \tag{3}$$

where p is the net return per hectare from timber sold at the end of the rotation and b is the value per hectare of annual non-timber benefits.

2.2 Value of Forest in the Presence of Disease

Consider the outbreak of a disease within the forest of interest. We assume that the future progress of area infected is uncertain due to the variability in infection transmission as a result of external factors such as weather. Therefore, the proportion of area infected over time (I) changes according to the following stochastic differential equation SDE, which we term the logistic SDE, (Dangerfield et al. 2017),

$$dI = \beta I(1-I)dt + \sigma I(1-I)dW, \tag{4}$$

where β is the mean transmission rate and σ is the level of uncertainty, (Keeling and Rohani 2008). We describe the evolution of the infected area using the logistic SDE rather than GBM that is typically used in the literature (Saphores 2000; Sims and Finnoff 2013), because the logistic SDE better captures key epidemiological features of disease spread (Dangerfield et al. 2017). In particular, this approach incorporates the upper boundary in the infected area, which arises due to the limited number of available hosts within a given spatial domain, directly into the equation for the growth in the proportion of area infected (equation (4)).

We assume that both the timber and non-timber benefits from the forest are reduced by disease (e.g. because of lower timber volume as a result of reduction in tree growth rate resulting in lower price for infected timber or lower amenity value from a diseased forest landscape). In particular we assume infected timber value is reduced to a proportion, ρ, of the original value, so when $\rho = 0$ timber is worth nothing and when $\rho = 1$ timber value is unaffected by disease. Similarly we assume annual non-timber benefits from infected trees are reduced to a proportion, φ, of the original value. We assume that ρ and φ are independent and consider the impact of a range of different combinations of ρ and φ on the optimal timing of control. The value of the forest, per hectare, in the presence of disease is given by

$$E\left[p\,L\,\big(1+(\rho-1)I(T)\big)e^{-rT} + L\int_{t}^{T} b\big(1+(\varphi-1)I(s)\big)\,e^{-r(s-t)}ds\right], \tag{5}$$

where $I(s)$ is the proportion of the forest area (L) that is infected at time s. Note that this is the expected value of the forest (E in equation (5) represents the expectation), since the future forest value is stochastic, due to the uncertainty in the future level of infection.

2.3 Optimal Timing of Disease Control

Consider a control policy that reduces the rate at which the disease spreads by a factor $0 \leq \omega \leq 1$, so the transmission rate after a control option is implemented is $\beta_A = \beta \times \omega$. Examples of such measures include increased biosecurity measures or chemical spraying treatments that reduce the susceptibility of trees but not the removal of trees.

We assume that control can be adopted for a fixed cost of K_A per hectare, and that there is a yearly maintenance cost of m_A per hectare to continue control. Fixed costs are non-recoverable, and represent a one-off upfront cost that could, for example, be the initial investment in specialist equipment, or the cost of time taken to initiate the control policy. The yearly cost represents the annual payment needed to continue the control programme, for example this could be the yearly payment to contractors to remove weeds or apply chemical sprays or alternatively the ongoing cost of increased biosecurity measures. Since many control measures can be cancelled at some point in the future, we assume that the control measure is temporary, and so we can consider the decision to invest in control as reversible. Therefore, if control is currently being adopted then such a programme can be cancelled at some point in the future. Cancellation incurs no additional costs, but leaves open the option to readopt control at some future time, if optimal. Therefore the decision to cancel is reversible and can be thought of as suspension of control measures.

Let $W_N(I,t)$ be the value of the forest when control is not currently adopted. It comprises two parts: the discounted expected value of the forest if control is never implemented and the value of the option to adopt control in the future. This option value arises since the future uncertainty in the proportion of infected area means that there is an opportunity cost of applying control immediately, rather than waiting to see what happens in the future. Similarly, if control measures are currently being applied then there is an opportunity cost associated with cancelling now rather than waiting. Therefore the value of the forest when control is being adopted, $W_A(I,t)$, is the discounted expected value of the forest obtained when control is applied indefinitely plus the value of the option to cancel control in the future.

If there are currently no control measures in place, then control should be adopted as soon as the area infected reaches I_A, which we term the ***adoption threshold***. At I_A the following two boundary conditions are satisfied:

$$W_N(I_A,t_A) = W_A(I_A,t_A) - K_A \quad (6)$$

$$\frac{\partial W_N}{\partial I}(I_A,t_A) = \frac{\partial W_A}{\partial I}(I_A,t_A), \quad (7)$$

where K_A is the fixed cost of adopting control. The first condition is called the value matching condition and ensures that the payoff from adopting control immediately is equal to the payoff from not adopting control. The second condition is called the smooth pasting condition and requires $W_N(I,t)$ and $W_A(I,t)$ to meet tangentially at I_A to ensure the optimality of I_A (see (Dixit and Pindyck 1994) for further discussion).

Similarly if control measures are currently being adopted then control should be cancelled as soon as the area infected reaches I_C, which we term the ***cancellation threshold***. At I_C the following two boundary conditions are satisfied:

$$W_A(I_C, t_C) = W_N(I_C, t_C) \tag{8}$$

$$\frac{\partial W_A}{\partial I}(I_C, t_C) = \frac{\partial W_N}{\partial I}(I_C, t_C). \tag{9}$$

Once again, the first condition ensures that the payoff from cancelling control immediately is equal to the payoff from not cancelling control while the smooth pasting condition (equation (9)) ensures optimality of I_C (Dixit and Pindyck 1994).

Following the standard dynamic programming approach, the value of the forest when control is not adopted, $W_N(I,t)$, and when it is adopted, $W_A(I,t)$, will satisfy the following partial differential equations (PDEs)

$$\frac{\partial W_N}{\partial t} + \frac{1}{2}\sigma^2 I^2 (1-I)^2 \frac{\partial^2 W_N}{\partial I^2} + \beta I(1-I)\frac{\partial W_N}{\partial I} - rW_N + b + b(\varphi - 1)I = 0, \tag{10}$$

$$\frac{\partial W_A}{\partial t} + \frac{1}{2}\sigma^2 I^2 (1-I)^2 \frac{\partial^2 W_A}{\partial I^2} + \beta_A I(1-I)\frac{\partial W_A}{\partial I} - rW_A - m_A + b + b(\varphi - 1)I = 0, \tag{11}$$

subject to the boundary conditions given by equations (6) – (9), $\partial^2 W_N / \partial I^2 = 0$ at $I = 1, 0$ and terminal conditions

$$W_N(I,T) = p(\rho - 1)I(T) + p, \tag{12}$$

$$W_A(I,T) = p(\rho - 1)I(T) + p. \tag{13}$$

Since the boundary conditions (6) – (9) are specified at points that are yet to be determined, this system is a free-boundary problem. The Appendix gives further details of the solution method. Solving the system (6) – (13) determines the adoption and cancellation thresholds, which are functions of time since we consider the timing of control over a finite time horizon. In this article we are primarily concerned with the optimal timing of control at the beginning of the time horizon of interest, that is $I_A(0)$ and $I_C(0)$. Therefore, unless specified otherwise, we use I_A and I_C to denote the adoption and cancellation thresholds at time $t = 0$.

Due to the logistic nature of both the drift and diffusion terms in the logistic SDE, it is not possible to obtain closed-form solutions to this problem. Therefore we solve the free boundary problem given by equations (6) - (13) numerically using the Euler method in MATLAB (Wilmott, Howison, and Dewynne 1995). Further details are given in the Appendix.

2.3 Managing for Timber versus Non-timber Objectives

Consider two managers with different objectives: a 'timber manager' who is concerned solely with the timber benefits ($b = 0$ in equation (5)), and a 'non-timber manager' concerned only with maximising the non-timber benefits ($p = 0$ in equation (5)). We assume that both managers take decisions with regard to disease control independently of the other and so they do not take into account expectations of the other's actions in their decision-making process. To ensure a fair comparison between the two cases, we set our baseline value of b so that the initial value of the forest in the absence of disease for the non-timber manager is the same as for the timber manager when $p = 1$. See Table 1 for a description of the parameters and the values used in simulations.

3. Results

We initially investigate the adoption and cancellation thresholds for the two managers when disease renders both the timber and non-timber benefits worthless. For both managers we find that there exist two adoption thresholds, I_A^L and I_A^U (Figure 1a and b), and similarly two cancellation thresholds I_C^L and I_C^U (Figure 1c and d). The two adoption and cancellation thresholds arise because of the bounded nature of the stochastic process used to describe the future uncertainty in the level of infection. When no control measures are in place, our results show that it is optimal for both managers to apply control immediately when the level of infection lies within the two adoption thresholds, that is providing $I_A^L \leq I \leq I_A^U$. We term this range of I values the ***adoption region***. If the area currently infected, I, is too small, the benefits of control do not outweigh the costs and so control should not be adopted until the proportion of area infected is large enough. Similarly when the proportion of area infected is close to 1 there is little benefit from adopting control measures, as most of the forest is infected. Such an upper threshold may be exceeded even at the initial time if the damage remains undetected, which could occur, for example, if insufficient resources are devoted to surveillance efforts.

If control is adopted then our results suggest that both managers should cancel control and go back to doing nothing as soon as the level of infection drops below or above the cancellation thresholds, that is when $I \leq I_C^L$ or $I_C^U \leq I$. We term this the ***cancellation region*** and we note that this region is disjoint. Similarly to the adoption thresholds, the upper and lower thresholds arise since at very low or high levels of infection the benefits from control no longer offset the costs, and so control measures should be cancelled immediately.

While both managers should not either adopt or cancel control when the level of infection is correspondingly high or low, the sizes of the adoption and cancellation regions vary between the timber and non-timber managers (compare Figure 1a and b, and also Figure 1c and d). This results from the differences in timing of the benefits from the forest (and loss of benefits resulting from infection) for each manager. Therefore, there is a larger region in the level of infection over which the timber manager should adopt control. In practice this can lead to situations where the non-timber manager may adopt control later than the timber manager (Figure 2a) or indeed the non-timber manager may never adopt control (Figure 2c).

3.1 Impact of increasing disease damage on timing of control

Independently varying the reduction in timber (ρ) and non-timber benefits (φ) as a result of disease, we examine the impact of increasing disease damage on the adoption regions (in Figure 3a and c) and cancellation regions of control (in Figure 3b and d) for the two managers. We find that for both forest managers, when the damage due to infected trees is very low (so $1 - \rho$ or $1 - \varphi$ are close to zero), the adoption thresholds do not exist and so it is never optimal to apply control. This result is denoted in Figure 3a and c by the '*never adopt control*' region. The advantage of adopting control is the reduction in the speed of infection spread and the resulting increase in the timber and non-timber benefits as more trees remain healthy for longer. When infection reduces the timber benefits by very little, the increase in the value of the forest when adopting control versus not adopting is small. Indeed, in the never-adopt region, the reduction in benefits from the forest due to slower spread of disease leads to an increase in the value of the forest under adopting control that does not outweigh the additional costs. Therefore the benefits of control do not justify the costs and so there is no level of infection at which control measures should be undertaken. As the damage due to disease increases ($1 - \rho$ or $1 - \varphi$ increase towards 1), the difference in the value of the forest when adopting control versus not adopting increases. This leads to the appearance of two adoption thresholds and so there is a region in which it is optimal to apply control. As ρ or φ approach zero, the benefit from adopting control rises and so the adoption region becomes larger (Figure 3a and c). Similarly the size of the cancellation region becomes smaller (Figure 3b and d). We term the level of damage at which the optimal strategy switches from 'never control' to 'control within the adoption region' the **strategy switch point**.

Providing the disease affects both timber and non-timber benefits to the same extent, that is $\rho = \varphi$, in the region where the adoption thresholds exist we find that the lower adoption threshold for the timber manager is always smaller than for the non-timber manager (Figure 3a). The opposite is true for the upper thresholds, so the adoption region for the timber manager is always larger than for the non-timber manager. Furthermore, the strategy switch point for the non-timber manager is higher than for the timber manager. Therefore, the reduction in non-timber benefits due to disease must be greater before it is optimal for the non-timber manager to adopt control for any level of infected area. However, the difference between the strategy switch points is very small when $\rho = \varphi$ and so the range where it is optimal for the timber manager to control within their adoption region, while the non-timber manager should never control, is very small. While in general we find that there are differences in the size and positioning of adoption regions between timber and non-timber managers, for diseases for which $\rho = \varphi$ there is a large overlap in the region in which both managers should adopt. Similarly, the cancellation regions for the two managers are very similar (Figure 3b). Therefore, in these situations differences in management objectives lead to similar control strategies for the two types of managers. We investigate the sensitivity of these results to epidemiological parameters in Section 3.2.

The reduction in timber and non-timber benefits will not always be the same and depends on the impact of a given disease on the trees. For example, Dothistroma needle blight, which affects pine trees, reduces timber values significantly, but has little effect on (the flow of) biodiversity or amenity value[5], whereas oak processionary moth has a relatively low impact on timber values but has detrimental health effects on human and animal contacts, potentially leading to a significant loss of amenity value[6]. We find that when $\rho \neq \varphi$, the difference between the adoption regions for the timber and non-timber managers diverge significantly. In Figure 3c we show the adoption regions for both types of manager in the case where $\rho = 1 - \varphi$, so along the x-axis reduction in timber benefits is increasing ($1 - \rho$ is increasing) while the reduction in non-timber benefits is decreasing ($1 - \varphi$ is decreasing). When the reduction to timber or non-timber benefits is in an intermediate range there is an overlap in the adoption regions between the optimal strategies of the timber and non-timber managers. However this overlap is significantly smaller than when $\rho = \varphi$. Similarly Figure 3d shows that the cancellation regions for the two managers begin to diverge as ρ and φ diverge. The difference between the optimal strategy for the timber and non-timber managers is greatest for extreme levels of reduction in benefits, i.e. when the disease has either a large impact on timber values (ρ close to zero) but a negligible effect on non-timber values (φ close to 1) or vice versa. In particular, depending on the extent to which ρ and φ differ, it may be optimal for the non-timber manager never to adopt control, while the timber manager should control when the proportion of area infected lies within the adoption region (and vice-versa). Such cases are summarised in the bottom two rows of Table 2, along with examples of diseases where such a situation arises.

3.2 Impact of Epidemiological Parameters on Adoption and Cancellation Thresholds

In Figure 4 we investigate the sensitivity of the adoption thresholds for each manager to epidemiological parameters, namely the transmission rate (Figure 4a), β, the reduction in spread (Figure 4b), ω, and the level of uncertainty (Figure 4c), σ (the results for cancellation

[5] https://www.forestry.gov.uk/pdf/fcrn002.pdf/$file/fcrn002.pdf
[6] https://www.forestry.gov.uk/oakprocessionarymoth

thresholds are similar). Other parameters are as before with an equal proportional reduction in timber and non-timber value ($\rho = \varphi = 0$).

As the mean transmission rate, β, increases, the upper adoption thresholds increase while the lower adoption thresholds decrease for both managers (Figure 4a). An increased transmission rate increases expected future infection levels and the resulting loss of benefits, hence increasing the relative benefits of control. Therefore, the range of I (level of infection) over which either manager should adopt control is widest when the rate of spread (β) is large. Furthermore, the rate of change in the thresholds as the transmission rate increases is greater for the non-timber-objective manager. This is because of differences in the timing of benefits from the forest: non-timber benefits accrue gradually over time, whereas timber benefits arise solely at the final time T. Whilst increases in β increase expected future losses for both types of manager, the effect is greater for the shorter-dated benefits because the forest area infected is limited above by the size of the forest itself. The non-timber managers' adoption thresholds are thus more sensitive to changes in β. This means the difference in the size of the adoption regions between the timber and non-timber manager is greatest for slow spreading pathogens (β small). Indeed, when β is very small, it is actually optimal for the non-timber- manager never to adopt control (left of dotted green line in Figure 4a), while the timber manager should adopt control providing the level of infection lies within a relatively large adoption region (for example when $\beta = 0.05$, the timber manager would adopt for $0.19 \leq I \leq 0.75$).

As the proportional reduction in spread due to control $(1 - \omega)$ increases, the upper thresholds increase and lower thresholds decrease (though to a lesser extent) for both types of manager (Figure 4b). Therefore, the more effective the control is at reducing the rate of spread of the pathogen, the greater range in the level of infection at which control should be adopted. The rate of change in the adoption thresholds is similar for both managers and so the difference in the adoption regions does not vary significantly as ω varies.

Figure 4c shows that as uncertainty increases (σ), the upper adoption thresholds decrease while the lower adoption thresholds increase for both the timber and non-timber managers, reducing the size of the adoption region. When uncertainty is high it is more valuable to wait before adopting control. Greater uncertainty increases the value of delaying and waiting for further information about the future evolution of infection. Switching (adopting or suspending control) only occurs when the benefits outweigh the costs, including the loss of the value of this option to delay. So the difference between the lower (upper) adoption and the lower (upper) suspension thresholds increases with uncertainty. The rate of change in the thresholds is once again greater for the non-timber manager and so the non-timber managers' thresholds are more sensitive to changes in σ. The difference in the size of the adoption regions between the two managers is greatest for large values of σ (Figure 4c).

In summary, the difference in adoption regions is greatest when the rate of infection is slow (low β) or when uncertainty about the transmission rate is high (high σ). In all these cases, the timber manager adopts disease control for a wider range of proportions of area infected than non-timber managers.

3.3 Summary of differences in the control strategies of the two types of manager

Differences in adoption (and cancellation) regions can arise for the two types of manager either because of the differing impact of a disease on timber and non-timber benefits ($\rho \neq \varphi$) or because of each manager's sensitivities to disease-related parameters. These differences are smaller when the impact of the disease on timber and non-timber benefits is similar ($\rho \approx \varphi$), when the disease is fast spreading (high β) or the level of uncertainty (σ) is low. In these cases, the adoption regions for the two managers largely overlap, and so there are no significant differences in the timing of control adoption for the different types of manager.

When the impact of disease on the different benefits of the forest are disparate, such as for Dothistroma needle blight or oak processionary moth, our results show the contrasting objectives between forest managers lead to significant dissimilarities in their optimal disease management strategies. This is important for the control of disease at the landscape scale since infection can spread from one forest to another (i.e. the spread of infection does not respect land ownership boundaries). Therefore if, for example, the non-timber manager never controls the disease, the benefits of control may be reduced for a neighbouring timber manager, as a result of an increase in the level of infection pressure from the non-timber manager's forest.

3.4 Subsidies to align disease control strategies of different forest managers

Heterogeneities in the adoption of control at the landscape scale due to divergent management objectives and the presence of a transferrable externality (the disease) may prompt a government or other national or regional decision-making body to attempt to align disease control boundaries more closely (for example, by targeting subsidies at managers for whom thresholds for control would not otherwise be triggered). We use our model to investigate the effect of subsidies on a managers' adoption and cancellation thresholds. In practice, subsidies for the adoption of disease control could have two components: a reduction in the one-off cost of initiating control or a reduction in the annual ongoing control cost. We consider two extreme types of subsidy: the first pays out a one-off fixed amount when control is initially adopted while the second pays out a yearly subsidy for the whole period over which control is adopted. The first scheme essentially reduces the fixed cost of adopting control, while the second decreases the yearly maintenance costs that a manager incurs whilst adopting control measures.

We take as an example a disease that has a high impact on timber benefits ($\rho = 0.4$) but lower effect on non-timber benefits ($\varphi = 0.6$). In this case it is optimal for the timber manager to adopt control immediately, providing that the proportion of infected area is within the region

[0.054, 0.73], while the non-timber manager should never adopt control. Figure 5 shows the adoption (a and c) and cancellation (b and d) regions respectively for the non-timber manager as the proportional reduction in fixed costs, that is subsidy scheme 1 (top), and the proportional reduction in yearly costs, that is subsidy scheme 2 (bottom), increase. For comparison we also show the adoption and cancellation thresholds for the timber manager. Note that we assume that both subsidy schemes are only targeted at non-timber managers: the timber managers' costs remain fixed at the baseline values.

Both subsidy schemes switch the optimal strategy for the non-timber manager from never-adopt-control to one where control should be adopted, providing that the level of subsidy is high enough (Figure 5a and c). Both types of subsidy therefore succeed in increasing the range of infected area for which the non-timber manager would start to control, bringing the non-timber manager's adoption thresholds closer to those of the timber manager.

While the adoption thresholds behave in qualitatively the same way for both subsidy schemes, this is not the case for the cancellation thresholds. For the lump-sum subsidy, the upper cancellation threshold decreases, while the lower threshold increases as the reduction in fixed costs increases (Figure 5a). Therefore, the overall effect is to increase the size of the cancellation region as the subsidy increases. In particular, when fixed costs are completely eliminated, the adoption and cancellation thresholds are identical (cf Figures 5a and b). This suggests that while there is a region over which it is optimal for non-timber managers to adopt control, they may cancel control almost immediately upon adoption (if the proportion of area infected moves back into the cancellation region). In contrast, for the annual subsidy, the cancellation thresholds behave in the same way as the adoption thresholds, and so the size of the cancellation region decreases as yearly costs are reduced (Figure 5d). Indeed, if subsidy payments are large enough to remove all yearly costs there is no longer a cancellation region. Therefore, once control has been adopted, the non-timber manager will not cancel control.

To further illustrate the impact of the difference in the cancellation regions for the two subsidy schemes on the control strategy we plot an example path in Figure 6. While under both schemes the non-timber manager would adopt control at the start of the outbreak, when fixed costs are eliminated (subsidy scheme 1) the manager would later cancel control (Figure 6a), while when yearly costs are eliminated (subsidy scheme 2) the manager would not cancel (Figure 6b).

These results rely on two effects. Firstly, in this dynamic model with two possible states (currently controlling / not controlling), the thresholds for moving between states take account of future costs only. Whilst both lump-sum and annual subsidies decrease future costs of control, once control has started, annual subsidies give greater incentives to continue controlling than lump-sum subsidies, which will only be received if control is first suspended and then re-started. Secondly, since the future infection proportion is stochastic, thresholds depend on the degree of irreversibility, (difficulty of switching back and forth between states). Lump-sum and annual subsidies have very different effects on irreversibility: lump-sum subsidies decrease irreversibility (reduce the costs incurred if control is adopted and subsequently cancelled), whereas annual subsidies leave irreversibility unchanged but instead increase the value of ongoing control. It is well-known in real options models that the lower the irreversibility, the closer together are optimal adoption and cancellation thresholds. In our model this increases the size of the region over which control is adopted and reduces the size of the region over which control continues to be implemented. For lump-sum subsidies and adoption thresholds, these two effects reinforce each other. However, for cancellation thresholds they work in opposite directions, and particularly for the upper cancellation threshold, the irreversibility effect dominates, so a larger lump-sum subsidy can cause a manager to cancel infection control earlier when his proportion of infected area is high. The dissimilarity in the effects of different types of subsidies on the cancellation thresholds suggests that subsidising ongoing costs (rather than one-off upfront costs) may be more effective in ensuring the *continuation* of disease control once it has been initiated.

4. Conclusions

There is a wide range of different management objectives amongst forest managers in the UK, as in other countries (Urquhart and Courtney 2011; Mizaraite and Mizaras 2005; Wiersum, Elands, and Hoogstra 2005). Understanding how this heterogeneity affects the disease control strategies adopted by forest managers, and, in particular, when individual managers initiate control measures, is therefore important for national decision-making institutions. The aim of decision-making institutions, such as Defra and the Forestry Commission, is primarily to minimise the spread of disease at the national, rather than at the individual forest, level.

We have used a real options approach to investigate how forest management objectives affect when (if ever) it is optimal for the forest manager to adopt control measures to reduce damage due to disease. Our analyses take account of uncertainty in the future spread of infection. We compare the adoption region for two forest managers with divergent objectives: the first manages the forest for the timber benefits only while the second manages the forest for the non-timber benefits only. We show that there are two adoption and two cancellation thresholds for both types of manager, and so it is not optimal for either manager to adopt control when the level of infection is very small or very high. However, the range of infected area over which it is optimal to adopt control (the adoption region) is broader for the timber than the non-timber manager. Therefore in practice it is optimal for the timber manager to adopt control earlier than the non-timber manager.

We find that when the reduction in benefits (timber and non-timber) is small the adoption thresholds do not exist and so control should never be adopted for either type of manager. As the reduction in benefits increases, the size of the adoption region also increases since there is more to be gained from adopting control measures. This is the case irrespective of the manager's objectives.

When the disease reduces timber and non-timber benefits to the same degree, the adoption thresholds for the non-timber manager are higher than for the timber manager but there is significant overlap between the two adoption regions (Figure 3a). Therefore, while it is optimal for the timber manager to adopt control earlier than the non-timber manager, the difference in adoption time is generally small, particularly when the disease is slow-spreading, there is little uncertainty and the control is very effective. For policy makers, this implies that in such situations the diversity in management objectives at the landscape scale does not lead to significant differences in the disease control strategy of timber- and non-timber managers. A uniform approach to disease management could therefore be achieved without the need for external intervention.

Discrepancies in the adoption regions for the two managers are enhanced for slow (β small) spreading epidemics or those characterised by large degrees of uncertainty (σ large). The divergence in adoption thresholds occurs even if the disease impacts equally on the value of timber and non-timber benefits: the extent of divergence increases as the impact of disease differs for the two classes of benefits. Indeed it can be optimal for some managers to adopt control while for others it is never optimal to adopt control (Figure 3c). In these situations, the divergent management objectives create a tension in landscapes with some managers controlling and others not, due to a transferable externality (the disease).

Our results have important implications for policy makers since they show that the diversity in management objectives alone does not lead to significantly different disease management strategies between different manager types. Rather, it is a combination of the diversity in management objectives and the way in which the disease affects these benefits that determines how uniform the adoption of control measures is at the landscape scale. Hence, it is important for decision makers to consider both the balance of management objectives and of the disease impacts on benefits to ensure effective adoption of control across the whole landscape.

When disease impacts differently on timber and non-timber benefits, we find that subsidy schemes that reduce either the fixed or yearly maintenance cost could modulate the discrepancy of adoption times for disease control between the two types of manager (Figure 5a and c). However, while a subsidy scheme that reduces only the fixed cost would bring forward the adoption for the non-timber manager (the manager-type targeted by the subsidy scheme), it would also bring forward the subsequent cancellation of control. Indeed, when fixed costs are eliminated then the cancellation and adoption thresholds coincide and hence control subsidies would not be sustained in the long term. Note however, that lump-sum subsidies combined with a penalty payment on cancellation would increase the irreversibility of control and so would increase the region over which the manager would continue controlling. However, such penalty payments may be difficult to enforce in practice.

Alternatively, a subsidy scheme that reduces yearly costs ensures that once adopted, control measures are likely to be sustained, since the size of the cancellation region decreases as the subsidy payments increase (yearly costs decrease). This has implications for policy makers on the performance of different types of subsidy schemes to support effective control of disease at the landscape scale. Subsidy schemes that reduce yearly maintenance costs may be more effective in ensuring continued implementation of disease control measures over the longer term.

The main aim of this article is to investigate the effect of contrasting management objectives on the timing of control, rather than to explore behavioural interactions between forest managers at the landscape scale. In particular, we have assumed that each manager makes decisions independently of neighbouring forest managers. However, the decision of a manager to adopt control measures or not impacts on the spread of the disease to their neighbours. A co-ordinated response is therefore required for effective control at the landscape scale.

Fenichel, Richards, and Shanafelt (2013) incorporate the potential increased risk of disease if a manager's neighbours do not adopt control measures by incorporating a constant term directly into the model of the disease dynamics. On the other hand, Epanchin-Niell and Wilen (2015) directly incorporate expectations of neighbours actions into the decision problem of a manager, which allows for the study of local cooperative and coordinated control agreements to manage invasions in a landscape. They find that the level of co-operation needed to mitigate damage caused by disease depends on the cost of controls. In particular, their work shows that strategic interactions between independent landowners can be important to ensure a successful control response at the landscape scale. An interesting extension to the work presented here would be to incorporate the expected actions of neighbouring forests into the decision-making process for a given manager.

In this article we have considered a control measure that reduces the rate at which a tree disease spreads, which could, for example, be the spraying of fungicides or pesticides that reduce the susceptibility of trees, removal of weeds to increase the vigour of the trees and reduce humidity or movement restrictions that reduce the chance of infected material being bought in from elsewhere. Other control measures involve the removal of infected material, or treating currently infected trees, (Ndeffo Mbah and Gilligan 2010; Cunniffe, et al. 2015; Cunniffe et al. 2016) rather than altering the transmission rate parameter. The model presented here could be extended to explore how the optimal timing of control depends on the way in which a control measure alters disease spread. The model could also be extended to consider the optimal timing of control over multiple timber rotation periods, which would allow us to take into account non-timber benefits that accumulate over multiple rotations.

This article represents the first attempt to investigate how the interaction between uncertainty in disease spread and forest management objectives affect when (if ever) it is optimal for an individual forest manager to adopt control measures to reduce damage due to invasive pathogens or pests. We have shown that managers adopt control at different times depending on the management objectives for the forest, specifically according to the relative value and impact of disease on timber and on-timber benefits from the forest. Furthermore, whilst subsidies always accelerate the adoption of disease control measures (the adoption region widens), once control has been adopted, different forms of subsidy can have opposite effects on the continuation of disease control (either widening or narrowing the cancellation regions). Therefore, policy makers need to take into account not only the range of different management objectives but also the effectiveness of alternative intervention measures if they wish to ensure a uniform approach to disease control at the landscape scale.

Tables

Table 1: Parameter values used in numerical simulations.

Model Parameter	Description	Base case (Range)
β	Initial infection transmission rate (i.e. transmission rate when no control deployed)	0.15 (0.05, 0.25)
ω	Reduction in infection transmission rate as a result of adopting control measures	0.1 (0.4, 0)
σ	Volatility of infection transmission rate	0.5 (0, 1)
b	Net value per hectare of annual non-timber benefits	0 for timber manager $re^{-rT}/(1-e^{-rT})$ for non-timber manager
p	Net return per hectare from timber sold	1 for timber manager 0 for non-timber manager
φ	Factor by which non-timber benefits are reduced as a result of infection	0 0.6 (in Figure 5), (0, 1)
ρ	Factor by which timber benefits are reduced by as a result of infection	0 0.4 (in Figure 5), (0, 1)
K_A	Fixed cost of control measures	0.0116 ([0, 0.0116)
m_A	Yearly maintenance cost of control measures	0.0005 ([0, 0.0005])
α	Proportion of initial sunk cost that is recouped upon cancelling control measures	0
r	Risk-free interest rate	0.03
T	Time period over which to consider the value of the forest	40 years

Table 2: Impact of different combinations of reductions to timber (ρ) and non-timber (φ) benefits on the optimal control strategy for a timber and non-timber manager, along with examples of diseases for which these combinations of ρ and φ arise.

Reduction in timber benefits	Reduction in non-timber benefits	Control strategy for timber manager	Control strategy for non-timber manager	Disease example
High ($\rho = 0.1$)	High ($\varphi = 0.1$)	Control when proportion of area infected within adoption region	Control when proportion of area infected within adoption region	Ash dieback
Low ($\rho = 0.9$)	Low ($\varphi = 0.9$)	Never adopt control	Never adopt control	
High ($\rho = 0.1$)	Low ($\varphi = 0.9$)	Control when proportion of area infected within adoption region	Never adopt control	Dothistroma
Low ($\rho = 0.9$)	High ($\varphi = 0.1$)	Never adopt control	Control when proportion of area infected within adoption region	Oak Processionary moth

Figures

Figure 1: Adoption (a and b) and cancelation (c and d) regions for the timber manager (a and c) and non-timber manager (b and d). The interval in the proportion of area infected over which a manager should adopt control immediately is shown by the green box in a and b. The region in the level of infection over which the manager should cancel control immediately is disjoint and in shown by the two red boxes in c and d. Note that the lower cancellation threshold is very close to 0 and so it appears as a line. Parameter values used are the baseline values given in Table 1.

Figure 2: Individual realisations in the level of infection and the time at which the timber manager (red dots) and non-timber manager (blue line) should adopt/cancel control for four different initial levels of infection.

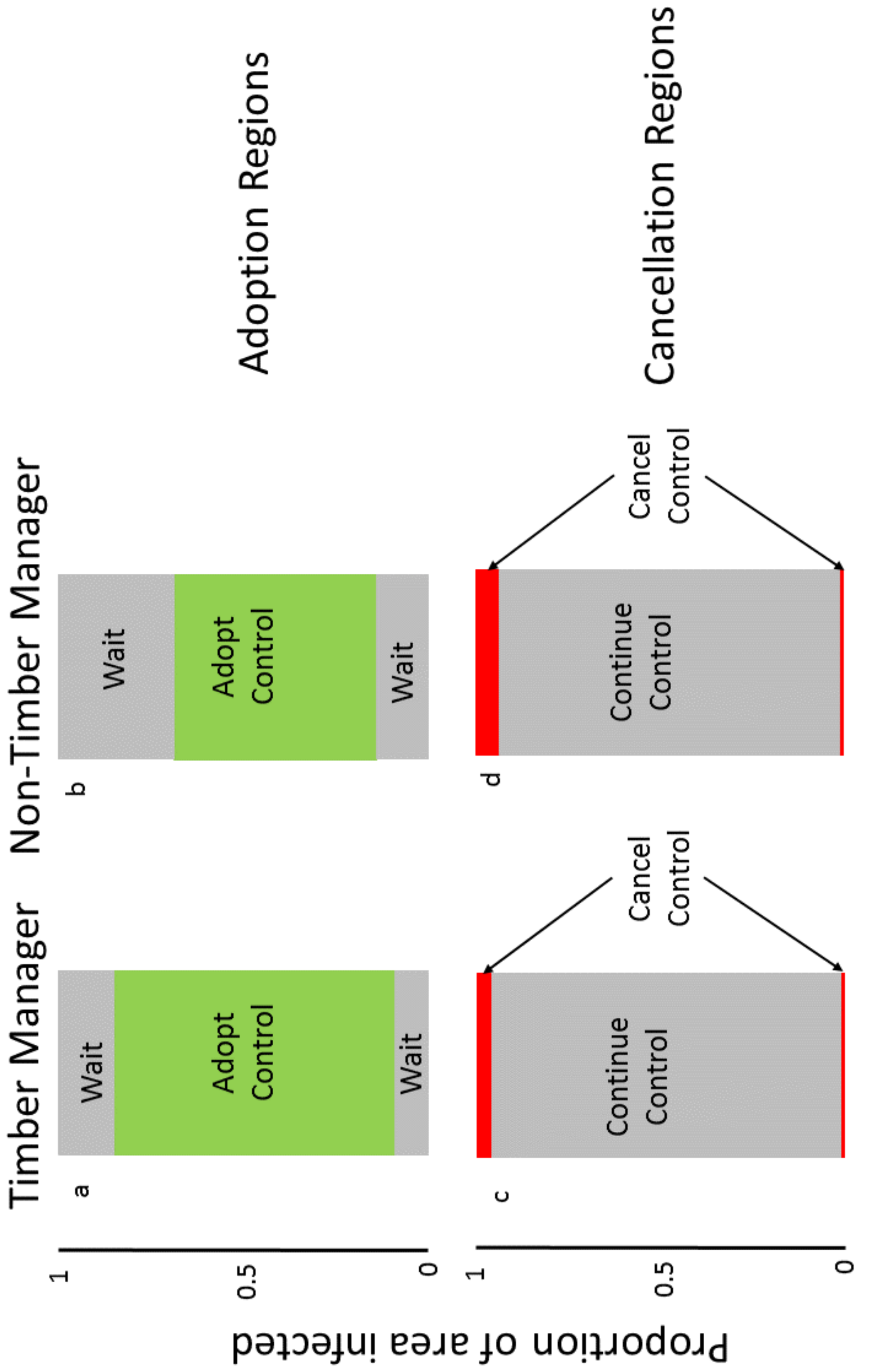
Figure 3: (a) and (c) Adoption regions for timber manager (red) and non-timber manager (blue) when (a) the reduction in timber benefits equals the reduction in non-timber benefits ($1 - \rho = 1 - \varphi$) and when (c) the reduction in timber benefits is not equal to the reduction in non-timber benefits ($1 - \rho = \varphi$). Dashed lines show the switch points when moving from a region where the adoption thresholds exist to one where control should never be adopted. (b) and (d) Cancellation regions for timber manager (red) and non-timber manager (blue) when (b) the reduction in timber benefits equals the reduction in non-timber benefits ($1 - \rho = 1 - \varphi$) and when (d) the reduction in timber benefits is not equal to the reduction in non-timber benefits ($1 - \rho = \varphi$). Dashed lines show the switch points when moving from a region where the cancellation thresholds exists to one where control should never be cancelled.

Figure 4: Upper and lower adoption thresholds ((a), (b) and (c)) and cancellation thresholds ((d), (e) and (f)) for timber manager (red lines) and non-timber manager (green square lines) as a function of: (a) and (d) the transmission rate β, (b) and (e) the reduction in transmission rate

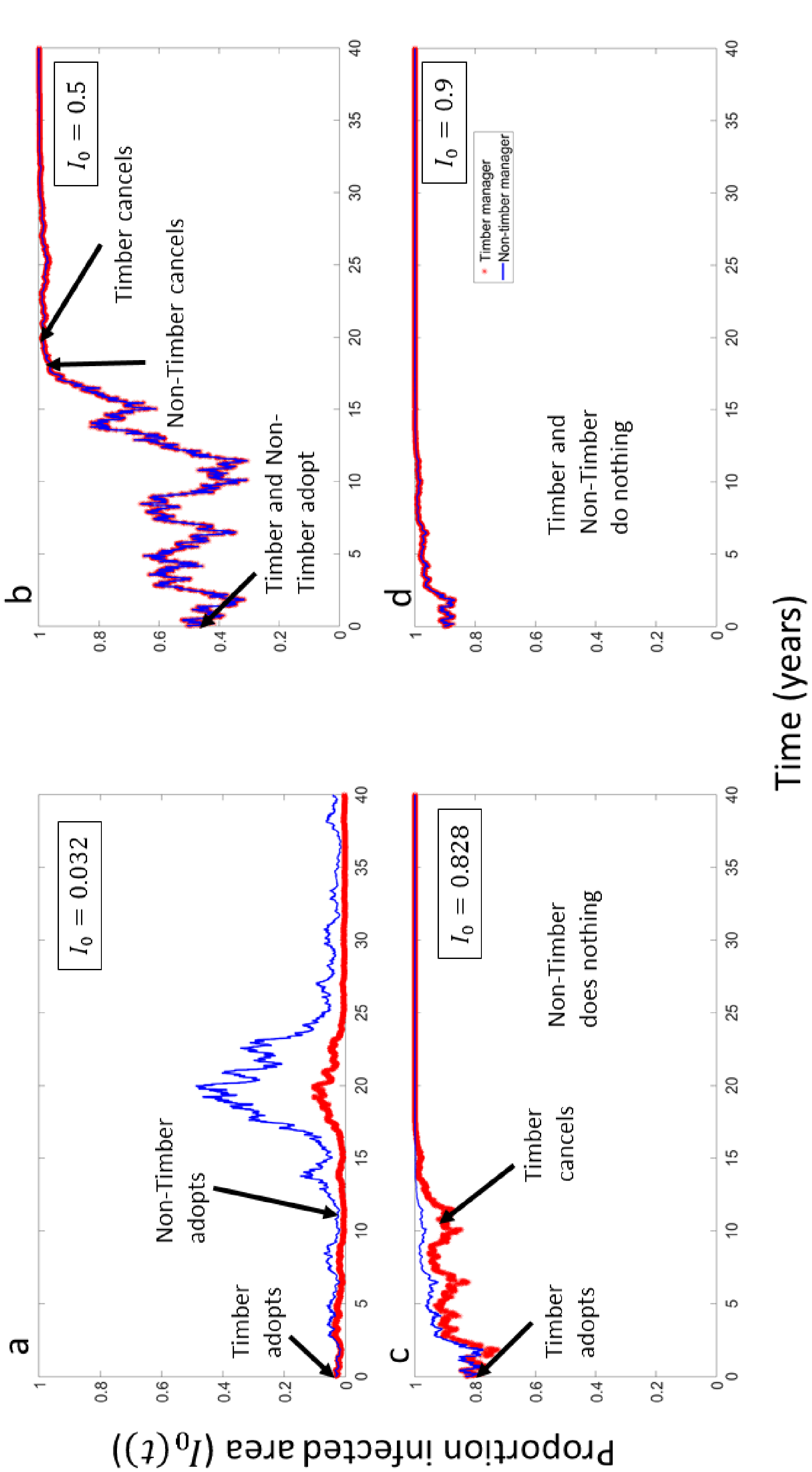
due to control ω and (c) and (f) the volatility σ. The reduction to timber and non-timber is assumed to be fixed $\rho = \varphi = 0$.

Figure 5: Impact of reducing fixed costs (a) and (b) and non-going costs (c) and (d) on the adoption region ((a) and (c), blue shaded area) and cancellation region ((b) and (d), red shaded area) for the non-timber manager, when the reduction in timber benefits is high ($\rho = 0.4$) and the reduction in non-timber benefits is low ($\varphi = 0.6$). The dashed lines show the adoption/cancellation thresholds for the timber manager when adoption costs are baseline values

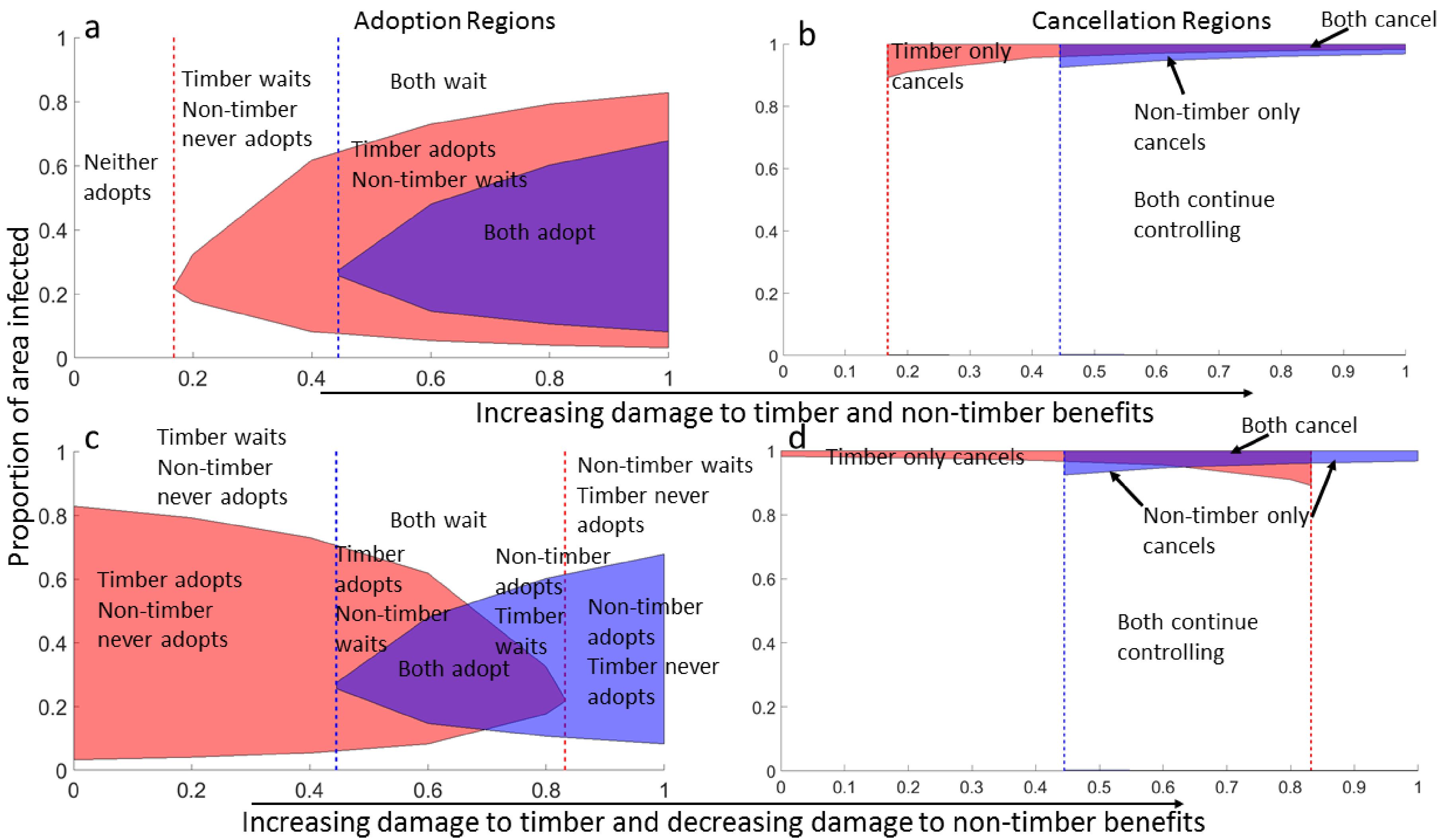
Figure 6: Individual realisations in the level of infection and the time at which the non-timber manager should adopt/cancel control for a subsidy scheme that eliminates fixed costs (a) and one that eliminates ongoing costs (b).

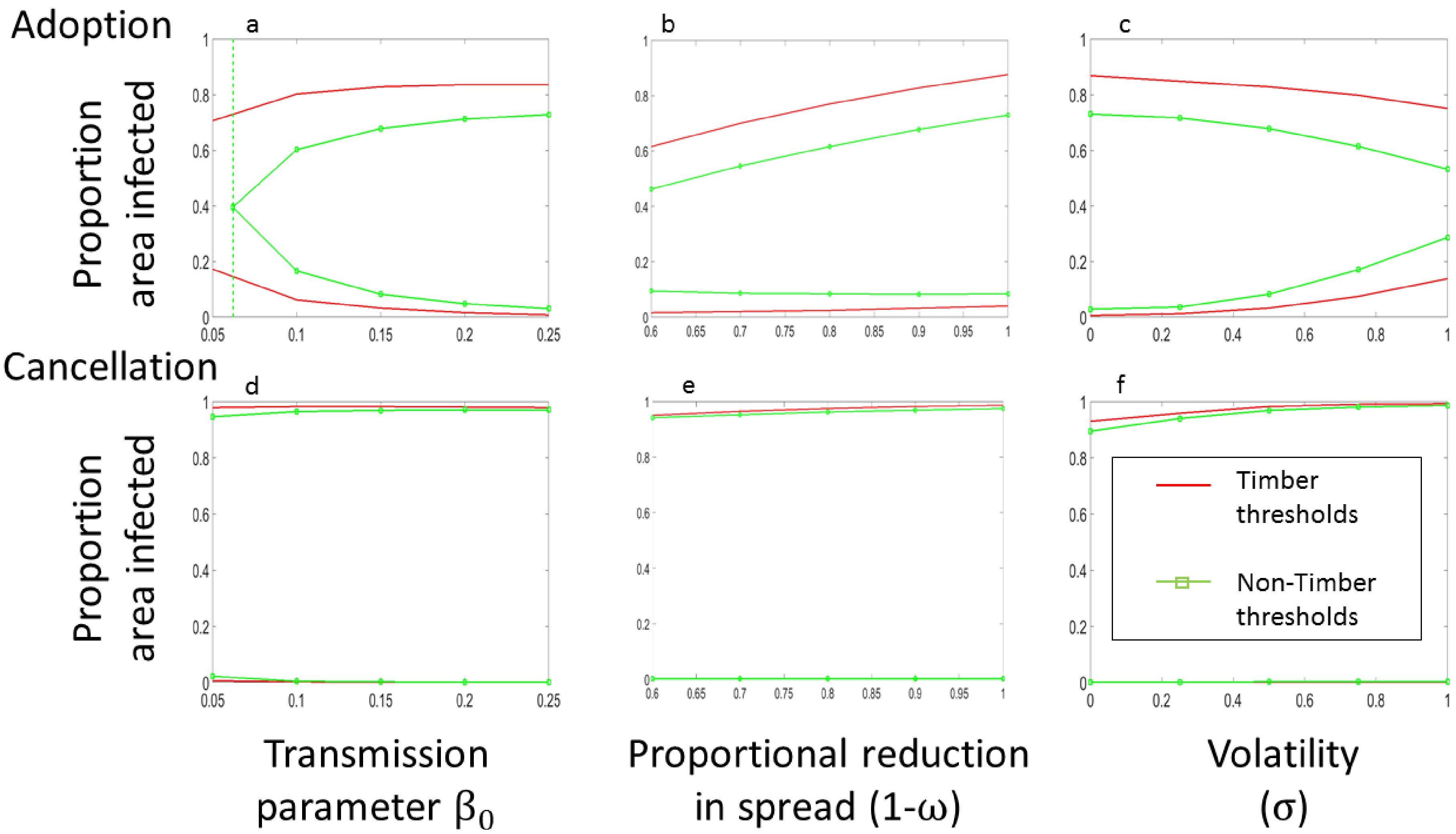


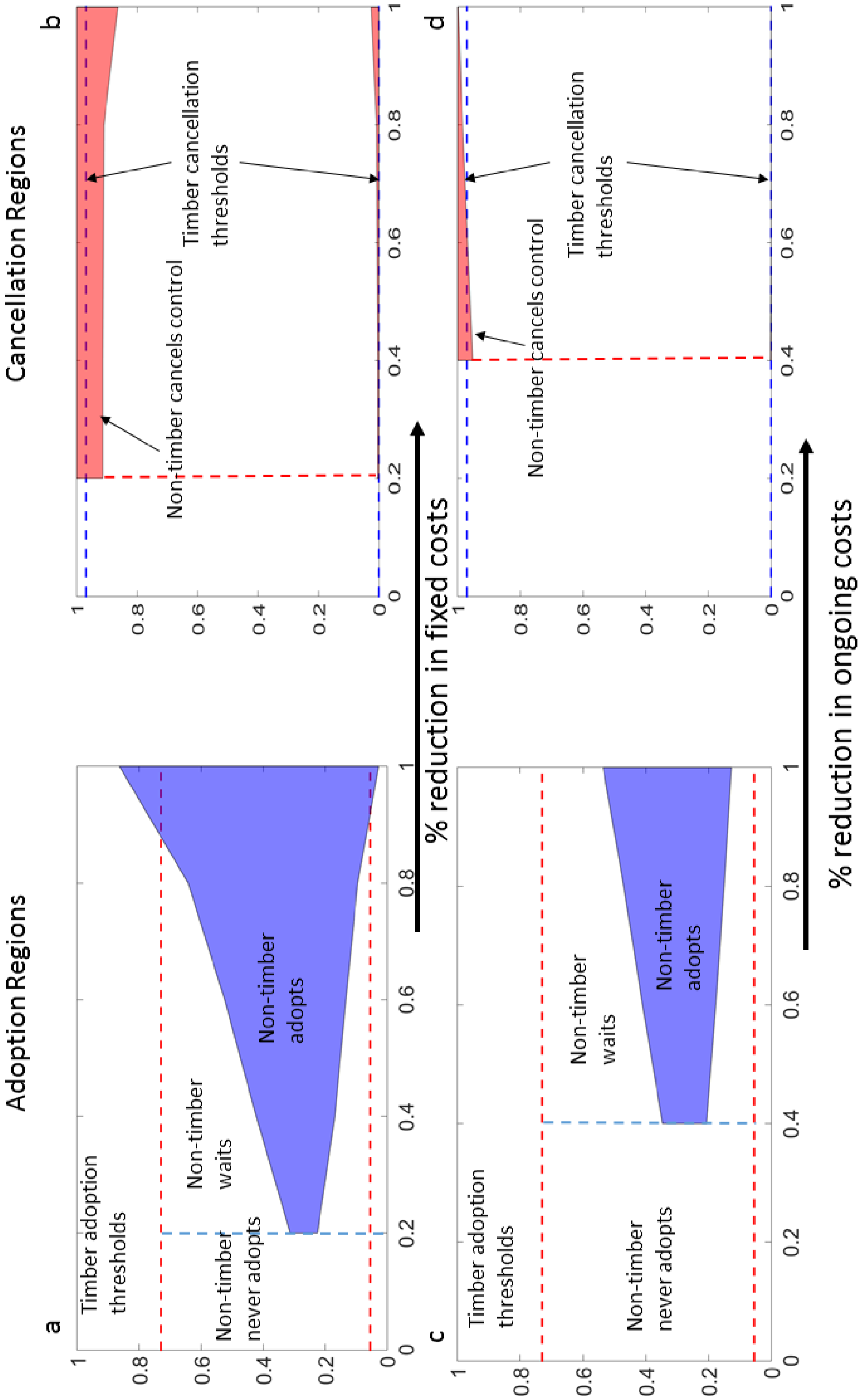
Timber Manager
Non-Timber Manager
Adoption Regions
Cancellation Regions
Proportion of area infected
1
0.5
0
a
b
c
d
Wait
Adopt Control
Continue Control
Cancel Control



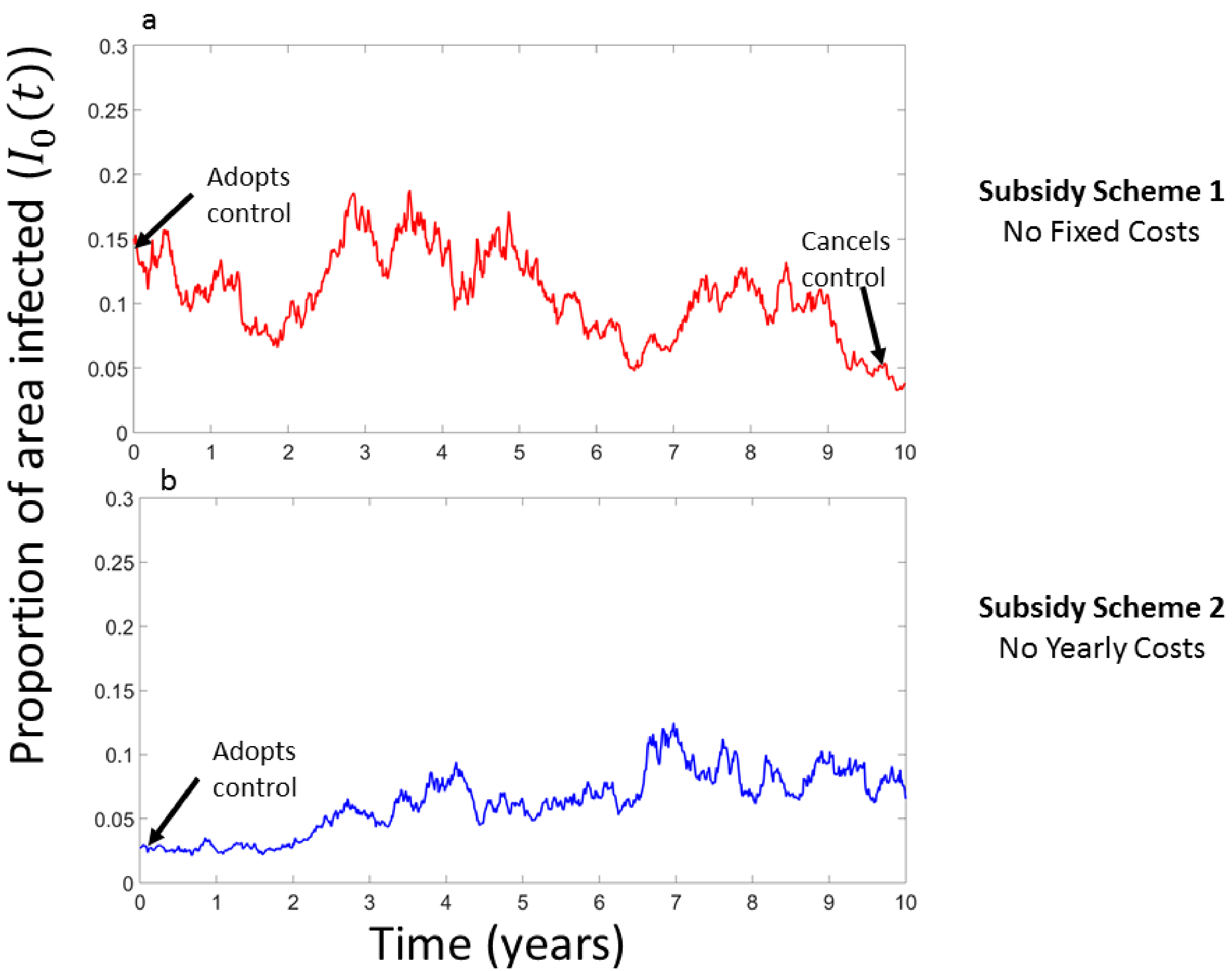
a
$I_0 = 0.032$
Timber adopts
Non-Timber adopts
b
$I_0 = 0.5$
Timber and Non-Timber adopt
Non-Timber cancels
Timber cancels
c
$I_0 = 0.828$
Timber adopts
Timber cancels
Non-Timber does nothing
d
$I_0 = 0.9$
Timber manager
Non-timber manager
Timber and Non-Timber do nothing
Proportion infected area ($I_0(t)$)
Time (years)


a
Adoption Regions
Neither adopts
Timber waits Non-timber never adopts
Both wait
Timber adopts Non-timber waits
Both adopt
b
Cancellation Regions
Both cancel
Timber only cancels
Non-timber only cancels
Both continue controlling
Increasing damage to timber and non-timber benefits
Proportion of area infected
c
Timber waits Non-timber never adopts
Timber adopts Non-timber never adopts
Both wait
Timber adopts Non-timber waits
Both adopt
Non-timber adopts Timber waits
Non-timber waits Timber never adopts
Non-timber adopts Timber never adopts
d
Both cancel
Timber only cancels
Non-timber only cancels
Both continue controlling
Increasing damage to timber and decreasing damage to non-timber benefits


Adoption
Cancellation
Proportion area infected
Proportion area infected
a
b
c
d
e
f
Timber thresholds
Non-Timber thresholds
Transmission parameter β_0
Proportional reduction in spread (1-ω)
Volatility (σ)



Adoption Regions
Cancellation Regions
a
b
c
d
Timber adoption thresholds
Non-timber waits
Non-timber never adopts
Non-timber adopts
Timber cancellation thresholds
Non-timber cancels control
% reduction in fixed costs
% reduction in ongoing costs



a
Adopts control
Cancels control
Subsidy Scheme 1
No Fixed Costs
b
Adopts control
Subsidy Scheme 2
No Yearly Costs
Proportion of area infected ($I_0(t)$)
Time (years)

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Appendix

The free boundary problem is given by equations (10) and (11) in the main text along with the boundary conditions given by equations (6) to (9), (12) and (13), in the main text, and conditions at $I = 0$ and $I = 1$. We solve this in MATLAB using the Euler method (Wilmott, Howison, and Dewynne 1995). To ensure numerical convergence, the time step used for numerical simulation, dt, must satisfy the following condition,

$$dt < \frac{1}{2(\sigma \times dI)^2},$$

where dI is the mesh size for the infected area variable (I) that is used in simulation (we take $dI = 0.002$ in all simulations). In order to obtain the finite difference scheme at the upper/lower boundaries (Insley 2002), we apply $\partial^2 W_A / \partial \mathrm{I}^2 = \partial^2 W_N / \partial \mathrm{I}^2 = 0$ at $I = 1, 0$.