

## Title: What makes or breaks an effective disease control campaign?

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**Abstract:** Diseases in humans, animals and plants remain an important challenge in our society. Effective disease control often requires coordinated concerted action of a large group of stakeholders. Both epidemiological and human behavioral factors influence the outcome of a disease control campaign. In mathematical models, that are frequently used to guide such campaigns, human behavior is often ill represented, if at all. Existing models of human, animal and plant disease that do incorporate participation or compliance are exclusively driven by pay-offs or direct observations of the disease state (1, 2). It is however very well known that opinion is the driving factor of human decision making (3). Here we show how coupling an epidemiological model with an opinion dynamic model it is possible to answer the question: What makes or breaks a disease control campaign? We use Huanglongbing disease of citrus as our case study.

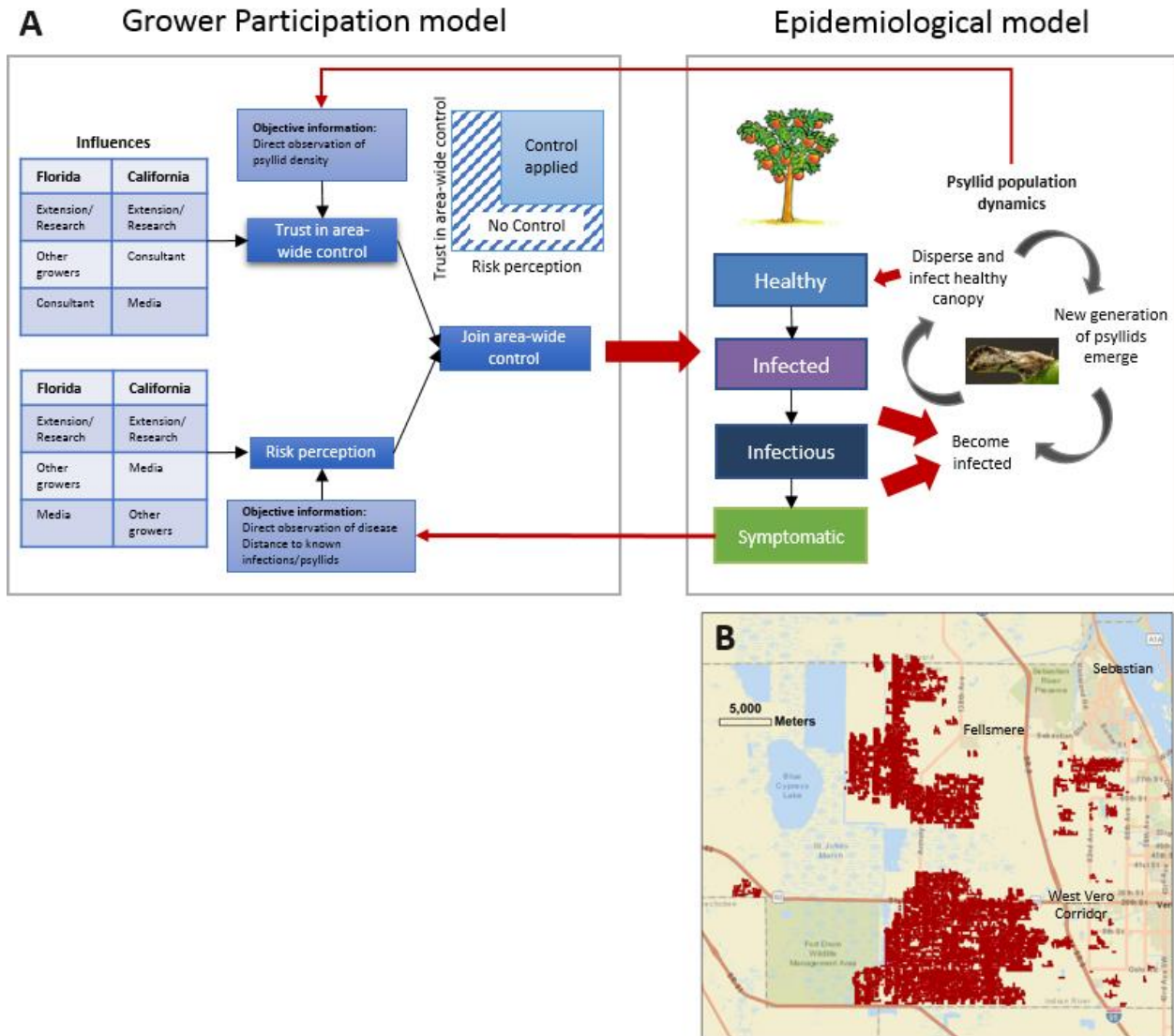
**One Sentence Summary:** Trust in a control strategy and expert guidance are more important to successful disease control than initial risk perception

### Main Text:

Huanglongbing disease (HLB), or citrus greening, is caused by a bacterial species (*Candidatus liberibacter asiaticus* [CLas]) that is transmitted between trees by an insect vector (the Asian Citrus Psyllid *Diaphorina citri*). Huanglongbing disease is an acute plant disease that threatens the sustainability of citrus production throughout the world (4). For example, in Florida the disease was first found in 2005 and has since caused more than an 80% reduction in citrus production (6, 7). It is now considered unlikely that the Florida citrus industry will survive in its current form. In 2012 the disease was found for the first time in California, and since that time over 600 trees have been confirmed to be infected. The industry, therefore, is in desperate need for guidance on the development of effective control methods. Disease control campaigns in both states are developed around spatially organized groups of growers taking concerted action against the psyllid vector. This is known as area-wide control.

Several models for the epidemiology of HLB have been developed and tested (7–10), and our model is a variant of these (full mathematical detail can be found in the supplementary materials). Healthy citrus trees may become infected with CLas when a psyllid carrying the bacterium feeds on that tree (Fig 1A). After infection, the CLas populations increase and begin to spread non-uniformly within the tree. Post infection, the tree enters a cryptic period when the tree becomes infectious allowing psyllids to acquire the bacterium, become bacterialiferous, and capable of spreading the pathogen. Eventually, after a latent period of a few weeks to multiple months the

tree becomes symptomatic. Psyllids are not adversely affected by the CLAs commensal and each psyllid develops, reproduces and dies unaffected by its presence. Psyllids fly, driven by air currents, to neighboring groves (11). The citrus tree population is structured in plantings of orchard blocks that are arranged in a spatial pattern in the landscape (Fig 1B). We used the citrus distribution of a management control area in Florida for the simulations shown here, but note that we have done the same for other management control areas with no difference in the qualitative results.



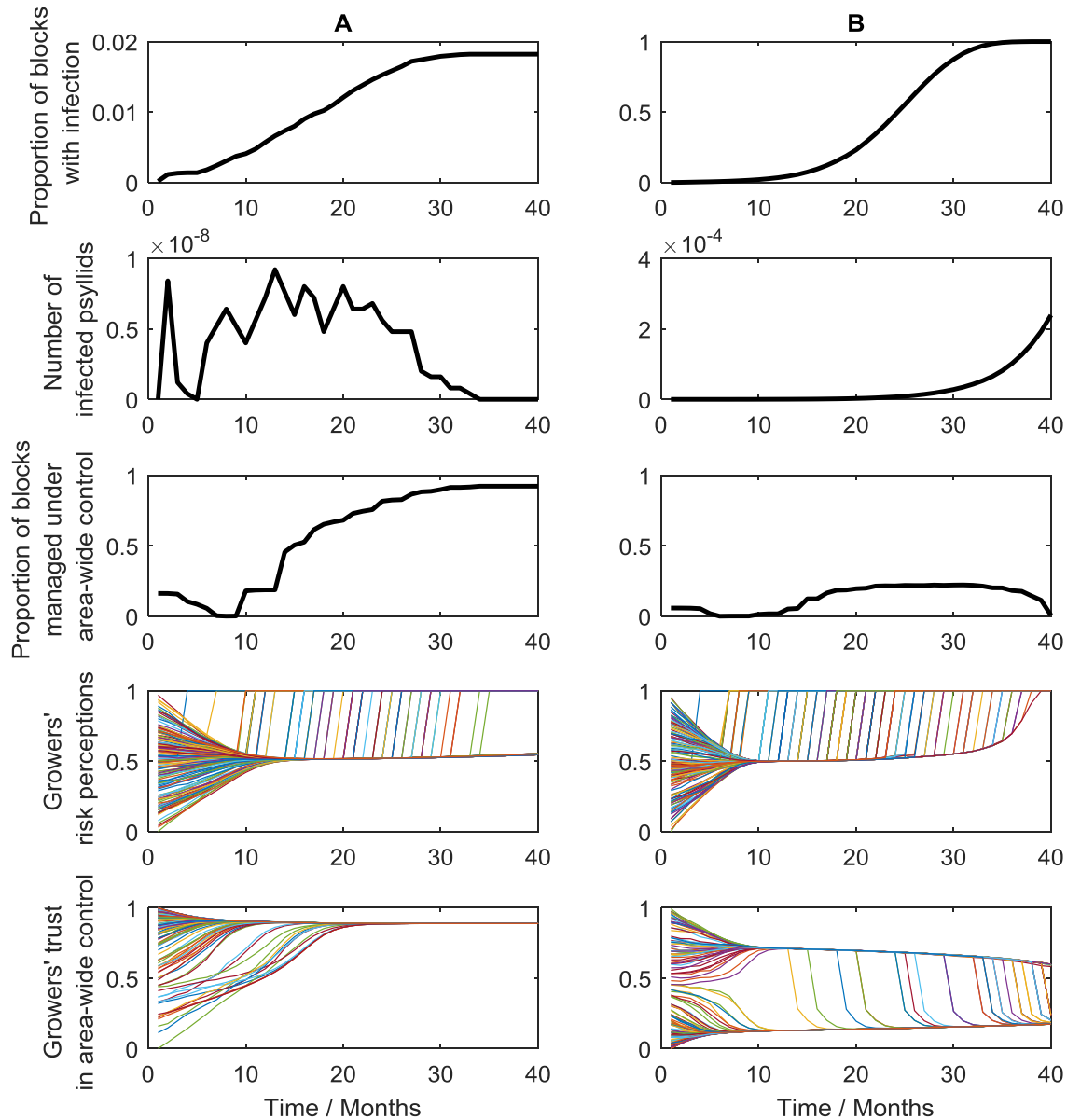
**Fig.1. A model of HLB in the landscape.** (A) A schematic showing how the grower participation model is linked to the epidemiological model. Growers join an area-wide control program if their risk perception and trust in area-wide control are high. This impacts on the psyllid population and so the dynamics of the disease in the landscape. Observations of infection increase risk perception and can erode the trust in area-wide control. Red arrows indicate where models interact. (B) A simulated landscape representing a typical Citrus Health Management Area in Florida. The area where commercial citrus is grown is indicated by green shading.

Before developing the opinion dynamic model, we surveyed growers in Florida and California to find out what the key drivers are for a grower to decide to join an area-wide control campaign (12). Figure 1A shows the conceptual model developed, where the two key drivers are the risk perception (quantified as a grower's perceived probability that their grove will become infected) and the trust in control (quantified by a grower's perceived probability that area-wide control is effective). These factors accord with those reported to affect the public's adoption of prevention measures for human diseases that are known to be difficult to cure (13). These opinions are influenced by other growers, consultants, extension workers and researchers and to a lesser extent by the media (12). When the perceived risk of infection as well as the trust in the control options are both high, a grower is inclined to join an area wide control scheme.

There are two sources of direct observations growers make that affect their opinions. Firstly, the observed state of the epidemic, for example by neighboring plantings becoming infected, increases the risk perception of the grower considerably. Secondly, when a grower applies the control and subsequently his plantings become infected, the trust in the control method decreases considerably.

Using the methods developed for opinion dynamic models (14–16) we assign each grower an initial risk perception and an initial trust in the control method. Subsequently each grower interacts with other growers, consultants etc. which affects their opinions (see supplementary material). Also, the direct observations of disease or failure of control methods influence opinions. When risk perception and trust in control are above a threshold value the grower joins the area wide control scheme (Fig 1A). We did not consider the importance of the economics of crop production and disease control in our model. By not including the economics of control we were able to pinpoint the opinion dynamics factors that affect the success or failure of a disease control campaign.

The epidemiological and the opinion dynamic model are coupled by (i) the direct observation growers make on the development of the epidemic affecting opinions on risk and trust in control, and (ii) growers joining or not joining the area-wide-control scheme that affects the course of the epidemic (Fig. 1A). Model parameters for the epidemiological model were based on published information on the epidemiology of HLB and from published models (7–10). For the opinion dynamics part of the model the situation is very different. There are no parameter values known quantifying the effects of interactions of growers on their opinion, no quantitative information is known about the effect of consultants, extension workers and researcher on grower opinion, nor is anything known about the level of risk and level of trust needed for a grower to join the area-wide control program. Before we explain how this problem was dealt with we will show the types of outcomes the model can produce. To this end, we parameterized the opinion dynamics model with plausible ranges of parameter values provided to us by experts (one of them is the second author).



**Fig.2 (A) A simulated scenario where control of HLB fails.** Grower uptake of control is not rapid enough to control the disease and so the disease becomes endemic and proliferates. Growers who have joined an area-wide control program observe that it is not working and drop out. **(B) A simulated scenario where control of HLB is successful.** The evolution of risk perception and trust in control is shown for each grower in the region (each growers perception is represented by a colored line). Risk sharply increases when growers observe disease in their orchards and then quickly persuade their neighbors the disease is a serious threat.

There are broadly two types of outcome found in our simulations. Firstly (Fig. 2A) control success, where the number of orchard blocks infected and the density of bacterium carrying psyllids initially increases, which increases the risk perception of growers to such an extent that they join the area-wide control program. This leads to a decrease in the density of bacterium carrying psyllids, the number of infected orchard blocks does not further increase, and the epidemic is under control: Control success. The second possibility (Fig. 2B) is control failure, initially growers start joining the area wide control scheme, but their trust in control is compromised because even joining the area wide control scheme their orchards become infected. This stimulates them to drop out of the area-wide control program, consequently the epidemic grows rapidly and eventually most orchards become infected: Control failure.

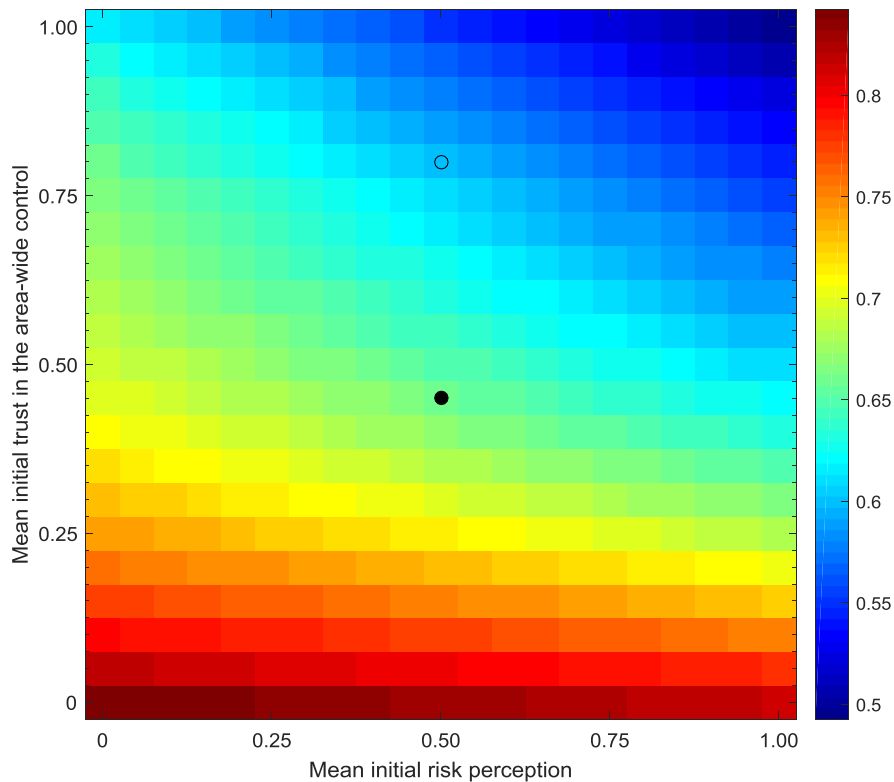
Surprisingly, the control success and the control failure as shown in Fig. 2 resulted from exactly the same set of parameter values! The only difference between the two simulations is the mean initial risk perception and the mean initial trust in control of the growers ('mean' because each grower has initial values for risk perception and trust in area-wide control that are drawn from a beta distribution with a defined mean and variance). The simulation which resulted in control success (open disc in Fig. 3) had a larger mean initial trust in area-wide control and a lower mean initial risk perception than the simulation that resulted in control failure (filled disc in Fig. 3). It must be said that the simulations shown were chosen from a set of runs where due to the stochastic nature of the model some of the runs show control success and others control failure. We did further simulations with this set of parameter values and calculated the probability of control success or control failure for a range of mean initial risk perception and main initial trust in the control options of the growers (Fig 3). This showed that the mean initial trust in the control options is an important factor in the success of the disease control campaign. The mean initial risk perception was of much less importance to successful control.

Is this result caused by the particular set of parameter values used or is it a more general phenomenon? Since we do not have estimates of the parameters in the opinion dynamics model we did a sensitivity analysis to establish which factors in our model were most important for control success. We assigned to each of the parameters in the opinion dynamic model a set of values that according to our experts spanned realistic ranges. Similarly, we assigned sets of values to the parameters that described the efficacy of the insecticide and the number of insecticide applications that were undertaken each year under area-wide control. The parameter values of the epidemiological model remained at the default settings as these parameter values are, as explained, relatively well known. Next a large series of simulations was done using all combinations of parameter values. We used analysis of variance to identify the factors (our model parameters) that best explained the variation in the area of citrus infected with HLB at the end of a 30-year simulation (see SI 2).

The statistical sensitivity analysis showed that the following factors increased the probability of a successful control campaign, in order of highest to lowest importance (Fig 4).

1. Number of insecticide applications per season
2. Efficacy of the insecticide (mortality rate)
3. Frequency that information is disseminated by extension agents
4. Mean initial trust in the area-wide control
5. Range of opinions listened to

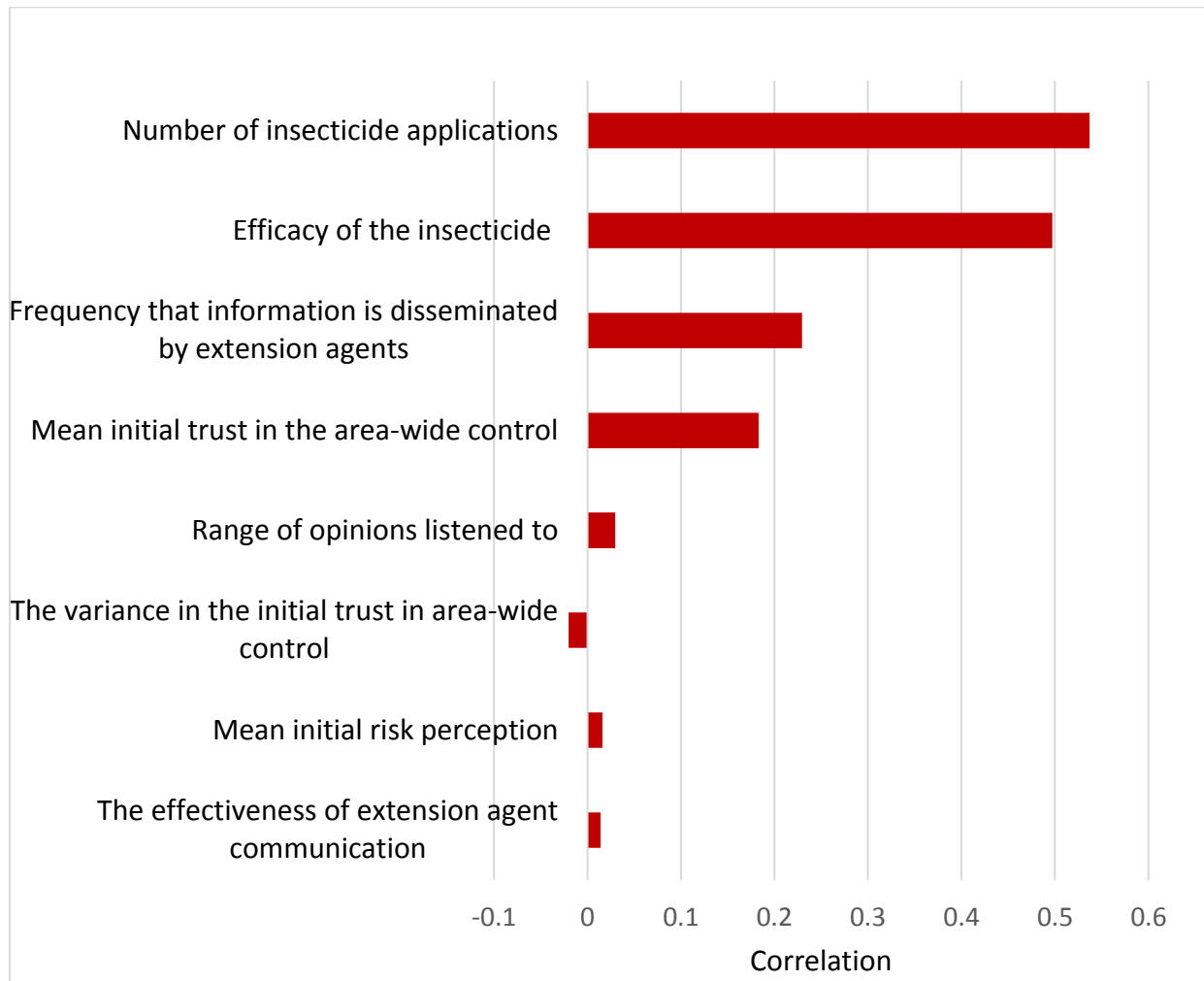
6. The variance in the initial trust in area-wide control
7. Mean initial risk perception
8. The effectiveness of extension agent communication



**Fig.3 The probability of control failure** for given means across the grower population for initial risk perceptions and a trust in area-wide control. The open disc relates to the simulation shown in Fig. 2A and the solid disc the simulation shown in Fig 2B.

Clearly, and intuitively, the efficacy of the control program, insecticide kill rate and number of applications, is the most important factor in the success of a HLB control campaign. Of the opinion dynamic parameters, the frequency of information dissemination is of great importance. If contact between extension services and growers becomes infrequent then important scientific messages can become forgotten or diluted. The initial trust in the control options is of key importance, just as in the simulations shown Figs 2 and 3. The most surprising finding is that the initial risk perception plays a relatively unimportant role in determining the success of a HLB control campaign. Further analysis of this phenomenon showed that the reason for this is found in the effect of the direct disease observations on the risk perception. When the epidemic starts to infect more and more orchards, growers form opinions from ‘direct’ observation concerning the chances that their orchards will also become infected. These direct observations start to override risk perception dynamics due to the ‘indirect’ opinions derived from other growers. This increased risk

perception does not apply to the trust in the control option. The social dynamics with advisors increasing the trust in control is still strongly, but negatively, affected when growers see the control failing.



**Fig. 4. Tornado graph showing the correlation between each variable and the proportion of cells infected.**

Opinions are the driving force behind human decision making. We have shown that coupling an epidemiological model with an opinion dynamic model can give insight in the question ‘What makes or breaks a disease control campaign?’ In many information programs aimed at informing and preparing the public, or a professional group, of a possible infectious disease there often is much emphasis on the risks the disease poses. Our research calls into question whether that is a necessary approach, especially in the light of the potential loss of trust with the public when in the end the epidemic does not actually take place, as was the case for the official swine flu warning in 2009 (13). For HLB we have shown that aiming to inform growers about the effectiveness of the regionally coordinated control actions and the efficacy of the insecticide program may be of much greater importance. It, of course, remains to be investigated whether this holds more generally or

that it should be decided on a case by case basis what the emphasis of information campaigns should be about.

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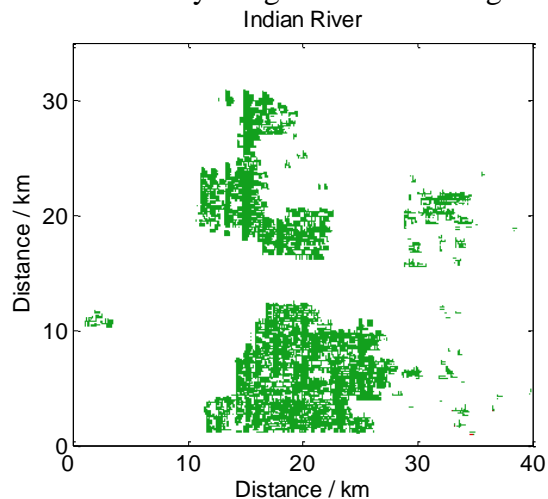
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## Supplementary Materials:

### Materials and Methods:

#### *The Epidemiological Model*

We developed a model of the spread of HLB in citrus orchards across an area typical of a Citrus Health Management Area (CHMA) in Florida. The modelled CHMAs were based on USDA statistics which describe the locations of citrus orchard blocks and their areas. We modelled each CHMA with a grid of cells, with each cell representing 1 ha of land. We approximated each block area to the nearest ha and located the associated number of cells around the centroid for this area. This resulted in realistic distributions of citrus across our modelled CHMAs (see Fig. S1-1). For one CHMA (Indian River County) we had data on the ownership of the orchard blocks (for anonymity purposes each owner was replaced by a numeric reference number). This allowed us to identify blocks that were assumed to be managed by the same grower/decision maker. For other CHMAs we used the distribution of blocks per grower from Indian River, as this is the only CHMA for which we have such data, to stochastically assign block sizes to growers.



**Fig. S1-1. A simulated CHMA** The area planted with citrus is shown in green.

We made the simplifying assumption that the Asian Citrus Psyllid (*Diaphorina citri*) populations only develop in grid cells with citrus. In each of these cells we use an abundance-based population model to describe the population dynamics of Asian Citrus Psyllid (ACP). Our model does not account for seasonal variation. The expected lifespan of the ACP is between 30 – 50 days on average. Therefore, we assumed that a generation of ACP live for a month and in this time they may become infected (bacteriliferous) by acquiring CLAs from infected trees during feeding and pass that infection on to the healthy trees that they subsequently feed on. We assume that there is no vertical transmission of infection in the population, based on van den Berg et al. and Pelz-Stelinski et al. (17, 18) who found little to no vertical transovarial transmission of the bacteria from psyllid parent to child. At the start of month  $t$ , the total number of ACP in cell  $i$  are given by

$$N_i(t) = \frac{KN_i(t-1)}{\frac{K}{\sigma} + N_i(t-1)} [1 - \theta_i(t)]$$

where  $K$  is the carrying capacity of the population,  $\sigma$  is the number of offspring at low density and  $\theta$  is the efficacy of the insecticide spray applied in month  $t$ . Of these a number  $\tilde{N}_i(t)$  are infected with the disease

$$\tilde{N}_i(t) = [1 - e^{-\beta[I_i(t) + S_i(t)]}]N_i(t),$$

where  $I_i(t)$  and  $S_i(t)$  are the numbers of infectious and susceptible trees in cell  $\mathbf{z}$  in month  $t$  respectively and  $\beta$  is the rate at which trees pass infection to the ACPs. Infected ( $\tilde{N}_i(t)$ ) and healthy ( $\hat{N}_i(t)$ ) populations of ACP disperse according to  $D_{ij}$

$$\tilde{Y}_i(t) = \sum_{j=1}^n D_{ij} \tilde{N}_j(t)$$

$$\hat{Y}_i(t) = \sum_{j=1}^n D_{ij} \hat{N}_j(t)$$

and so  $N_i(t) = \tilde{Y}_i(t) + \hat{Y}_i(t)$ . The infected psyllids that land in cell  $\mathbf{z}$  in month  $t$  then infect healthy trees  $H_i(t)$  in cell  $\mathbf{z}$

$$E_i(t+1) = (1 - \gamma)E_i(t) + H_i(t)(1 - e^{-\alpha\tilde{Y}_i(t)})$$

$$H_i(t+1) = H_i(t)e^{-\alpha\tilde{Y}_i(t)}$$

where  $E_i(t)$  is the proportion of infected trees in cell  $i$  in month  $t$ ,  $\gamma$  is the probability that trees in a cell become infected given that an infected psyllid has fed from them. Over time, the infected trees become infectious  $I_i(t)$  is according to

$$I_i(t+1) = \gamma E_i(t) + (1 - \rho)I_i(t)$$

where  $1/\gamma$  is the mean time that trees are infected but infected host tree cells are rare and insignificant epidemiologically before passing to the infectious state, and eventually the infectious trees become symptomatic  $S_i(t)$  according to

$$S_i(t+1) = S_i(t) + \rho I_i(t).$$

Where  $1/\rho$  is the mean time that trees are cryptically infectious before passing to the symptomatic state.

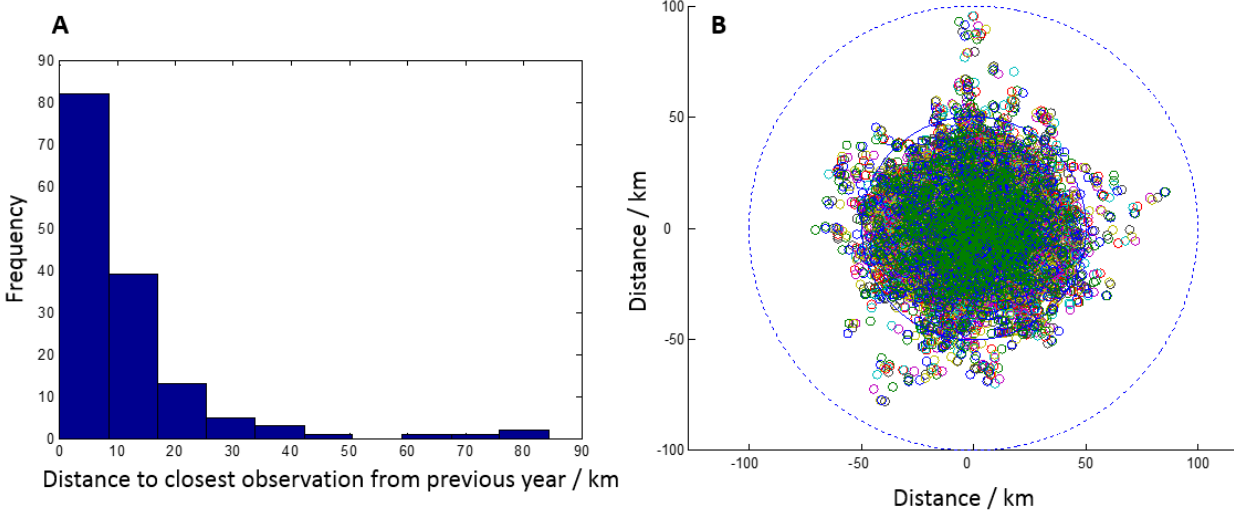
We modelled the dispersal of ACP with an exponential dispersal kernel. This function is commonly used in insect dispersal models (8, 19, 20). The function defines the probability  $p_{ij}$  of ACP starting in cell  $i$  and landing in cell  $j$ . Starting with the cell south of the cell  $i$  and working around and outwards, we determined how many ACP landed in each cell by sampling from a

binomial function with parameters defined by  $p_{ij}$  and the number ACP dispersing (i.e.  $D_{ij}\tilde{N}_j(t) \sim B(\tilde{N}_j(t), p_{ij})$ ). After determining how many ACP land in a particular cell the remaining probabilities are adjusted to sum to one and the number of ACP dispersing ( $\tilde{N}_j(t)$ ) is adjusted by subtracting the number that have already been assigned cells from the original number dispersing. The model parameter values (based on 7–10) are shown in Table S1-1 along with their source.

**Table S1-1:** The parameters for the population dynamics model and the disease model

Name	Symbol	Value
Carrying capacity of ACP in a cell	$K$	150000 (Based on 300 ACP per tree and 500 trees ha <sup>-1</sup> )
Number of surviving offspring at low density	$\sigma$	12
Probability infection is passed from tree to ACP	$\beta$	0.0033*
Probability infection is passed from ACP to tree	$\alpha$	0.0033
Average time (months) for tree to pass from an infected to an infectious state	$1/\gamma$	1
Average time (months) for tree to pass from an infectious to a symptomatic state	$1/\rho$	6
Dispersal parameter	$\lambda$	0.00035 (Based on data about the rate of spread of disease. See Fig S1-2)

\*We assumed  $\alpha = \beta$  and fitted to data on the rate that the number of infected trees increases in a block



**Fig. S1-2. The modelling the dispersal of the ACP.** (A) The shortest distances observed between each disease observations in Florida in 2007 and those observed in 2008. This gives some indication of the extent of the spread of the ACP in Florida in a year. (B) The simulated dispersal of 1000 agents from point (0,0) following exponential dispersal ( $\lambda=0.00035$ ) with weekly time steps over a year. The extent of the spread is similar to the data. The solid circle shows the 50km radius from the center and the dotted circle the 100km radius.

### *Modelling the decision process*

In the model, growers face the decision of whether to join an area-wide-control program or not. Their decision is based on their perception of the risk of infection of their orchard by HLB (quantified as,  $x_r$ , the perceived probability that their orchard will become infected) and their perception of the effectiveness of area-wide control (quantified by,  $x_c$  the perceived probability that area-wide control is effective). We quantified these factors for each grower as a value between zero and one, where  $x_r = 0$  represents a perception that there is no risk from HLB and  $x_c = 0$  that they have no faith in area-wide control, and  $x_r = 1$  represents a perception that their orchard will certainly become infected and  $x_c = 1$  that they are convinced that area-wide control is effective. We modelled the evolution of  $x_c$  and  $x_r$  over time using opinion dynamics modelling methods (16). Models of opinion dynamics allow us to simulate opinion formation within a group of interacting individuals. The opinion  $x(i, t)$  of an individual  $i$  changes from one time step  $t$  to the next by incorporating the opinions of others with their own

$$x(i, t + 1) = \sum_{j=1}^{N+1} w_j x(j, t)$$

Where  $w_j$  is the weight given to the opinion of individual  $j$  and  $\sum_{j=1}^{N+1} w_j = 1$ . The weights can

depend on several factors such as the probability individuals meet (which may depend on geographic closeness or some communication network) or the closeness of opinion (individuals

with quite different opinions may never be influenced by one another). In our model, an individual  $i$  interacts with  $n$  other individuals who are chosen at random with probability proportional to  $\exp\left(-\frac{d}{\kappa_D}\right)$ , where  $d$  is the distance between individuals' orchards and  $\kappa_D$  is the range parameter. The weights are determined by the closeness of opinion and are proportional to  $\exp\left(-\frac{|x(i,t) - x(j,t)|}{\kappa_O}\right)$  where  $\kappa_O$  is the opinion range, and there is a parameter to weight an individual's own opinion to allow growers to be less willing to change opinion ( $W_G$ ). We also included the influence of extension agents on the opinions of the growers. In the model, extension agents disseminate information on HLB control at a frequency of  $E_f$  times per year, and so increase the growers' perceptions of the risk of becoming infected by HLB ( $x_r$ ) and belief that area-wide control is effective ( $x_c$ ) by a given amount  $E_I$ . If a grower observes more than 0.2% of trees in a cell with infection (which equates to a whole tree) then  $x_r$  becomes one. Similarly, if a grower joined an area-wide control program at least  $h_m$  months ago but still observes an average increase in disease greater than 1% across his groves then  $x_c$  reduces by a factor of  $\delta$ .

In the model growers join the area-wide-control program if  $x_c$  and  $x_r$  exceed given thresholds ( $x_r > 0.6$  and  $x_c > 0.4$ ). An insecticide spray is applied a fixed number of times per year to all orchards managed by individuals who have joined the area-wide-control program. The opinion dynamics model parameters and the control parameters are listed in Table S1-2 with the sets of values that we used in our simulations.

**Table S1-2:** The parameters for the grower-decision and the control models, with the values used in our analysis. The numbers in bold were used in the simulations except for when otherwise stated.

Name	Symbol	Parameter values explored
Number of individuals that communicate	$n_c$	10, <b>60</b> , 120
The range parameter determining the probability two growers communicate (km)	$\kappa_D$	1, <b>3</b> , 12
The range parameter determining the weighting of opinions based on closeness of opinion	$\kappa_O$	<b>0.05</b> , 0.2, 0.5
Frequency that information is disseminated by extension agents (number of times per year)	$E_f$	<b>0</b> , 3, 6, 12
Impact of information from extension agents	$E_I$	<b>0.2</b> , 0.4, 0.6
History of control (months)	$h_m$	<b>2</b> , 6
Reduction in belief if infection is observed despite control being applied	$\delta$	<b>0.4</b>

Mean initial belief in control across the population of growers	$\mu_c$	<b>0.2</b> , 0.5, 0.8
Variance of initial belief in control across the population of growers	$\sigma_c^2$	0.01, 0.05, <b>0.1</b>
Mean initial risk perception across the population of growers	$\mu_r$	0.2, <b>0.5</b> , 0.8
Variance of initial risk perception across the population of growers	$\sigma_r^2$	0.01, 0.05, <b>0.1</b>
Frequency of control	$C_f$	<b>6</b> , <b>12</b>
Kill rate	$\theta$	0.7, <b>0.94</b>

## Supplementary material 2

### *Analysis of Simulation Results*

The opinion dynamics model parameters and the control parameters are listed in Table S1-2 with the sets of values that we used in our simulations. We ran the model with the different combinations of these parameters for a simulated period of 36 months and recorded the proportion of cells with infection at the end of this period.

We used ANOVA with up to three-way interactions to identify most important factors for controlling the epidemic (measured as the proportion of cells infected at the end of 36 months). We could not treat all 11 parameters as factors because we had no replication. Therefore, we used combinations of eight parameters at a time as factors and compared the percentage variance accounted to determine which factors best explained the proportion of infected cells. Then we used the F-probability to order the importance of the six factors used in the selected model.

In total 209952 simulations were needed to explore all combinations of the parameters. The model that accounted for the most variation in the response variable (the proportion of cells infected) was

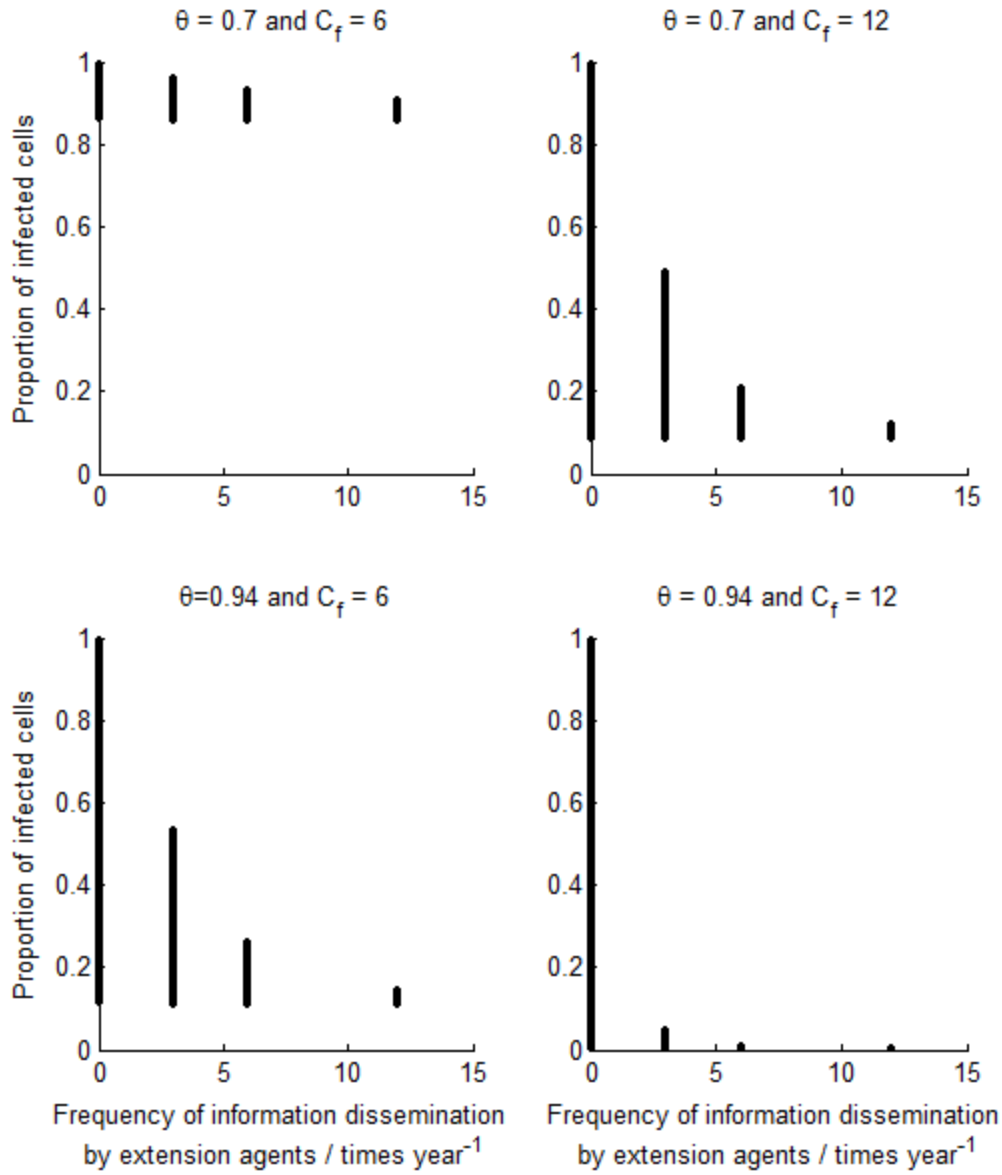
$$\kappa_O \times E_F \times E_I \times \mu_c \times \mu_r \times \sigma_c^2 \times C_f \times \theta$$

All of the F-probabilities for these factors and many of their combinations were highly significant <0.001, which largely resulted from the large size of the data set. The ANOVA table including main effects only is shown in Table S2-1. The variance ratios show that of the eight factors, the most important in determining the success of control are: the frequency that information is disseminated by extension agents ( $E_F$ ), the initial mean belief in control ( $\mu_c$ ), the spray efficacy ( $\theta$ ) and the frequency of spraying ( $C_f$ ) (Figs S2-1– S2-3).

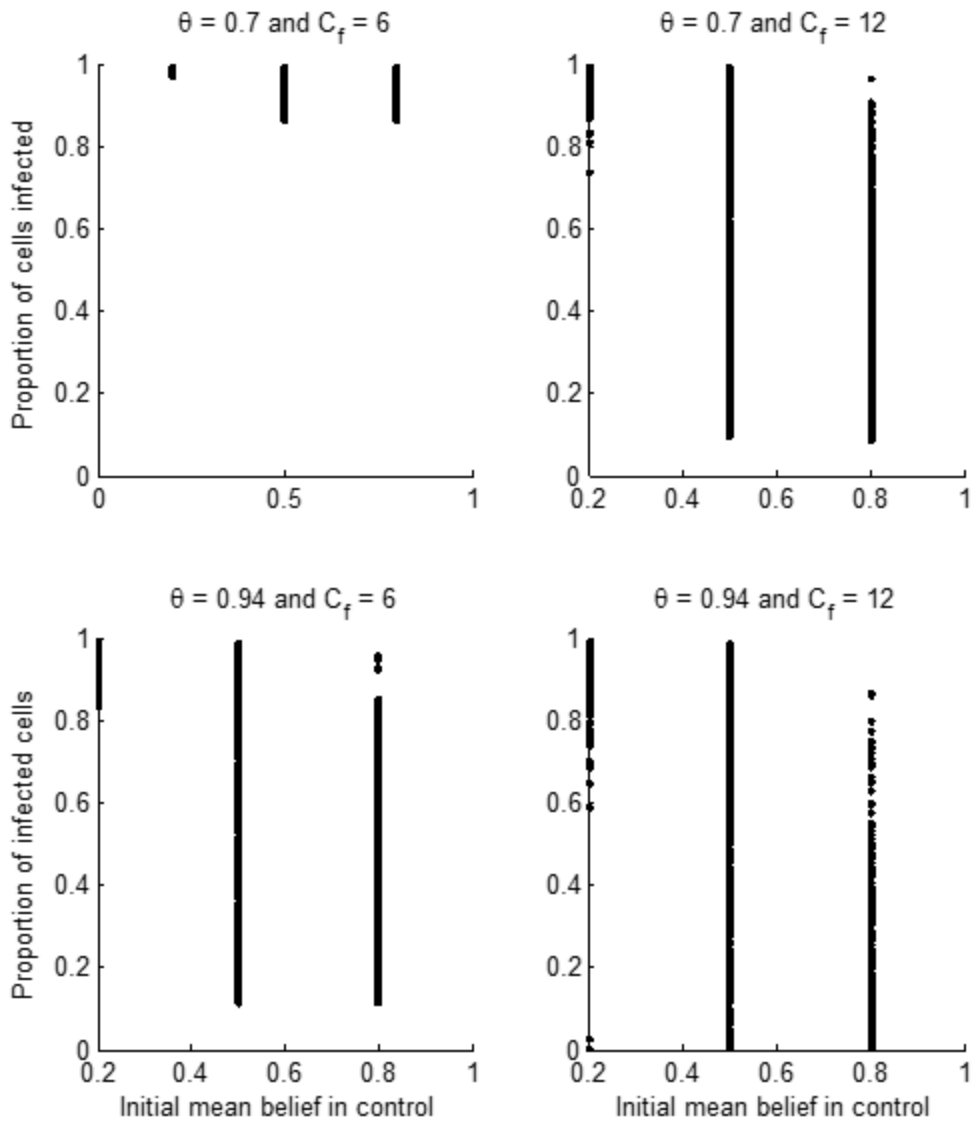


**Table S2-1: Analysis of variance**

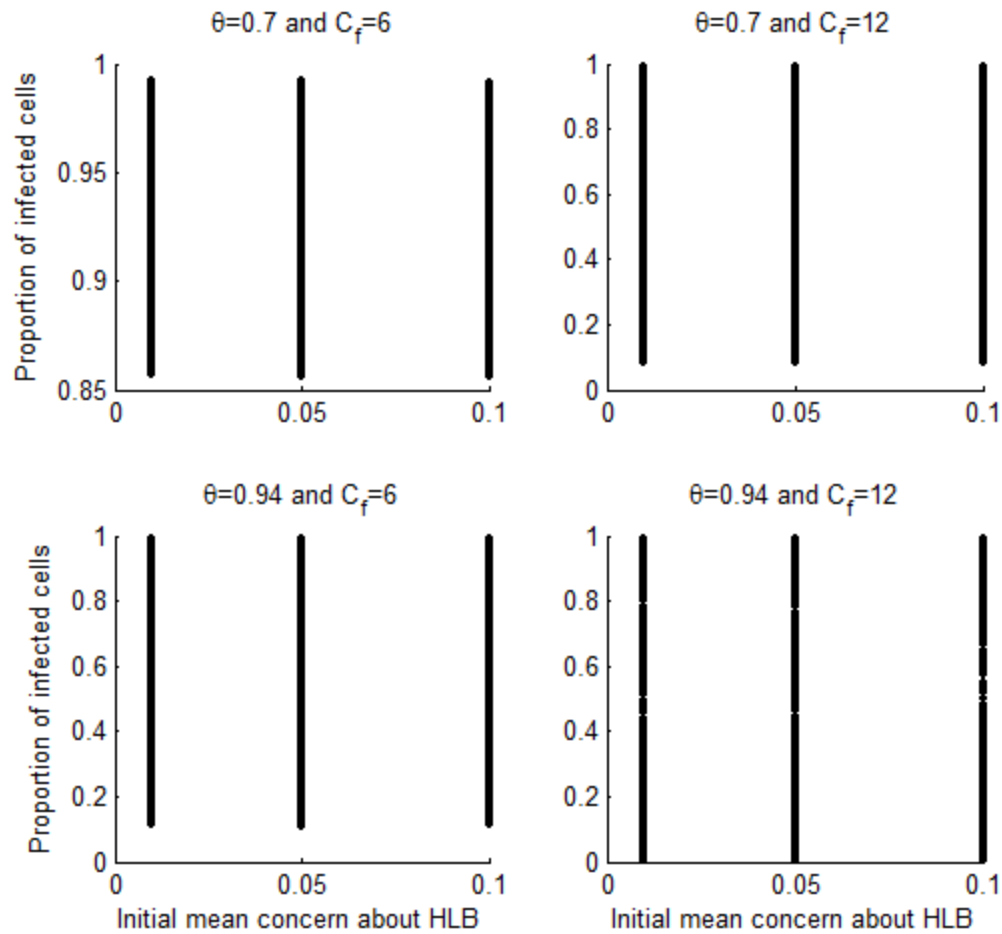
<b>Source of variation</b>	<b>Degrees of freedom</b>	<b>Sum of squares</b>	<b>Mean squares</b>	<b>Variance ratio</b>	<b>F pr.</b>
Opinion range ( $\kappa_o$ )	2	43.77	21.89	450.45	<.001
Extension information freq. ( $E_f$ )	3	3158	1053	21664.67	<.001
Extension information effect ( $E_i$ )	2	7.345	3.673	75.59	<.001
Mean initial risk perception across the population of growers ( $\mu_r$ )	2	8.083	4.041	83.18	<.001
Mean initial belief in control across the population of growers ( $\mu_c$ )	2	1309	654.7	13475.39	<.001
Variance in belief ( $\sigma_c^2$ )	2	13.02	6.512	134.03	<.001
Freq. of spray ( $C_f$ )	1	9166	9166	188600	<.001
Spray efficacy ( $\theta$ )	1	7854	7854	161700	<.001
Residual	209936	10200	0.04859		
Total	209951	31760			



**Fig. S2-1: The results of the simulations.** The proportion of cells (1 ha areas) infected at the end of the simulation is plotted against the frequency at which information is disseminated by extension agents for each combination of spray efficacy ( $\theta$ ) and spray frequency ( $C_f$ ).



**Fig. S2-2: The results of the simulations.** The proportion of cells (1 ha areas) infected at the end of the simulation is plotted against the initial belief in the control method for each combination of spray efficacy ( $\theta$ ) and spray frequency ( $C_f$ ). on all simulations the frequency information was disseminated was set to zero ( $E_F = 0$ ).



**Fig. S2-3: The results of the simulations.** The proportion of cells (1 ha areas) infected at the end of the simulation is plotted against the initial risk perception about HLB for each combination of spray efficacy ( $\theta$ ) and spray frequency ( $C_f$ ) on all simulations the frequency information was disseminated was set to zero ( $E_f = 0$ ).