Final Report

Banana Bunchy Top Virus Control Data

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Delivery partner:

The University of Queensland

Project code:

BA17001

Project:

Banana Bunchy Top Virus Control Data – BA17001

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Content

Summary

The primary objective for this project was to provide epidemiological tools/models that could be used to guide and inform the management of banana bunchy top disease (BBTD) in Australia: in particular to ensure containment in endemic areas within southern Queensland and northern New South Wales and to prepare for managing new incursions in other production areas. To do this requires an understanding of the factors that influence the risk of spread.

A modelling framework was developed for spread of infection and disease control in northern New South Wales and southern Queensland. This was used to examine the effectiveness of current management strategies, taking the current practice as a baseline. Alternative surveillance and management scenarios were then considered, and their risk of increased disease incidence estimated. The potential for adoption of the model was then assessed for the north Queensland situation, with large plantations and different cropping practices.

Essentially these objectives require us to understand and model the risk of an outbreak of BBTD in a given plantation, to understand the risk of subsequent spread into other plantations and to identify more cost-effective control strategies for surveillance and management in plantation and backyard populations. To achieve this, we have analysed the dynamics of spread at a range of scales from within plantations to landscape scales incorporating multiple small plantations interspersed with backyard banana plants, typical of southern Queensland and New South Wales.

We used data from inspections carried out in northern New South Wales and southern Queensland between 2008 and 2017. The following information was available in the data: inspection date, plant location, infection status of banana plant, detection and treatment date if symptomatic during the survey, number of symptomatic leaves (indication of time of infection). In addition to the information of surveyed plants, polygons representing the size and location of each farm was used to estimate plantation size.

Modelling Overview: We developed stochastic, spatially-explicit, epidemiological compartmental model to describe the spread of BBTV at within-farm level and a mechanistic, spatio-temporal framework for modelling individual-to-individual transmission (contact model) at a larger scale in order to estimate the risk of incursion from one farm/region into another, taking account also of backyard infections.

Inference on the model parameters was performed using Bayesian computation methods involving Markov chain Monte Carlo (MCMC) coupled with data augmentation techniques. Data augmenation enables us to augment the data with the unknown/hidden events such as the transmission network and infection times, as additional unknown 'parameters' in order to investigate the posterior distributions for the key epidemiological parameters (combination of the likelihood of observing the data given the estimated parameters and the prior belief on the virus spread).

Investigating impact of control scenarios 2018-2022: Large numbers of individual model simulations were performed to measure the predicted impact (monthly numbers of infections and numbers of plant removals) for an extensive range of management scenarios. We compare the outcomes with current surveillance and management practices. Our results take account of the inherent uncertainties in epidemic spread and the estimated parameter values and are thus characterised by a median trajectory over time of the levels of disease and numbers of plant removals as well as a distribution of possible outcomes.

Key results in the southern Queensland and northern New South Wales region:

- Continuing with the baseline scenario for surveillance and management is likely to continue to keep the disease in check if backyards play a minor role in the epidemics.
- New infections in plantations where detection occurred over the previous year are likely to be picked up before the epidemic 'explodes'.
- Scenarios that are less stringent than the baseline have some risk of later epidemic re-occurrence. There is a delay of several years, however, before less stringent scenarios begin to diverge from the baseline but once they do, disease spreads rapidly.
- The frequency of visiting plantations has a big effect on disease risk.
- Sweeping the surrounding plantations (e.g. sweeping to assess 50% or 100% of plantations out to 1km) has relatively little effect in improving overall disease management.

- Reducing the frequency and efficiency of surveillance implies a rapid rise in infections by 2020/21 onwards.
- The disease status of plantations where either BBTV has never been recorded or no BBTV is recorded for 2 years and surrounding backyards is very important in driving the epidemic.
- Backyards play a role in driving the epidemic but in quite a complicated way. If backyards play a major role, then they can contribute to cryptic build up of disease and subsequent epidemics.
- During the early years, less intensive scenarios sometimes look good compared with the current practice, but the epidemic is building up cryptically and our results suggest there could subsequently be a rapid spike in infection.

Keywords
Banana bunchy top virus; modelling; epidemiology; disease control; Bayesian computation methods

A large component of this report is taken directly from or adapted from Appendix 2. "Spatio-Temporal dynamic of the banana bunchy top virus (BBTV) – modelling spread and management" Final Report, by Dr Hola Kwame Adrakey and Prof. Christopher Gilligan, University of Cambridge.

Introduction

Banana bunchy top virus (BBTV) is recognized as causing the most serious virus disease of bananas worldwide, resulting in complete yield loss in infected plants. BBTV is transmitted by the black banana aphid, *Pentalonia nigronervosa*, and in infected planting material. BBTD has been present in Australia for over 100 years, and before control measures were instigated, caused losses of 90-95% in the industry. Similar scenarios continue to occur around the world today.

Magee (1927) devised a control strategy based on quarantine, eradication and clean planting material. Detailed epidemiological studies were done by Allen in the 1970s-1980s resulting in a computer simulation model to study the effects of various management parameters on disease control (Allen 1977a, 1977b, 1987). Magee's strategy together with Allen's epidemiology inputs and the assumption that there are no non-banana hosts, forms the basis of the current control program in Australia, where the disease is now maintained at a very low level.

BBTD only occurs in northern NSW and southern Queensland, and not in Australia's major production areas. The value of excluding BBTV from these areas has been estimated at $15.9- 27.0 million in annual losses. Despite the large value of exclusion, the control program represents an ongoing investment for the banana industry, and with limited resources there is a need to maximise both the cost and control efficiency of the program. With current practices, the disease has been contained, but rarely eliminated for districts. Gaps in our knowledge that require investigation include:

- the possibility of latent infection that can go undetected for months or years. This could result in undetected disease outbreaks in plantings that are being infrequently inspected, allowing the disease to become established before its presence is recognized.
- recent evidence for alternative hosts overseas. Plants such as alpinia, heliconia, canna, and taro could provide a reservoir for reinfection of banana. Although proven overseas, we are uncertain of their role in Australia.
- inefficiencies in the eradication method. We know from recent research that pseudostem injection of insecticide and herbicide does not kill all the aphids feeding on the youngest leaf, and that plants remain a positive source for virus transmission for some days or weeks after injection (depending on the season).

Mathematical models can play a crucial role in providing insight into the spread of plant viruses and in the design of control strategies. Here, building on Allen's work and using recent inspection and eradication data supplied through Hort Innovation projects BA15006 and BA15007, modern statistical approaches and methods have been used to develop a stochastic, spatially-explicit, epidemiological compartmental model to describe the spread of BBTV at within-farm level and a mechanistic, spatio-temporal framework for modeling individual-to-individual transmission (contact model) at a larger scale in order to estimate the risk of incursion from one farm/region into another, taking account also of backyard infections.

These models provide the opportunity to examine effects of modifications of the control strategy on likely resultant disease levels. These models can also be applied to north Queensland production areas to predict likely patterns of spread should an incursion of BBTV occur, and are thus of great value to biosecurity of the industry in general.

Methodology

Details of model development are shown in Appendix 2, and only the general outlines are shown in the Methodology section here.

Here, we are concerned with developing a modelling framework for the spread of BBTV and investigate a general approach to informing the choice of control strategies - comparing the current practices with some alternative scenarios in a Bayesian framework. We provide a modelling framework that integrates data from different sources (surveyed data and expert knowledge) to build a quantitative understanding of BBTV dynamics. This understanding enables us to characterise the epidemic spread and support the longer-term aim of building a predictive model of spread that can be used to predict infection risk and assess the impact of different control strategies. The key steps of the modelling approach adopted are given in Figure 1.

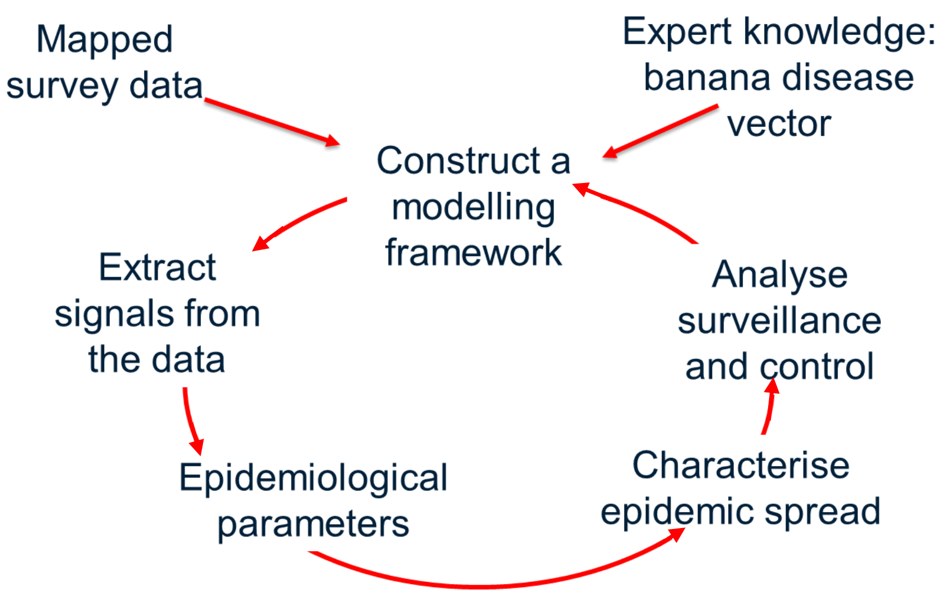

Figure 1: Graphical representation of the epidemiological approach: using data and models

Data were supplied, through Hort Innovation projects BA15006 and 15007, on inspections carried out in northern NSW and southern Queensland between 2008 and 2017. The following information is available in the data: inspection date, infection status of plant, detection and treatment date if symptomatic during the survey, information related to the plant (e.g. number of mats, number of symptomatic leaves and stems) and the location of banana plants surveyed.

1. Model for within-plantation spread of infection and disease

Modelling approach: We consider a mechanistic compartmental (SEIS) model to describe the spread of BBTV within farms considered (Figure 2). In the SEIS model, plants are categorized by infection status. Plants that are able to contract the infection are Susceptible (S) until they become Exposed (E) at which point they are infected but not infectious. After a random period of time, plants become infectious (I). Plants become susceptible again (S) once detected as infectious, removed and a new sucker replanted. Although in reality, the replacement with a new sucker after detection/removal is delayed. The introduction of aphids into the system is considered t_0, the start of the epidemic. In general, this time is unknown, and therefore treated as an additional parameter to the model.

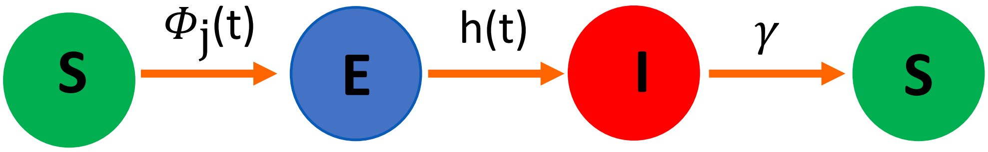

Figure 2: Graphical representation of the mechanistic model. Circles represent compartments and arrows represent transition between compartments, and:

ϕ_j(t) is the hazard or the force of infection on host **j** at time **t**

h(t) denotes the rate at which a leaf emerges which is used as a surrogate for the emergence of symptoms

γ denotes rate of replacement of infected plant

Model development has incorporated the parameters below, which are estimated from the input data.

	Process	Symbol	Description
Plantation	Dispersal	α	Scale parameter for within plantation
	Infection	ε	Primary infection rate
		β	Secondary infection rate
		b	Seasonality effect on the rate
	Symptom expression	λ_0	Seasonality effects on leaf emergence rate
		λ_1	Seasonality effects on leaf emergence rate
	Removal and replanting	γ	Rate of replacement
		t_0	Time of first infection
Landscape	Dispersal	α_1	Scale parameter for local spread
		α_2	Scale parameter for long range spread
	Infection	ε	Primary infection rate
		β_0	baseline or average transmission rate
		β_1	Seasonality effect on the rate
	Symptom expression	λ_0[1]	Seasonality effects on leaf emergence rate
		λ_1[1]	Seasonality effects on leaf emergence rate
		λ	Mean of the latent period
		μ	Variance of the latent period
	Removal and replanting	γ	Rate of replacement
		t_0	Time of first infection

[1] Parameters are fixed when using the leaf emergence rate.

2. Model for spread at larger scale (between plantations, across landscapes)

Based on analysis of disease spread on selected individual plantations, a common model was developed across these plantations. The model takes account of seasonal variation, hosts growth dynamics and inherent uncertainties. The model can be used to assess control strategies within plantations and to predict spread of infection once the pathogen is introduced into a plantation. To look at spread on a wider scale, and with these factors in mind, an approach is followed whereby the spatio-temporal spread of BBTV is represented stochastically (i.e. allowing for random variation in one or more inputs over time) and in which different mechanisms of spread are combined. In particular, the system is represented as an extension of the model described at the plantation level, where the landscape is subdivided into grids. In selecting an appropriate epidemiological model for landscape scale spread and control of disease, one was chosen from a a large range of candidate models considered (see Appendix 2, Table A.1). These differed with respect to the number and type of dispersal kernel, the nature of the latent period and the transmission process.

We represent the spread of BBTV through a network of premises in continuous time and space over a heterogeneous landscape with varying plant population density, so no information on the exact location of susceptible plants is available. A key feature of our modelling approach is that we avoid the need to represent the susceptible population by, in a sense, combining the generation of the susceptible population with the spread of the disease within that population. This greatly simplifies the challenge of constructing and fitting a model. This modelling framework is known as a contact type model (Mollison, 1987) and has been successfully applied to model the spread of peste des petits ruminants (PPR) (Adrakey, 2016; MacCalman et al., 2016) and extended by (Lau, Marion, et al., 2015) to incorporate heterogeneity in host-population.

3. Surveillance strategies and management

Baseline surveillance and management scenario. Farms are categorised as per the current practice from 'Category A' to 'Category E':

- Category A – BBTV never recorded
- Category B - No BBTV recorded for 2 years
- Category C - No more than 1 infection in the previous 12 months
- Category D - More than 1 infection in the previous 12 months
- Category E - More than 10 infections in the previous 12 months

To set a baseline, or current practice, scenario, a set of standard inspection conditions was identified to define parameters for the modelling. Though some of the conditions are variable in practice, a reasonable average value was assumed (Table 1). Overlaying these standard inspection conditions, the simulations were run on the assumption that either the backyards played i) a minor role or ii) a major role, in the epidemics. A number of inspectors (trained to identify BBTV symptoms) undertake surveillance following the situation in Table 1. If during an inspection an infection is found in a plantation, it is re-inspected in the following month. This continues monthly until no new infections are found. At this point inspections continue at 3 monthly intervals for the following year, and further reduced to 6 monthly intervals the year after, assuming no new infections. If a new infection is found, the surveillance process returns to monthly inspections. In addition, a sample of infected farm (sweep proportion), for which a sweep of surrounding backyards is carried out within a certain radius (sweep radius), is considered. Finally, within a sweep the proportion of backyards visited and checked (efficiency of the visit and check) is assumed to be ca 70% overall. We account for the sensitivity of the detection assuming that inspectors monitor plantations and detect infection at 100% efficiency at later than three-leaf stage.

Table 1: The baseline control management.

<table>
<tr><th>Farm category</th><th>A</th><th>B</th><th>C</th><th>D</th><th>E</th></tr>
<tr><td>BBTV detections in the last 12 months</td><td>0</td><td>0</td><td>1</td><td>1-10</td><td>>10</td></tr>
<tr><td>Time since last positive</td><td>Never recorded</td><td>≥ 24 months</td><td>Variable ≥ 12 months</td><td>Variable ≥ 12 months</td><td>Variable ≥ 12 months</td></tr>
<tr><td>Revisit interval</td><td>12 months</td><td>12 months</td><td colspan="3">• 1 month intervals after infection recorded and removed for as long as infection is recorded at successive visits. If no new infection recorded, switch to:
• 3 months during 1st year
• 6 months during 2nd year</td></tr>
<tr><td>Sweep proportion[1]</td><td>0</td><td>0</td><td colspan="3">• ≈ 50% Qld
• ≈ 30% NSW</td></tr>
<tr><td>Sweep radius[2]</td><td>0</td><td>0</td><td colspan="3">1 km</td></tr>
<tr><td>Efficiency of visit and check</td><td>0</td><td>0</td><td colspan="3">≈ 70% overall</td></tr>
</table>

[1] Proportion of plantations with BBTV infection for which a sweep of surrounding backyards is carried out

[2] Radius surrounding infected plantation in which surrounding backyards are checked

The baseline scenario was then projected in southern Queensland until 2023, using 500 iterations of the epidemic. The epidemic was initiated at a randomly chosen location from plantations categorized as C, D or E with weight proportional to the size of detection. By sampling the locations of the primary infections in this manner we implicitly assume that plantations where high number of plants were detected are likely to behave as a source of secondary infection as the likelihood of having cryptically infected (infected but not detected since symptoms are not yet visible) plants is higher. This allows, for instance, category E plantations to be sources of secondary infection.

For comparison, a range of alternative control scenarios was used (Table 2) and the results of the simulations compared with the baseline scenario.

Table 2: Alternative management scenarios

Farm category	**A**	**B**	**C**	**D**	**E**
BBTV detections in the last 12 months	0	0	1	1-10	>10
Time since last positive	Never recorded	≥ 24 months	Variable ≥ 12 months	Variable ≥ 12 months	Variable ≥ 12 months
Revisit interval	12 months 18 months 24 months	12 months 18 months 24months	• 1 month • 3 months • 6 months		
Efficiency of detection at the 3 leaf stage			• 80% • 100%		
Sweep proportion[1]	0	0	• 100% • 50%		
Sweep radius[2]	0	0	• 1 km • 0:5 km • 0:25 km		
Efficiency of visit and check	0	0	≈ 70% overall		

[1] Proportion of plantations with BBTV infection for which a sweep of surrounding backyards and properties is carried out)

[2] Radius surrounding infected plantation in which surrounding backyards are checked

A and B plantations are assumed to be monitored by the growers themselves with 30% efficiency of detection, beginning at the later 6 leaf stage. We assume that the start of year 2019 marks the introduction of these comparative strategies, with the baseline carried out from June 2017 to December 2018.

Some additional work was undertaken to develop and adapt the computationally rapid contact model for applications in large plantations typical of north Queensland and to examine the currently difficult to control outbreak at Newrybar, NSW.

Future work will involve fitting this model (with environmental covariates such as temperature and precipitation) to data from both southern Qld and northern NSW, examine in the process the effect of climate change on the transmission of the BBTV. This will facilitate the adoption of the model for the north Qld.

Outputs

Model for within-plantation spread of infection and disease

Models for the spread of BBTV within plantations have been developed and tested. The estimated parameters are consistent for plantations selected from southern Qld and northern NSW, which means the same parameter distributions can be used for both regions. The model can be adopted for application within plantations in north Qld.

These studies indicate that the mean inoculum source distance of 15.5 m estimated from the Alstonville outbreak (Allen, 1987) lies in the 95% credible interval of the dispersal parameter of the farm at Eungella, but not for Montville. This is may be due to the geographical proximity and likely similar epidemic parameters of the Eungella farm to the farm at Alstonville, where Allen's work was done. There is strong evidence for seasonal effects on the dynamics of the epidemics, and that virus spread within plantations is driven mostly by secondary spread.

The actual epidemics at Eungella and Montville were shown to fit the data reasonably well (Figure 3). The model also shows effectiveness of controls in bringing the epidemics under control, with occasional seasonally driven outbreaks on an otherwise decreasing epidemic.

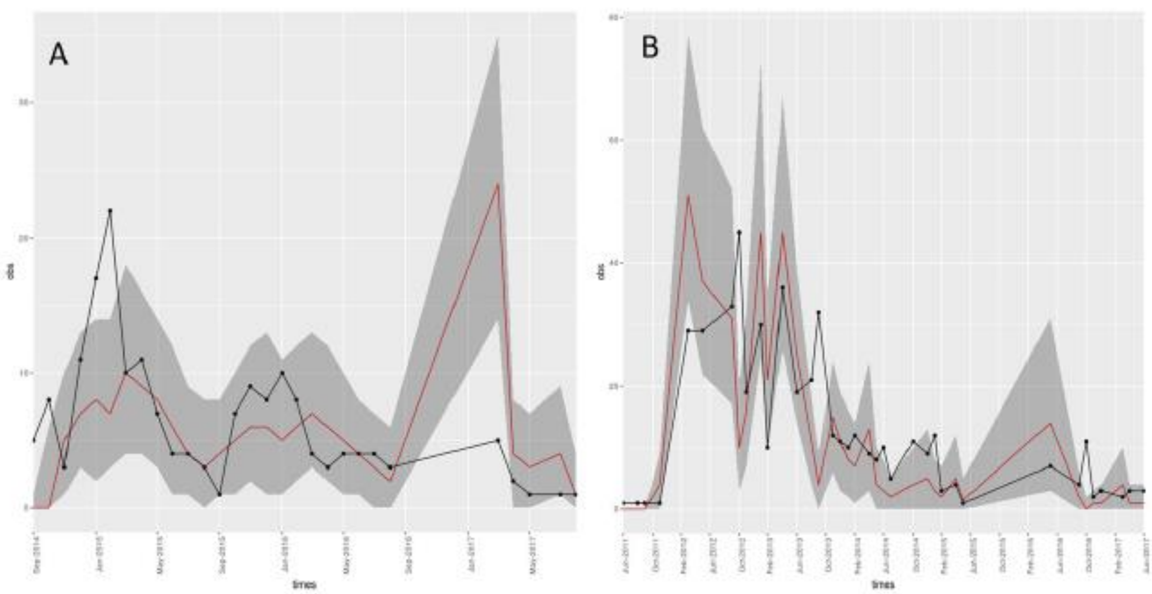

Figure 3: Prediction of temporal evolution of epidemic simulated from estimated parameters. Actual observation (black line) and median of the simulated epidemics (red). Shaded region represents the 95% credible region. Farm at Eungella (A) and Montville (B).

Model for spread at larger scale (between plantations, across landscapes)

A parameterised epidemiological model has been developed for the spread of BBTV at the landscape scale, taking account of seasonal variation and inherent uncertainties. The model can be used to predict spread and to compare strategies for management.

Figure 4 shows the performance of the estimated model for the southern Qld data in which it is clear for the first four years of data (2011-2014; high disease incidence) there is a remarkably close fit with the recorded disease progression curve lying within the 95% credible bands. Later years in which disease was lower fitted less well but sufficiently to support the model.

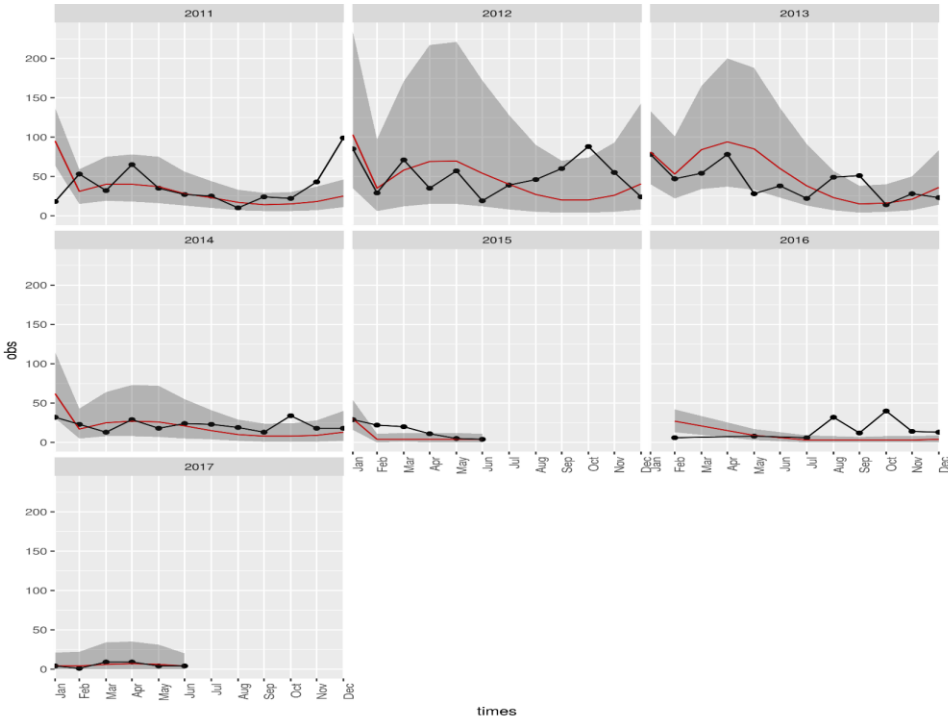

Figure 4: Prediction of temporal evolution BBTV of epidemic simulated from estimated parameters using the contact model. The leaf emergence rate is considered for the latent period. Actual observation (black line) and median of the simulated epidemics (red). Shaded region represents the 95% credible region.

Surveillance strategies and management

Using southern Qld as an exemplar, our models show that continuing with the current baseline scenario is likely to continue to keep the disease in check when backyards are assumed to play a minor role as sources of infection (Figure 5). We show two output variables, the number that would be expected to be removed under the baseline scenario and the number of exposed plants (i.e. those plants that are infected). The exposed class is therefore a measure of infection that has occurred but whose effects will be seen in succeeding years.

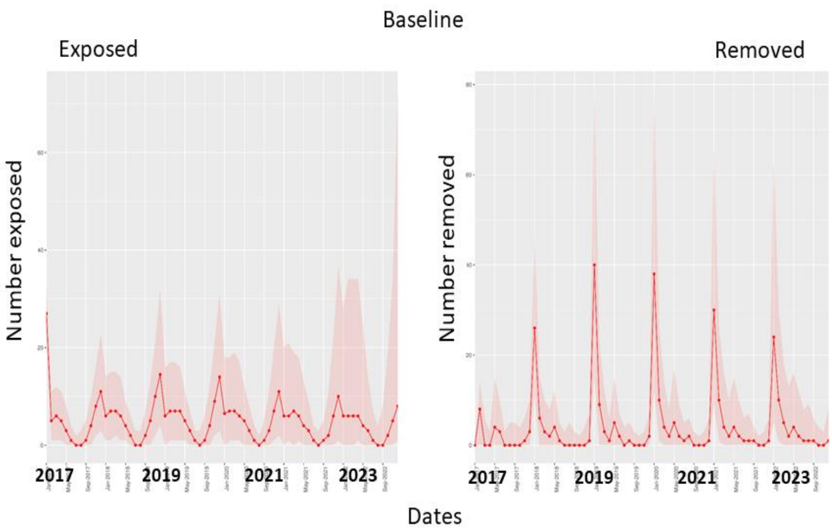

Figure 5: Predicted (posterior predictive) distribution of the baseline control scenario (see Table 1) by year 2023, with backyards playing a minor role as external sources of infection.

For comparison, a scenario is presented where backyards are presumed to play a major role as a source of infection, and inspection efficiencies of 80% and 100% at the 3 leaf stage are compared (Figure 6). We also analysed a range of scenarios for relaxing the levels of surveillance. Our results show that while some scenarios may appear to be as good as the baseline for the first two years, the disease incidence is likely then to increase sharply. A range of scenarios are given in Appendices 2 and 3, with several presented here (Figs. 6, 7, 8) as examples.

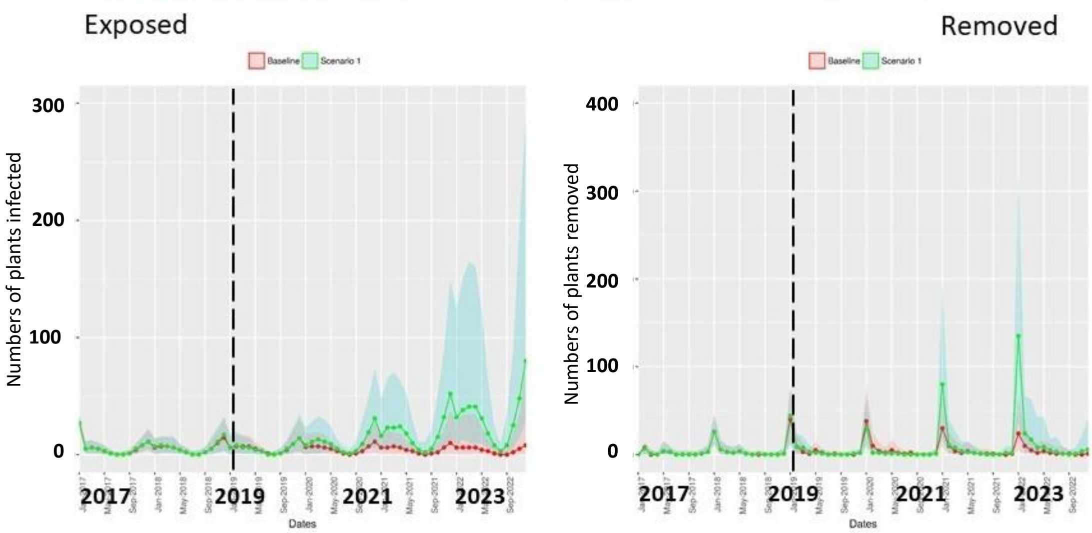

Figure 6: The predicted (posterior predictive) distribution of the plants exposed (infected) and removed by 2023 considering the baseline control scenario (red) and the alternative scenario (green). In this example;

- the frequency of visits for C, D and E is 1 month
- we assume a 100% detection rate at 3 leaf stage for these plantations
- a 50% sweep proportion with a 1km sweep radius in which 70% of backyards are assessed
- Inspection frequency of A and B plantations is fixed at 12 months with 30% detection rate at 6 leaf by growers only
- shaded region corresponds to the 95% credible region obtained using 500 forward simulations
- dashed line mark the date of introduction of the alternative control

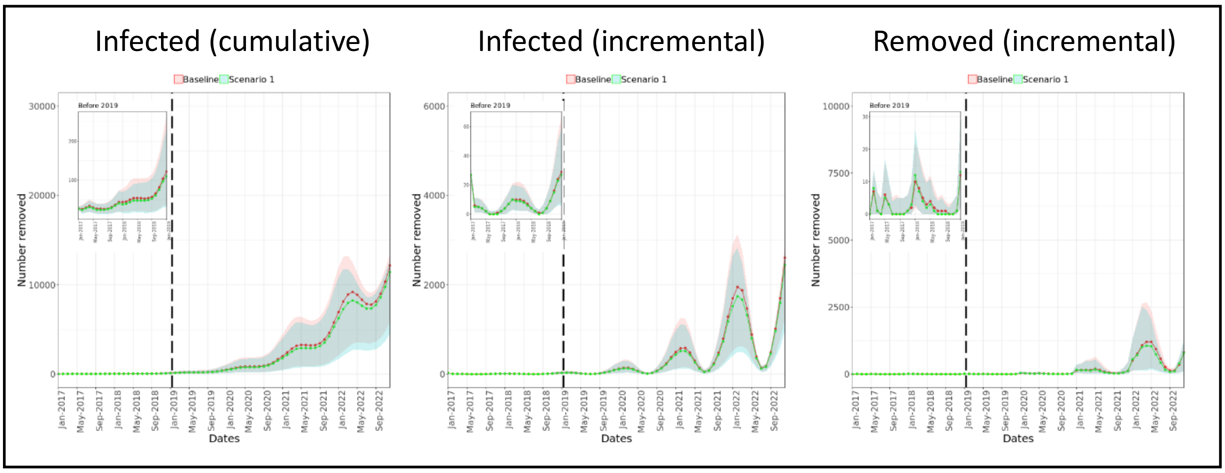

Figure 6: Predicted (posterior predictive) distribution of the baseline control scenario (see Table 1) by year 2023, with backyards playing a major role as external sources of infection. The red line shows the scenario with 80% inspection efficiency at the 3 leaf stage, the green line shows100% inspection efficiency at the 3 leaf stage.

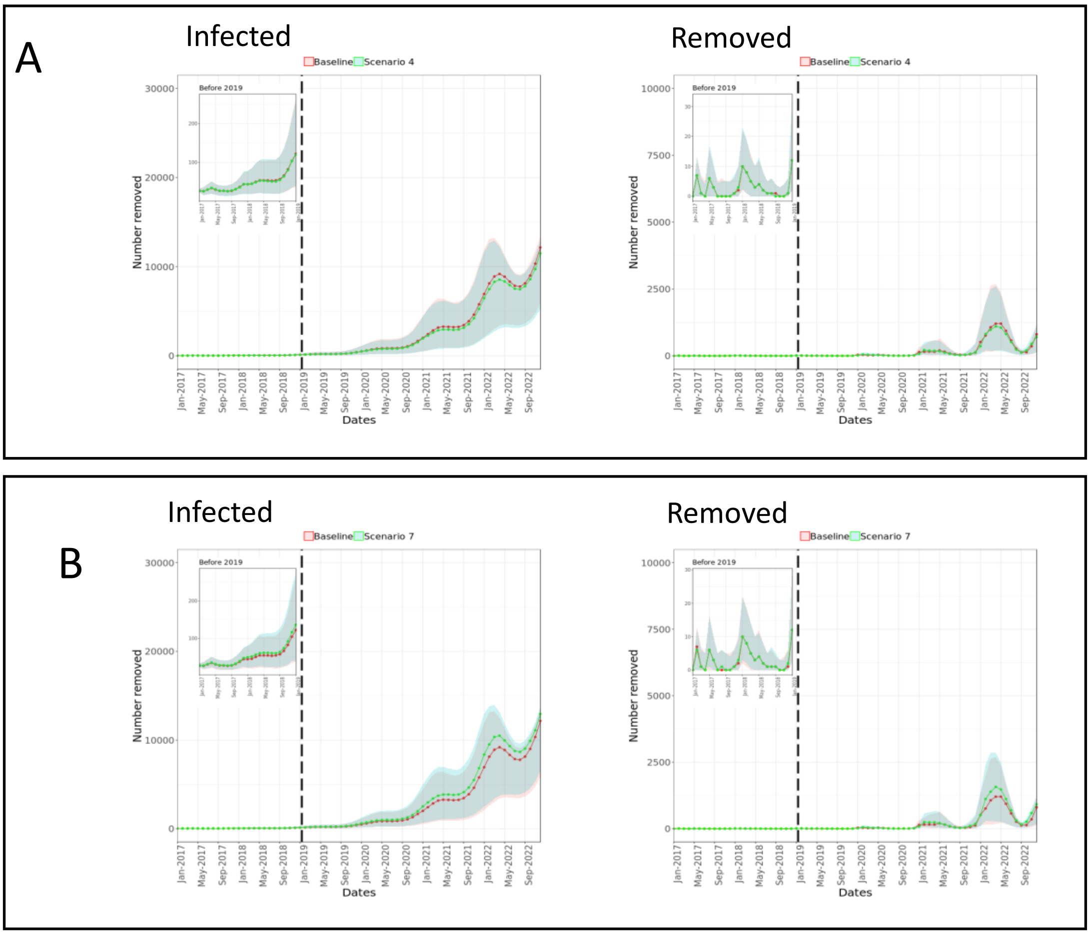

Figure 7: Predicted (posterior predictive) distribution of the baseline control scenario (see Table 1) by year 2023, with backyards playing a major role as external sources of infection. Panel A includes a 1 km sweep radius, Panel B a 0.5 km sweep radius. The red line shows the scenario with 80% inspection efficiency at the 3 leaf stage, the green line shows100% inspection efficiency at the 3 leaf stage.

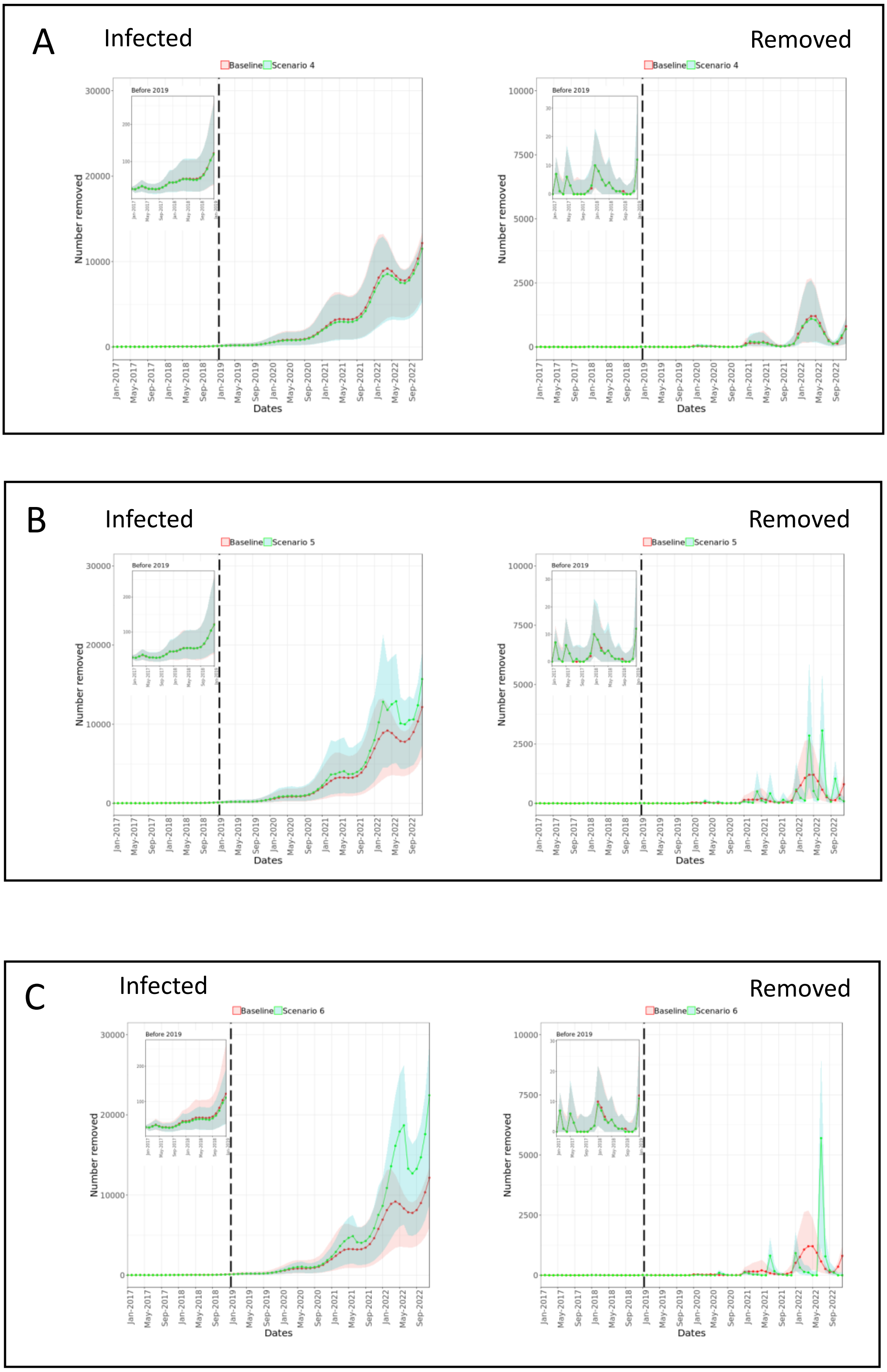

Figure 8: Predicted (posterior predictive) distribution of the baseline control scenario (see Table 1) by year 2023, with backyards playing a major role as external sources of infection. Inspection frequencies for C/D/E plantations are 1 month (A), 3 months (B) and 6 months (C). The red line shows the scenario with 80% inspection efficiency at the 3 leaf stage, the green line shows100% inspection efficiency at the 3 leaf stage.

Outcomes

The banana industry faces a challenging time with many calls on resources, which potentially places constraints on current BBTV control activities. The primary outcomes of this project focus on;

1. developing epidemiological models for understanding the progress of BBTV epidemics in individual plantations and between plantations across larger landscapes.
2. applying these modern disease modelling procedures to maximize the control and cost efficiencies of the BBTV control program.
3. contributing to risk and incursion management strategies for BBTV for currently unaffected areas, such as north Queensland.

This project provides tools for assessing BBTV management options. The models developed have enabled the assessment of a range of management scenarios with varying levels of input and professional expertise. The outcomes of this work will be used as a critical resource in planning future BBTV management investment by the industry in the immediate future.

A stakeholder workshop was held towards the end of this project (7th August 2018), and the 25 participants included representatives of industry including growers, HIA, BBTV inspection staff, BBTV control project PSC members, state Departments of Agriculture research, extension and biosecurity staff and university research staff. After presentations on BBTV research and control, the development and use of the models was presented. With this background, stakeholders developed consensus recommendations for future BBTV control-related activities for submission to the SIAP. These activities comprised:

1. continued national surveillance and management of BBTV
2. research into understanding and addressing latency with BBTV infection
3. a grower and community education program for BBTV
4. improving banana aphid control for better BBTV management

The activities and outcomes of this project align to the Australian Banana Industry Strategic Investment Plan (2014-2019) Objective 3: Improve industry capacity and R&D adoption; and demonstrate benefit of levy investments. Specifically;

Strategy 3.2 - Continue to build industry skills and develop appropriate structures and resources to meet industry needs. Sub-strategy 3.2.3 - Continue to develop international networks proactively,…, and

Strategy 3.3 Ensure the industry has appropriate processes, resources and risk management strategies to function effectively. Sub-strategy 3.3.3 - Maintain risk planning activities and associated training to ensure appropriate responses to issues and events that may affect the viability of the Australian banana industry (e.g. crisis management planning).

Monitoring and evaluation

Effectiveness:

The project has comfortably achieved its primary aim and delivered the desired outcome i.e. to develop a model(s) to predict the progress of BBTV epidemics and to utilize the model to examine the effect of various control scenarios on the progress of the epidemics. Epidemiological modeling of BBTV has not been studied for over 30 years, and the availability of new statistical methods has allowed this project to use a novel approach for modelling BBTV epidemics. The simulations run to examine various parameters affecting the epidemics is very resource intensive, requiring considerable computing time on high powered computer clusters. This has limited the range of control options that can be studied within the constraints of the current project, but ample have been run to gauge the merit of various alternative control strategies.

Relevance:

This project is highly relevant to the Australian banana industry. In focusing on BBTV, it addresses a major biosecurity target. Containment and management of this virus is of vital concern to the industry, as incursions in the major production areas would necessitate expensive management inputs. The models developed in this project are applicable not only to BBTV control in the affected areas, but for incursion planning and management in currently unaffected areas. With the current intensive, and necessary, industry focus on TR4 there is the danger that other important biosecurity issues can be overlooked. The exclusion value to the Australian industry in containing BBTV to its current limited distribution has been valued at $15.9 to $27 million annually (Cook et al. 2012). The future direction of the industry-funded BBTV control program is currently under consideration, and the likely impact of any possible reductions in funding need to be carefully assessed. The models developed in this project will underpin these assessments.

Appropriateness:

There is no feasible alternative for assessing alternative BBTV control strategies than to run predictive models. Current legislation precludes field experiments requiring the establishment of BBTV-infected plants, or knowingly neglecting to eradicate infected field plants. An additional practical issue is that it is not feasible to run scientifically sound, controlled field experiments on BBTV eradication, as replication is not practical. BBTV field epidemiology has been well-studied in the past, providing a reasonable framework for estimating relevant parameters for epidemic development. Additionally, comprehensive surveillance and eradication data have been collected through Hort Innovation projects BA15006 and BA15007, which allow models to be developed for virus spread within farms and across districts.

Efficiency:

The basic aim of this project was to use modeling to assess ways of maximizing the efficiency of the BBTV control program. We have been extremely fortunate to be able to establish a collaboration with Prof. Gilligan and his colleagues at the University of Cambridge, world leaders in modeling of plant disease epidemics. Their familiarity with the required methodologies and experience across a wide range of pests and diseases and the immediate availability of local surveillance data and scientific expertise on BBTV has allowed a very efficient undertaking of the project. The level of input to the project by the University of Cambridge has greatly exceeded that supported by the project funding, resulting in enhanced quality of the models developed.

Recommendations

The models developed in this study give an estimate of the likelihood of BBTV epidemic scenarios developing, given a certain set of environmental and management conditions. They are predictions, with a stated level of uncertainty, not confirmed outcomes. Nevertheless, they are the best tools available to allow an unbiased assessment of BBTV control options.

Assumptions and Caveats

In constructing fitting and using the model, reviewing the literature on BBTV as well as expert advice from our collaborators, we note that there are currently significant gaps in the understanding of the epidemiology of BBTV. The predictions from the models must be considered in this light. It should be noted that the impact of the different control scenarios on BBTV spread is sensitive to the assumption that the latent period corresponds to the time it takes for three leaves to emerge. Relaxing this assumption leads to greater uncertainty in the other parameters with consequently greater variance in the predicted impact of controls. It is assumed that initial infections are located in plantations C, D and E. This assumption can be relaxed by considering scenarios in which A and B plantations are sources of primary infection with a consequent inflation of the uncertainty in predictions. For modelling at the larger scale, it is assumed that plants occupy the whole area corresponding to the farm, the best estimate that is currently practicable given the data - this leads to overestimating the population density per farm. Again, relaxing this assumption by using the appropriate density per farm will lead to a greater uncertainty into the model parameters, subsequently impacting the conclusion on the control scenarios.

Key results

For southern Queensland and northern New South Wales:

- Continuing with the baseline scenario for surveillance and management is likely to continue to keep the disease in check if backyards play a minor role in the epidemics.
- New infections in plantations where detection occurred over the previous year are likely to be picked up before the epidemic 'explodes'.
- Scenarios that are less stringent than the baseline have some risk of later epidemic re-occurrence. There is a delay of several years, however, before less stringent scenarios begin to diverge from the baseline but once they do, disease spreads rapidly.
- The frequency of visiting plantations has a big effect on disease risk.
- Sweeping the surrounding plantations (e.g. sweeping to assess 50% or 100% of plantations out to 1km) has relatively little effect in improving overall disease management.
- Reducing the frequency and efficiency of surveillance implies a rapid rise in infections by 2020/21 onwards.
- The disease status of plantations where either BBTV has never been recorded or no BBTV is recorded for 2 years and surrounding backyards is very important in driving the epidemic.
- Backyards play a role in driving the epidemic but in quite a complicated way. If backyards play a major role, then they can contribute to cryptic build up of disease and subsequent epidemics.
- During the early years, less intensive scenarios sometimes look good compared with the current practice, but the epidemic is building up cryptically and our results suggest there could subsequently be a rapid spike in infection.

Refereed scientific publications

Two or three publications for peer-reviewed journals are being considered from this work, and drafts are currently being discussed and prepared.

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Intellectual property, commercialisation and confidentiality

No project IP, project outputs, commercialisation or confidentiality issues to report

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Barry Sullivan, Lagom Agriculture Pty Ltd and project leader for Hort Innovation projects BA15006 and BA15007, for supply and validation of data and discussion on BBTV management practices

BBTV surveillance team, for collection of comprehensive surveillance records over an extended period of time

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Hort Innovation, The University of Queensland and Queensland Department of Agriculture and Fisheries for funding

Appendices

Appendix 1: Some statistical and modelling terms

Appendix 2: “Spatio-Temporal dynamic of the banana bunchy top virus (BBTV) – modelling spread and management” Final Report, by Dr Hola Kwame Adrakey and Prof. Christopher Gilligan, University of Cambridge.

Appendix 1

Some statistical and modelling terms

Dispersal kernel is a 2-dimensional probability density function describing the probability for a seed (or seedling/infectious entity) to **disperse** (or **disperse** and establish) to any position relative to the maternal tree or source.

Prior probability – probability that an event will happen *before* you take the *new* evidence into account.

Posterior probability – probability that an event will happen *after* all evidence or background information is taken into account.

Many **probability distributions** have unknown parameters. These are estimated from sample data, The **likelihood function** gives us an idea of how well the data summarises these parameters.

Posterior distribution – a way to summarize what we know about uncertain quantities in Bayesian analysis. It summarizes what you know after the data have been observed.

Posterior distribution = prior distribution + likelihood function (“new” evidence)

A **parameter** is a characteristic of a **whole population** that is estimated as a **statistic** from a **sample** of that population.

Stochastic model – for estimating probability distributions of potential outcomes by allowing for random variation in one or more inputs over time (usually based on historical data for a selected period)

Deterministic model - fully determined by the parameter values and initial conditions (cf stochastic →possesses some inherent randomness)

A **compartmental model** provides a framework for study of transfer between different compartments of a system. For models of infectious disease in a large population, each individual (plant) is considered as being in a particular state (or **compartment**) , the simplest being susceptible or infectious.

Spatially-explicit models (or **spatially-distributed** or **landscape**) attempt to incorporate a heterogeneous spatial environment into the model.

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Updated control scenarios

Baseline 80% detection efficiency at the 3 leaf stage

Backyards playing an important role in epidemics

Epidemiology and Modelling Group, University of Cambridge

1

Baseline with 80% detection at 3 leaf

Baseline

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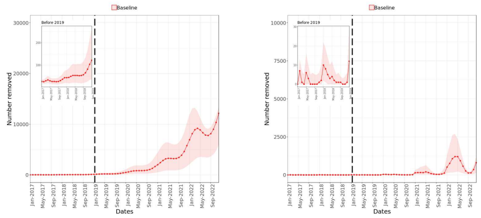

CDE: Sweep = 50% backyard=70% @1km

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2

Baseline with 100% detection at 3 leaf

Baseline

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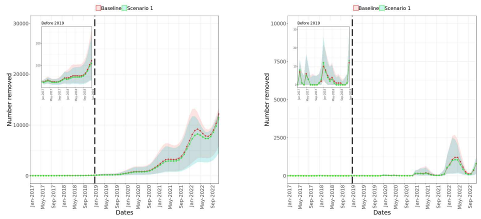

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3

Baseline with 80% detection at 3 leaf

Baseline

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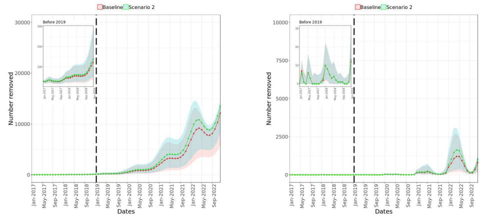

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4

Baseline with 100% detection at 3 leaf

Baseline

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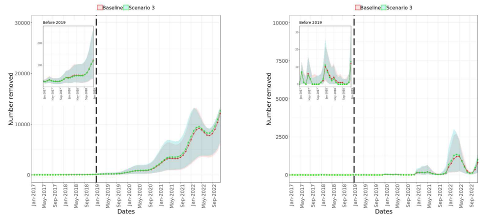

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5

A,B=12mo; 30% detection at 6 leaf C,D,E= 1mo 80% detection at 3 leaf

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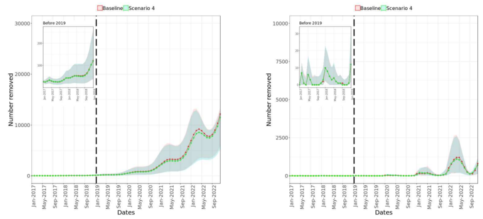

CDE: Sweep = 50% backyard=70% @1km

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6

A,B=12mo; 30% detection at 6 leaf C,D,E= 3mo 80% detection at 3 leaf

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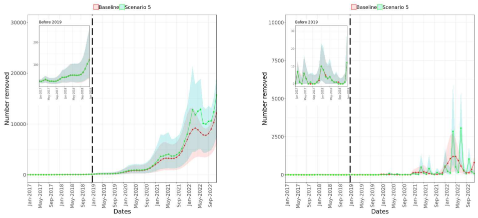

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A,B=12mo; 30% detection at 6 leaf C,D,E= 6mo 80% detection at 3 leaf

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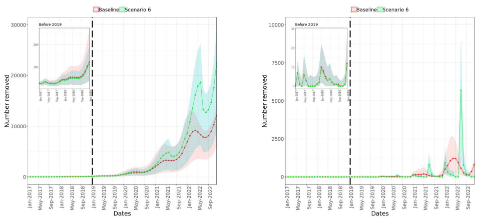

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A,B=12mo; 30% detection at 6 leaf C,D,E= 1mo 80% detection at 3 leaf

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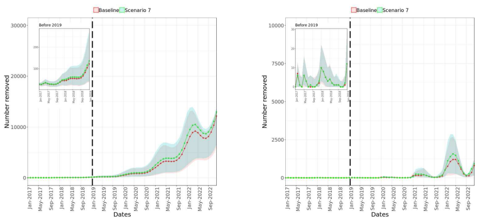

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A,B=12mo; 30% detection at 6 leaf C,D,E= 3mo 80% detection at 3 leaf

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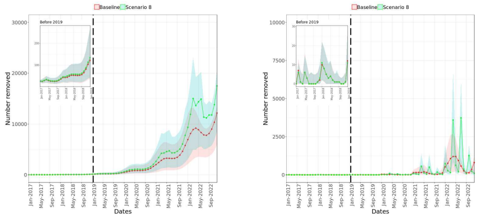

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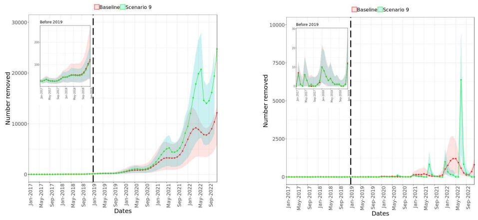

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Incremental version

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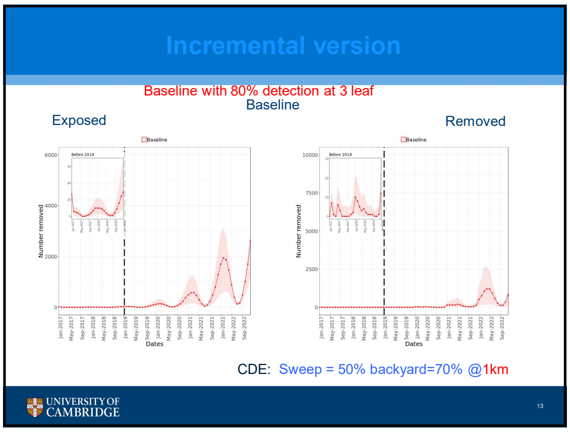
Incremental version
Baseline with 80% detection at 3 leaf
Baseline
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CDE: Sweep = 50% backyard=70% @1km
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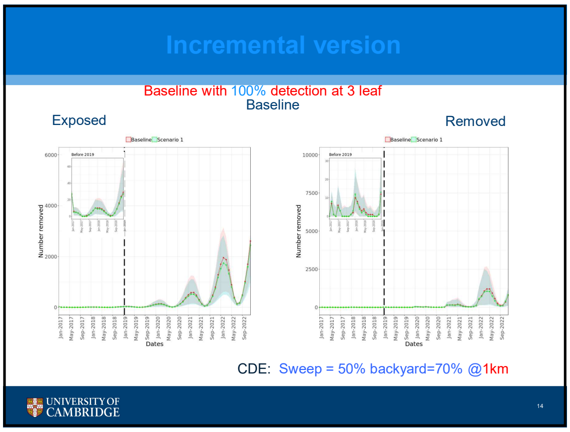
13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Baseline with 100% detection at 3 leaf
Baseline
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CDE: Sweep = 50% backyard=70% @1km
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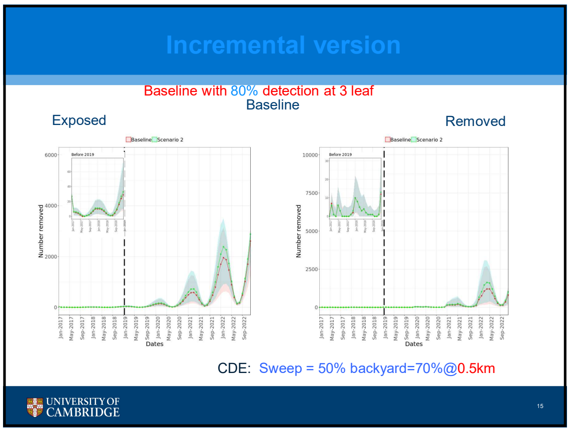
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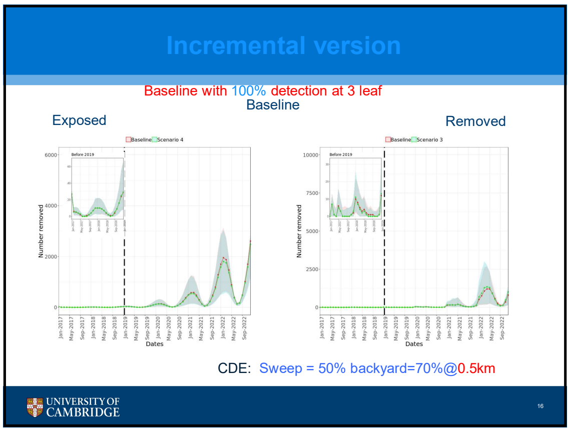
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Baseline
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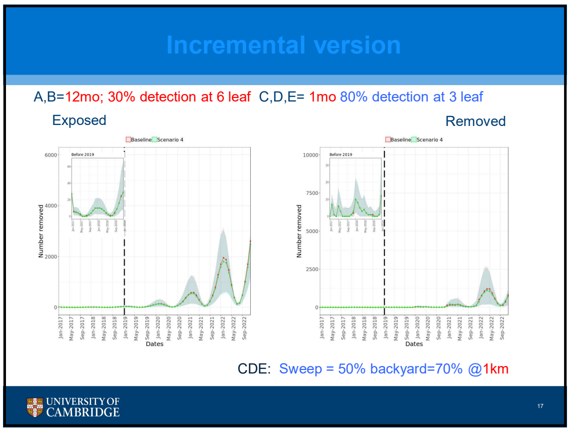
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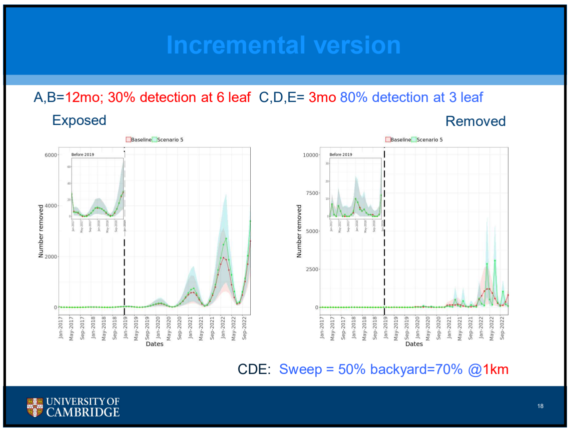
17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CDE: Sweep = 50% backyard=70% @1km
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Incremental version

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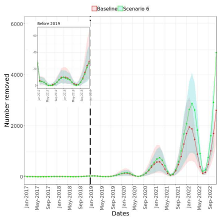

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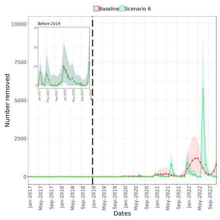

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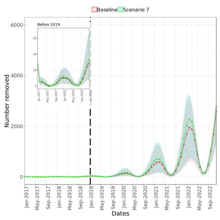

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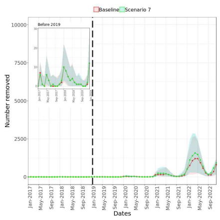

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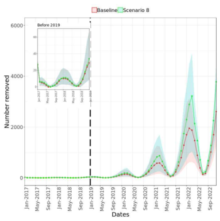

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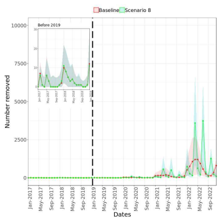

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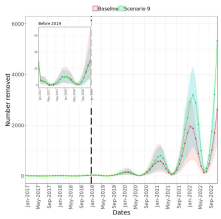

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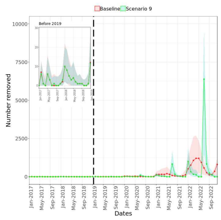

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