Modelling the efficacy of different sampling strategies for estimating disease levels and detecting the spread of new pests

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Modelling the Efficacy of Different Sampling Strategies for Estimating Disease Levels and Detecting the Spread of New Pests

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EXECUTIVE SUMMARY

Background

The New Zealand Forest Owners' Association (NZFOA) surveillance system is presently being modified to provide improved information on both forest health condition and pest status. The system is also intended to be capable of detecting new pest organisms. While we have a good understanding of the efficacy of individual survey techniques, combining and applying the survey techniques in a practical, cost-effective manner is not straightforward. Surveillance systems are complex, and there are many possible and plausible combinations of plotting intensity, sampling methods (random, systematic, or stratified), and seasonal timings. An effective sampling strategy would employ the minimal amount of effort and expense required to provide estimates of forest health condition and pest status that are accurate and precise enough to support the forest management objectives of the NZFOA. It would also promptly detect newly arrived pests. Identifying the optimal sampling strategy requires an understanding of the trade-offs between survey intensity through time and space, the quality of the disease severity estimates, and the ability to detect new pests. The aim of this project was to support the development of an optimised surveillance scheme for estimating pest status and pest detection by quantifying the trade-offs between sampling type, intensity, timing and costs, and the benefits in terms of the quality of the collected data.

Results

For both forest health status estimation and new pest detection, regular sampling and stratified sampling without size restriction outperformed random sampling and stratified sampling with size restriction at low sampling intensities (0.1-0.4%). There was little apparent improvement in the precision of pest status estimates by sampling more than 0.5% of the forest area.

The ability of a survey regime confined to the plantation forests to detect pests originating from high-risk zones improved with additional sampling effort. However, such a scheme was consistently unable to detect pests at population sizes that were small enough to contemplate a national eradication programme, as there was too much opportunity for a pest to spread before it invaded any of the forests. When considering just the spread of the pest within forests at the time of first detection, the survey system was able to detect pests at eradicable population sizes. This indicates the potential for the scheme to detect pests that self-disperse directly into the forests.

Recommendations

In an operational situation it is likely that planning costs will be cheaper for regular sampling than for stratified sampling, and field activities may also be cheaper when a regular sampling system is used. We recommend that both regular sampling and stratified sampling without size restriction are trialled in terms of time taken for preparation and field operations. We also recommend that random sampling and stratified sampling with size restriction survey methods are not to be evaluated further.

For successful detection of forest pests at infestation areas small enough for eradication to be feasible, it will be necessary to rely primarily on high-risk site surveillance in areas outside of the forests for initial detection, complimented by forest surveys to detect those organisms that arrive in forests first.

INTRODUCTION

The New Zealand Forest Owners' Association (NZFOA) forest health surveillance system aims to provide information to owners on both forest health condition and pest status (Bulman & Kimberley 2005). The system is also intended to be capable of early detection of new pest organisms. It is presently being modified, and an independent review was conducted in November 2007 (Leibhold & Callan 2007). In devising a surveillance system it is necessary to consider the trade-off between running costs and the precision and reliability of the collected information in the context of the management decisions that hinge on the information. It is obviously prudent to implement a system that minimises the running costs whilst still providing information that is of sufficient quality to enable reliable decisions to be made (Ben-Haim 2006).

This project aimed to assess the cost and efficacy of different sampling strategies at different intensities for (i) estimating disease levels and (ii) detecting the spread of new pests.

MATERIALS AND METHODS

Forest Health Condition Monitoring

Data

In order to compare and assess the different sampling strategies and intensity levels, six annual datasets of assessments of Dothistroma needle blight from aerial surveys conducted in Kaingaroa Forest (2815955E, 6285715S; New Zealand Map Grid) between 2000 and 2005 (Nigel Heron, NZFOA, unpub. data) were assembled. The databases consisted of ArcGIS shapefiles that included information on stand identification number, year of establishment, and a field corresponding to the estimated disease level for each stand sampled that year. The range of the values of the disease level field varied from 0 to 100, indicating the disease rate of the stand that year. The number of stands and the total area sampled changed between years (Table 1). The sampling effort increased through time. The sampling design covered all parts of the forest (Figure 1).

Table 1. Description of the datasets from aerial Dothistroma infestation surveys in Kaingaroa Forest showing the number of stands and the total area sampled each year between 2000 and 2005. The total area of the whole forest is 163 880 ha

	2000	2001	2002	2003	2004	2005
Number of stands sampled	1 847	1 953	2 538	3 196	3 385	3 925
Total area sampled (ha)	74 130	67 919	80 165	74 784	75 798	82 570

The area-weighted observed mean level of Dothistroma needle blight in Kaingaroa Forest increased between 2000 and 2002 (from 4.0% to 23.6%; Figure 2) followed by a net decrease in 2003 (2.2%). Disease rate increased again following years to 14.1% in 2005. The calculation of mean observed rates on a stand-basis gave similar results (Figure 2). Since the area-weighted mean gives the best assessment of the true spatial infestation of the forest as a whole, it was chosen as the base with which to compare the sample estimates for each strategy being explored here.

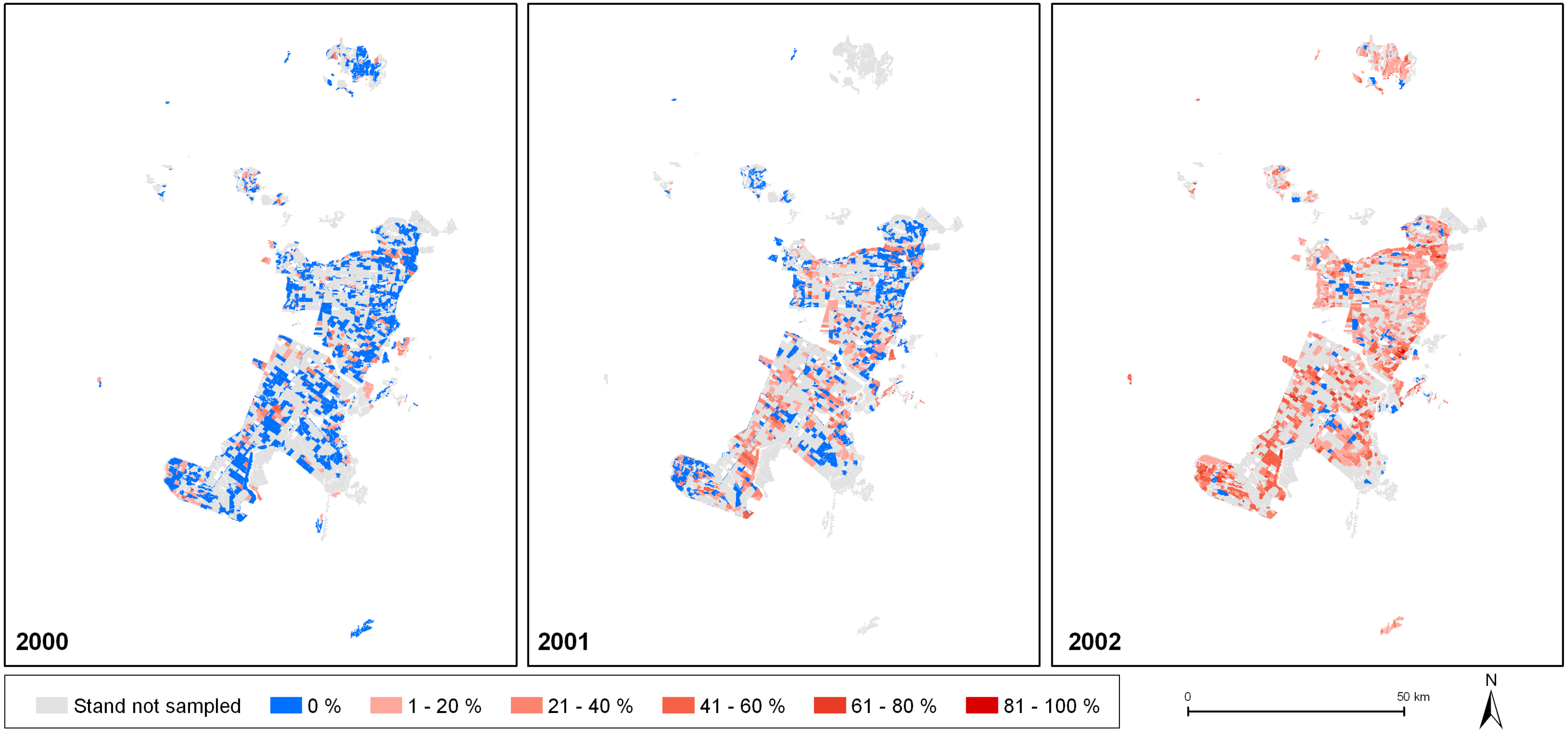


Figure 1a. Dothistroma infestation patterns in Kaingaroa Forest between 2000 and 2002

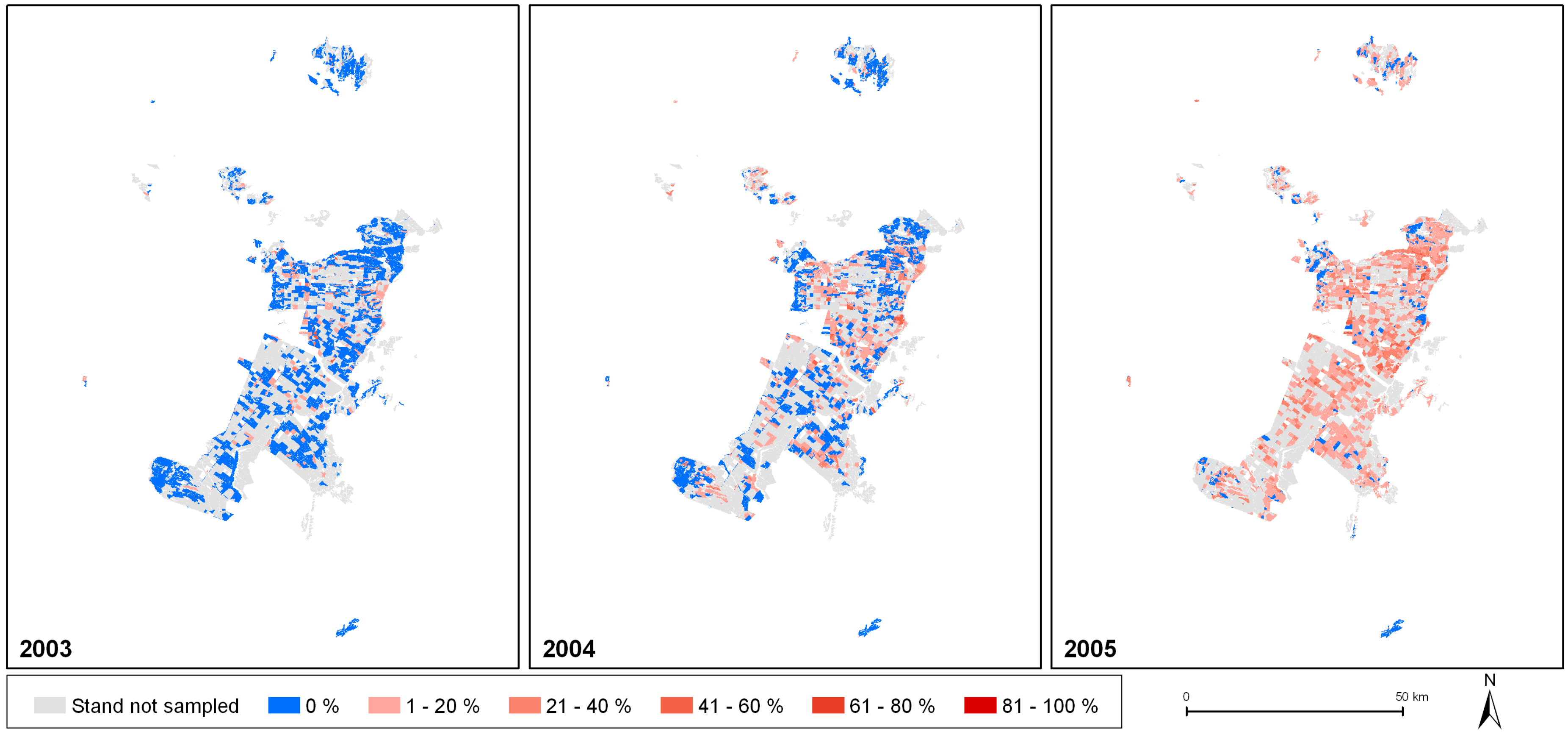


Figure 1b. Dothistroma infestation patterns in Kaingaroa Forest between 2003 and 2005

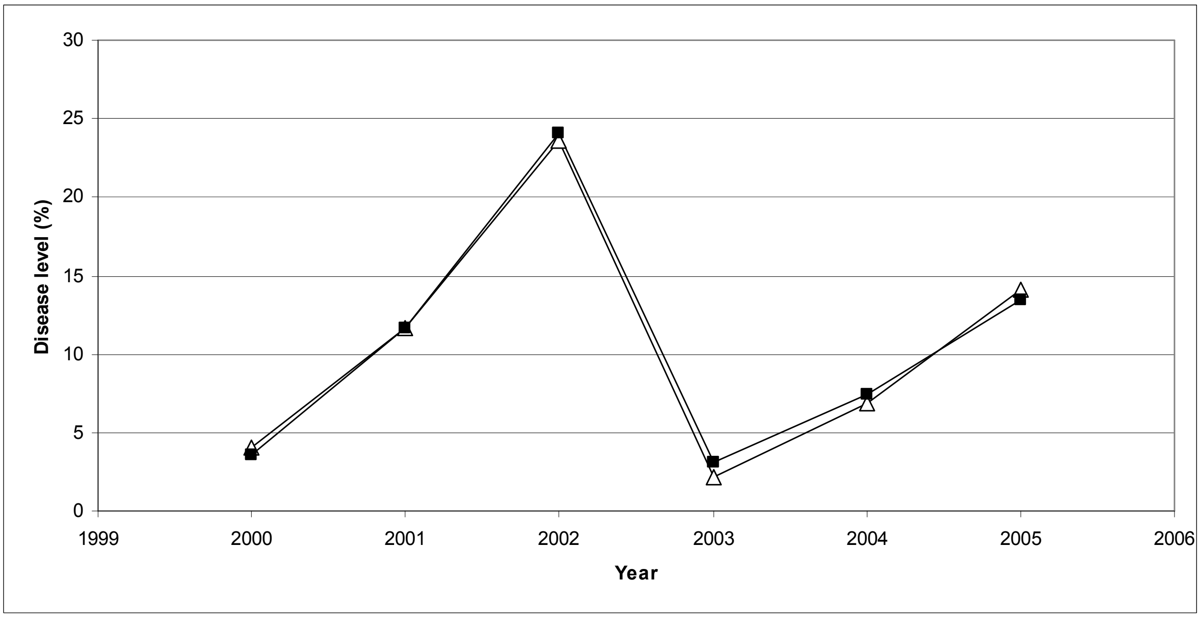


Figure 2. Average *Dothistroma* disease levels in Kaingaroa Forest between 2000 and 2005; average rates ($M_{observed}$) calculated on a stand basis $M_{observed} = \Sigma(rate_{stand})$/number of stands [—■—]; and average rates ($M_{observed}$) weighted by stand area $M_{observed} = \Sigma(rate_{stand} * area_{stand}) / \Sigma(area_{stand})$ [—△—].

Sampling strategies

In order to assess the most cost effective sampling strategy for estimating the average *Dothistroma* disease level across the whole forest, three sampling strategies (random, regular and stratified random) were tested on observed yearly data with six sampling intensities (0.1; 0.2; 0.4; 0.6; 0.8 and 1% of the total plantation forest area). A pair of key assumptions was developed based on input from the NZFOA. Firstly, the area effectively sampled at each sample point represented a 1 ha sample, and secondly, where possible, a stand would not be sampled more than once (this assumption was relaxed for the regular sampling strategy). The sampling strategies to be explored were prescribed by the NZFOA (L.S. Bulman, pers. comm.).

Three programs were developed with python (dynamic object-oriented programming language) to simulate the sampling of stands in the Kaingaroa Forest following the 18 sampling scenarios (3 strategies* 6 intensities). The numbers of points to be sampled for each simulation varied by year (due to the changing area sampled in the baseline datasets), and these are indicated in Table 2.

The number of points that must be sampled in future surveillance survey was calculated considering all the planted stands, not just those sampled in the Dothistroma surveys. This is because a general forest health survey system would need to consider stands of all ages because other forest health issues are being noted at the same time.

Table 2. Number of sampling points to simulate different intensity of sampling on existing survey data for 2000 to 2005 and the number of points that must be sampled in future surveys considering all planted stands relative to sampling intensity.

	Simulation on survey data						Future sampling design
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	
0.1	17	35	73	11	33	73	164
0.2	33	70	145	22	67	146	328
0.4	66	140	290	43	133	292	657
0.6	100	209	435	65	200	438	985
0.8	133	279	580	86	266	584	1 313
1	166	349	725	108	333	730	1 642

Random sampling

Description the random sampling strategy corresponds to the sample of *n* locations (Table 2) randomly selected within the surface area of the forest. In order to optimize the cover of the forest, the random strategy was defined as sampling without replacement, i.e. each stand can be sampled only once per survey (replacement strategy is discussed further in this report). This means that sampling is done on a stand basis (a 1 ha area of sampling point on the field represents the whole stand).

Simulation simplified csv datasets for each year were extracted from the geographical datasets, including the total sampled area for the year as a headline and for each stand a unique ID, the observed disease level, and the area. A python script was developed to randomly select *n* stands for each sample intensity level, calculate the weighted disease level per stand and the average disease level for the forest each year. This process was replicated fifteen times and a final mean disease level (*M*) was calculated for the forest from the fifteen replicate means (*m*) together with the standard deviation. The standard deviation indicates the level of risk of under- or over-estimating the true disease level.

Quantiles of the normal distribution and the sample mean and standard deviation were used to calculate confidence intervals for the mean. The following expression was used to calculate $U_{y,i}$, ***uncertainty*** for a given year (*y*) and a given intensity (*i*) with 95% confidence:

$U_{y,i} = 1.96 * SD$

where SD is the standard deviation of the sample, and 1.96 is the 0.975th quantile of the normal distribution

The simulation process is:

```
for each year
    for each sampling intensity
        calculate n in relation to the total area sampled that year in source datasets
        while number of replicates <= 15
            randomly select n stands
            calculate m_{r,y,i} = Σ(rate_stand*area_stand)/Σ(area_stand)
    calculate M_{y,i} = Σ(m_{r,y,i})/15; standard deviation and uncertainty U_{y,i}
```

The simulated mean infestation rates per year and per sample intensity were compared to the observed area-weighted mean rate ($M_{observed}$; Figure 2).

Regular sampling

Description the regular sampling strategy uses a regular grid of points, the distance between points depending on the sampling intensity (Table 3). In each year, where the points spatially intersected a stand with a disease rating, the stand was sampled. The intrinsic characteristics of regular sampling allow replacement, and so a stand with a larger area has a higher probability of being sampled more than once.

Table 3. Calculation of the distance between points of the regular grids in relation to the sampling intensity. Total forest area = 164 170 ha.

Sampling intensity (%)	Area that must be sampled (intensity*total area)	Number of points in the grid (a sample is a 1 ha area)	Each point represents (total area/number of points); ha	Cell size (m)
0.1	164.2	164	1 001.05159	3 164
0.2	328.3	328	500.525795	2 237
0.4	656.7	657	249.8819798	1 581
0.6	985.0	985	166.672549	1 291
0.8	1 313.4	1 313	125.0361468	1 118
1	1 641.7	1 642	99.98322823	1 000

Simulation fifteen independent grids of points were created for each sampling intensity following mesh sizes detailed in Table 3. Each grid was generated from a randomly chosen point of origin. All grids were oriented directly North-South and East-West according to the New Zealand Map Grid.

The original datasets of disease level per year were converted to rasters of stand IDs. A python script was written to extract stand IDs that intersected each of the 90 grids (15 replicates * 6 intensity levels), join the ID information to the csv databases and calculate the average disease level ($m_{r,y,i}$) per replicate (r), per year (y) and per sampling intensity (i) together with the average disease level of 15 replicates ($M_{y,i}$) per year (y) and intensity (i), standard deviation of replicates and uncertainty (see details in previous paragraph "Random sampling").

for each year
    for each intensity
        for each of the 15 grids corresponding to a single sampling intensity
            extract n values of stand ID from raster corresponding to the year
            join to csv database to obtain n rates
            calculate $m_{r,y,i} = \Sigma(\text{rates})/n$
        calculate $M_{y,i} = \Sigma(m_{r,y,i}) / 15$; standard deviation and uncertainty $U_{y,i}$

These simulated mean disease levels pe`r year and per intensity were compared to the observed area-weighted mean rate ($M_{observed}$; Figure 2).

Stratified random sampling

Description the stratified random sampling strategy is a mix between regular and random sampling strategies. The forest area is divided into a 1 000 ha fishnet and *b* locations corresponding to [Σ(area of forest in fishnet's cell) * sampling intensity] are randomly sampled. In order to optimize the cover of the forest, the stratified random strategy was without replacement.

Simulation simplified csv databases similar to those created for random sampling were developed but included a fishnet ID coming from the intersection between the original shapefiles for each year and a 1 000 ha fishnet shapefile. The simulation process is similar to the random simulation process except that the number of selected stands is calculated using Σ(area) within a fishnet cell.

for each year
    for each intensity
        while number of replicate <= 15
            for each cell of 1000ha
                calculate *b* in relation to the area of forest in the cell
                randomly select *b* stands
                store $[\Sigma(\text{rate*area})]_{cell}$ and $[\Sigma(\text{area})]_{cell}$ from sampled stands
            calculate $m_{r,y,i} = \Sigma([\Sigma(\text{rate*area})]_{cell}$ and $[\Sigma(\text{area})]_{cell})/\Sigma([\Sigma(\text{area})]_{cell})$
                calculate $M_{y,i} = \Sigma(m_{r,y,i})$ /15; standard deviation and uncertainty $U_{y,i}$

These simulated mean infestation rates per year and per intensity were compared to the observed area-weighted mean rate ($M_{observed}$; Figure 2).

A systematic under-sampling problem was uncovered in the original runs where the requirement to sample a 1 ha area was included. Subsequently, new scripts were developed to simulate the stratified-random strategy with the requirement for the sample to encompass 1 ha relaxed in order to test the effect of under-sampling.

Comparison of the precision of the sampling strategies

In order to compare the efficiency of the three sampling strategies, the ***precision*** of each sampling strategy (*P*) was calculated for each sampling intensity. This represents the minimum interannual variation that can be reliably detected using each method. The formula for a given intensity (*i*) is:

$P_i = \sqrt{2} * 1.96 * \text{mSD}$

where mSD is the mean standard deviation, in this case over six years.

Pest Spread Detection

This part of the project aimed to assess the cost and efficacy of a random and a regular sampling strategy at different intensities for detecting the spread of new pests. Simulations of sampling were conducted on results from runs of a model of spread of the Argentine ant.

<u>Study species and data from spread model</u>

Linepithema humile is a world-wide pest that is regarded as one of the six worse invasive ants (Holway *et al.* 2002). When it was first recorded in New Zealand in 1990 (Green 1990), there was no attempt to control this species as it was considered to be already well established. The Argentine ant is a successful 'tramp' ant species (Passera 1994) in part due to the following characteristics: a strong tendency to move and associate with humans (Suarez *et al.* 2001), unicoloniality (Holway 1998), strong interspecific aggression (Holway 1999), polygyny (Keller 1990) and budding dispersal, where a queen supported by as few a 10 workers can establish a new colony (Hee *et al.* 2000). *Linepithema humile* is a threat to New Zealand's biodiversity because in addition to potential negative impacts on wildlife, it readily displaces other ant species (Holway *et al.* 2002) and the displacement of existing ant species can cause existing mutualisms to be disrupted (Bond and Slingsby 1984, Lach

2003), and disrupt other ecosystem processes (Harris 2002). Because *L. humile* was considered well established and there were limited means to control it, the species was for the most part left to spread unhindered and therefore provides a good example for studying the spread of an invasive species.

International data on *L. humile* distribution were used to parameterise a modular and flexible framework called Modular Dispersal in GIS (MDiG) to simulate the species spread from the site of its initial invasion. Graphs derived from the New Zealand occurrence data were used to guide model creation and check that human-assisted dispersal occurred at the same scale between locations. However, explicit spatial locations from New Zealand occurrence data were kept for model validation. An extensible, modular, spatially-explicit, and high-resolution dispersal simulation model, integrated with a Geographic Information System (GIS), was used to recreate the historical spread of *L. humile* in New Zealand (Pitt *et al.*, unpublished data). High resolution probabilistic maps (0 for absence and 1 for presence) simulating local and human assisted spread across the study area (63 600 km^2 area around Auckland, New Zealand, Figure 3) were generated at a yearly time step (Figure 4).

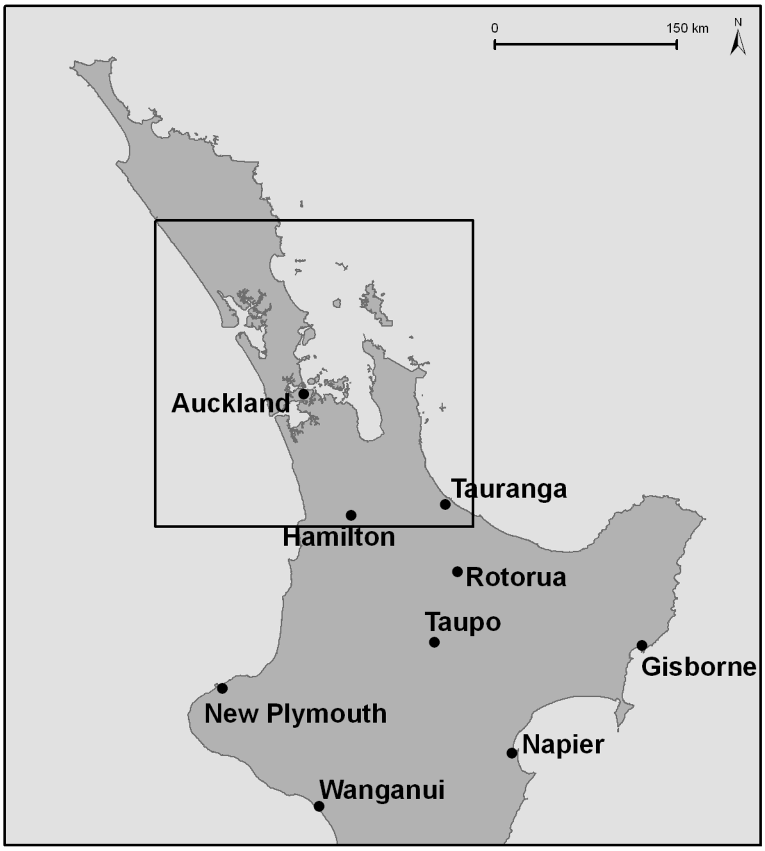


Figure 3. The North Island of New Zealand showing the area where simulations of Argentine Ant spread were run.

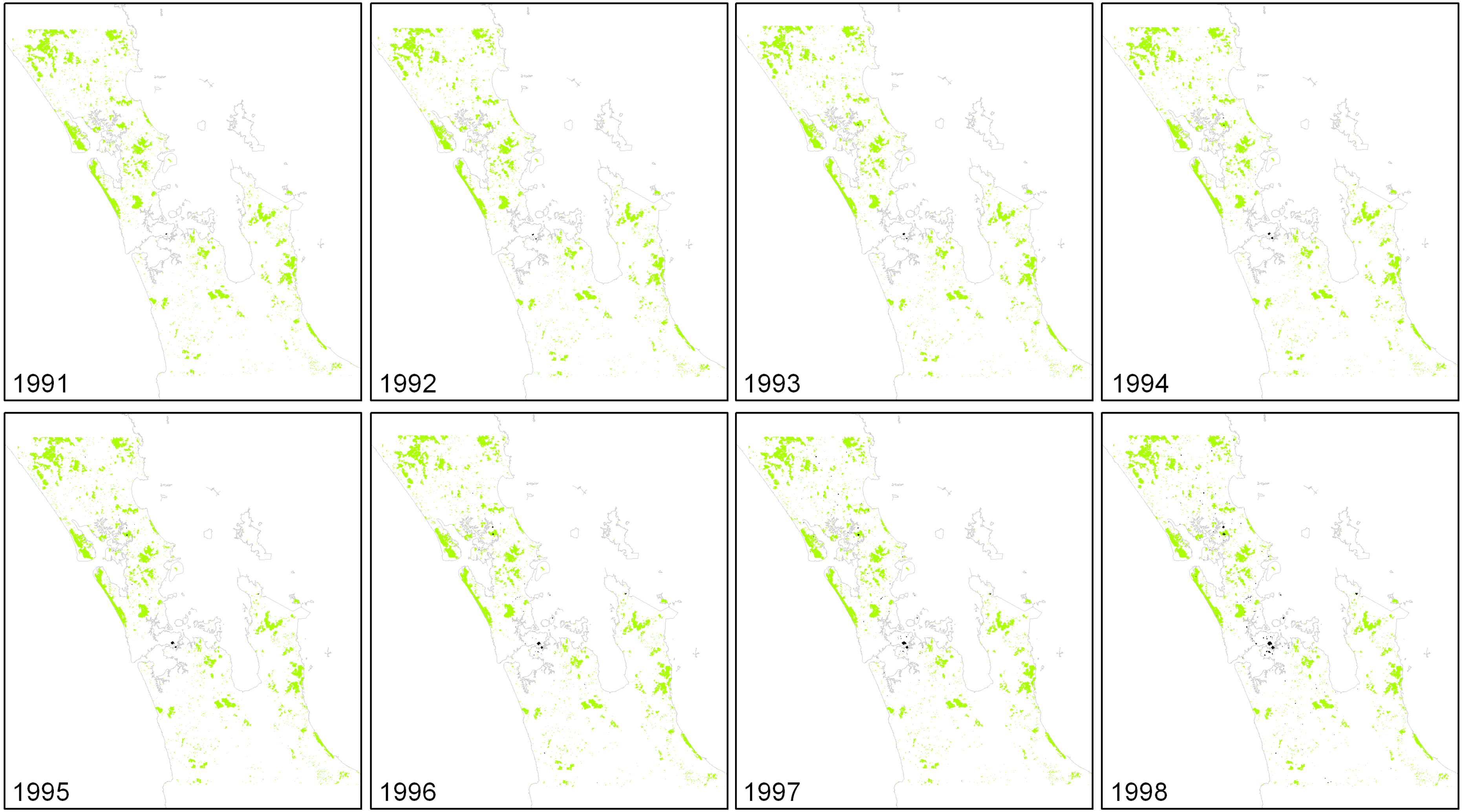


Figure 4a. Example of spread of ***Linepithema humile*** **from 1990 (date of introduction in New-Zealand) to 1998 in the study area, predicted by one run of the Argentine ant spread model; Forest; Presence of Argentine ant.**

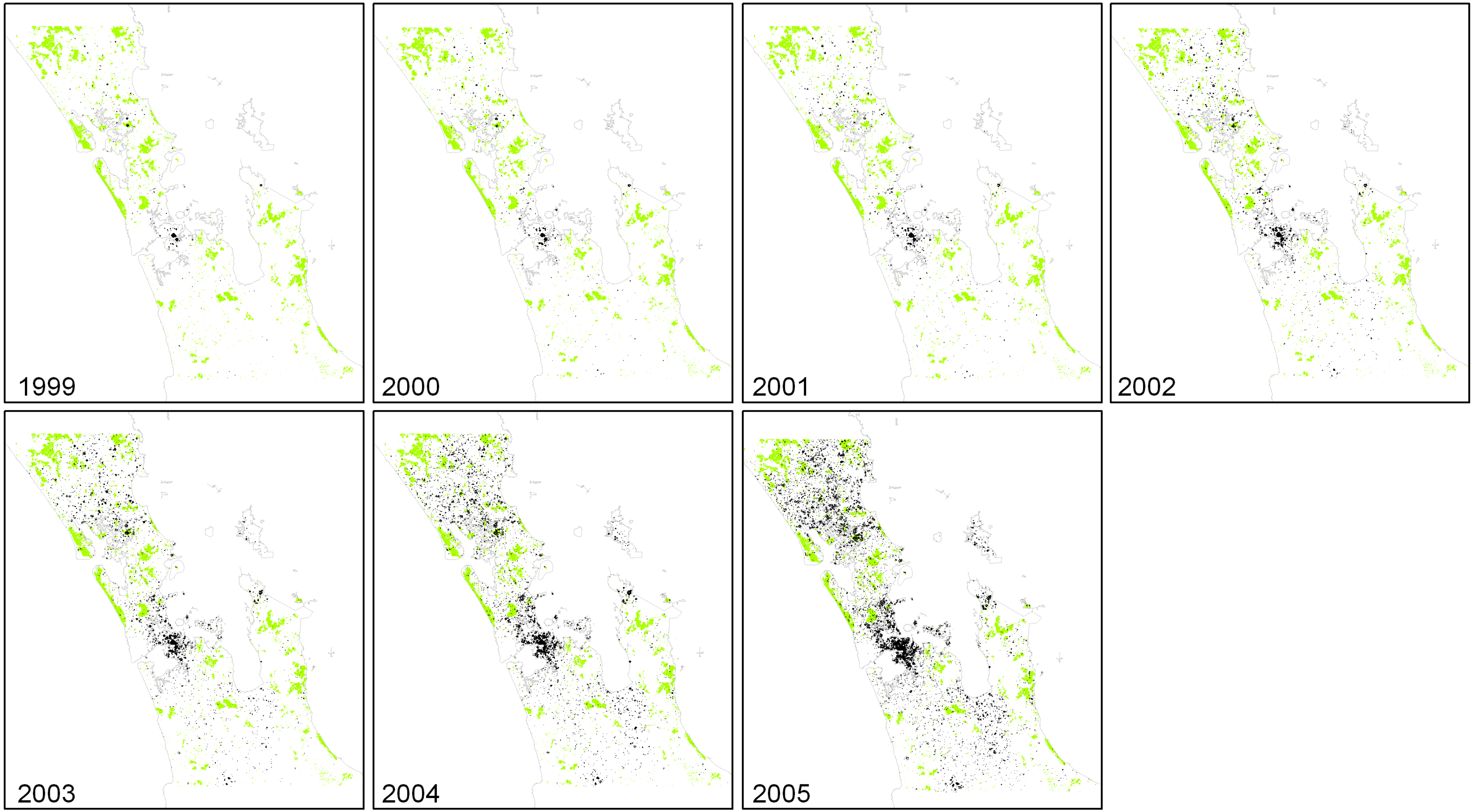


Figure 4b. Example of spread of *Linepithema humile* from 1999 to 2005 in the study area, predicted by one run of the Argentine ant spread model; Forest; Presence of Argentine ant.

Sampling strategies

In order to assess which sampling strategy is the most cost effective for detecting a newly arrived pest, random and regular sampling strategies were tested on five simulations from the Argentine ant spread model with five sampling intensities (0.2; 0.4; 0.6; 0.8 and 1%).

Two programs were developed with python (dynamic object-oriented programming language) to simulate sampling all forests present in the study area, following the 60 sampling scenarios (2 strategies* 5 intensities*5 spread simulations). The numbers of points sampled for each simulation per sampling intensity are indicated in Table 4. Input spatial layers of forest distribution were generated for the study area in ArcInfo from Land Cover Database (LCDB) using classes 63, 64, 65 and 66 of LCDB (Pine forest areas; Table 5).

Table 4. Number of sampling points to simulate different intensity of sampling on plantation forest present in the study area and the number of points that must be sampled in future surveillance surveys considering the total plantation forest area in New Zealand, assumed to be 1 775 200 ha.

Sampling intensity (%)	Simulation on study area (n)	Future sampling design, whole NZ
0.2	362	3 550
0.4	724	7 101
0.6	1 087	10 651
0.8	1 449	14 202
1	1 811	17 752

Random sampling

Description The random sampling strategy corresponds to the sample of (n) locations (Table 4) randomly selected within the surface area of the forest (ArcInfo polygons from LCDB).

Simulation a script developed using Python was used to randomly create n points (Table 4) within the entire plantation forest area within the study region and extract values of the raster corresponding to the pest distribution in a given year at these points. The values of presence (1) of Argentine ant were weighted by a probability of being detected in the field in relation to seasonality (the probability of detecting a pest that is visible all year round during a non-specific survey is higher than the probability of detecting a pest species that is only apparent in one season). The weight factor was 0.25 (species apparent in only one of the 4 seasons) for seasonal species and 1 for annual species (species apparent throughout the year). The values of presence are also weighted by a factor of visibility (cryptic or obvious) that could be also interpreted as effectiveness of the inspector. The weight factor was 0.1 for the cryptic species (hardly detected, and poor effectiveness of the inspector) and 0.9 for the obvious species (high probability of being detected, good effectiveness of the inspector). Field detection trials showed that only 21% of cryptic targets were found compared with almost 80% of obvious symptoms (Hosking *et al.* 1999). For the purposes of this project we tested the extremes and therefore took values of 0.1 and 0.9 for cryptic and obvious symptoms, respectively. The sampling simulations started in 1990. If the pest was detected, the sampling stopped and the total area and forest area colonised by Argentine ant when it was first detected (equal to the cover area in the simulation raster that year) was recorded. Ten replicates of the process were performed.

Table 5. Description of Land Cover Database classes corresponding to Pine forest.

Class	Name	Description
63	Afforestation (imaged and post-LCDB 1):	Areas of *Pinus radiata* forest visible in the imagery and located on sites recorded as non-forested in LCDB 1. These areas represent young forests that were not visible in the imagery used for LCDB 1 or have been planted since. Young plantations are identifiable in satellite imagery 4-5 years after planting, depending on initial stocking.
64	Pine Forest – Harvested	Areas showing obvious signs of recent harvesting, e.g. skid tracking, new roading, landings. The classification assumes these sites to have been replanted, and this will be checked in the next iteration of the database. By this time, if the areas were replanted, the trees will be at least 5 years old and identifiable. The purpose of this class is to confirm the extent of harvested pine forest that is replanted.
65	Pine Forest - Open Canopy	Plantations of *Pinus radiata* showing significant reflectance of understorey land cover. The reflectance values for stand biomass and pine canopy indicate that trees are in an age class of approximately 6 - 15 years.
66	Pine Forest - Closed Canopy	Plantations of *Pinus radiata* where reflectance is dominated by the pine canopy. Reflectance values for stand biomass and shadow from canopy texture indicate that trees are likely to be older than 15 years. The purpose of this class is to highlight stands likely to be harvested within 10 - 15 years of the image date.

The simulation process is:

```
For each spread simulation (5 runs of the Argentine ant model)
    for each year
        calculate the surface area covered by the species
        while number of replicates <= 10
            for each sampling intensity
                test if the pest has been detected previous year (warning index <> 0)
                   if not
                   randomly create (n) sampling points
                   for each sampling point
                       extract the value of the raster (year simulation) at that point
                       if value <> 0 (mean presence of the pest detected)
                           -randomly create a number between 0 and 1
                            -it checks if this random number is < or > to the combination:
                           (presence * probability to be detected due to seasonality of the species
                           * probability to be detected due to pest state)
                                   seasonal and cryptic 1*0.25*0.1
                                   seasonal and obvious 1*0.25*0.9
                                   annual and cryptic 1*1*0.1
                                   annual and obvious 1*1*0.9
                           -it increments the "warning index" for the sampling effort and the state
                           (since different from '0", the following year is not processed)
```

Where (n) is the number of sampling points as in table 4.

Regular sampling

Description the regular sampling strategy uses a regular grid of (n) points, n depending on the sampling intensity (Table 4).

Simulation ten grids of points were created for each sampling intensity. Each grid was generated from a randomly chosen point of origin. All grids were oriented directly North-South and East-West according to the New Zealand Map Grid. A script was developed using Python to extract from each of the fifty grids of regular points (5 sampling intensities*10 replicates) the values of the raster corresponding to the pest distribution a given year. Data were formatted and date of first detection and total area covered recorded as for random strategy.

The simulation process is:

```
For each spread simulation (5 runs of the Argentine ant model)
    for each year
        calculate the surface area covered by the species
        for each grid of regular points (corresponding to 10 replicates*5 sampling intensities)
            test if the pest has been detected previous year (warning index <> 0)
                if not
                    for each sampling point of the regular grid
                        extract the value of the raster (year simulation) at that point
                            if value <> 0 (mean presence of the pest detected)
                                -randomly create a number between 0 and 1
                                -it checks if this random number is < or > to the combination:
                                (presence * probability to be detected due to seasonality of the
                                species * probability to be detected due to pest state)
                                        seasonal and cryptic 1*0.25*0.1
                                        seasonal and obvious 1*0.25*0.9
                                        annual and cryptic 1*1*0.1
                                        annual and obvious 1*1*0.9
                                -it increments the "warning index" for the sampling effort and the
                                state (since different from ‘0”, the following year is not be
                                processed)
```

Cost assessment

For both forest health monitoring and pest detection, the cost of sampling at each sampling intensity versus precision (forest health monitoring) and area colonised by the pest when it is first detected (pest detection) was assessed using the relationship in Fig. 5. This relationship is an approximate estimate, based upon limited consultation. Several factors such as the spatial configuration of the survey sites and accessibility of the sites could affect the true survey costs. The downward sloping relationship in Fig 5 indicates that there are large economies of scale in survey costs, and the plateau on the right hand side is indicating the region beyond which per unit costs are minimised.

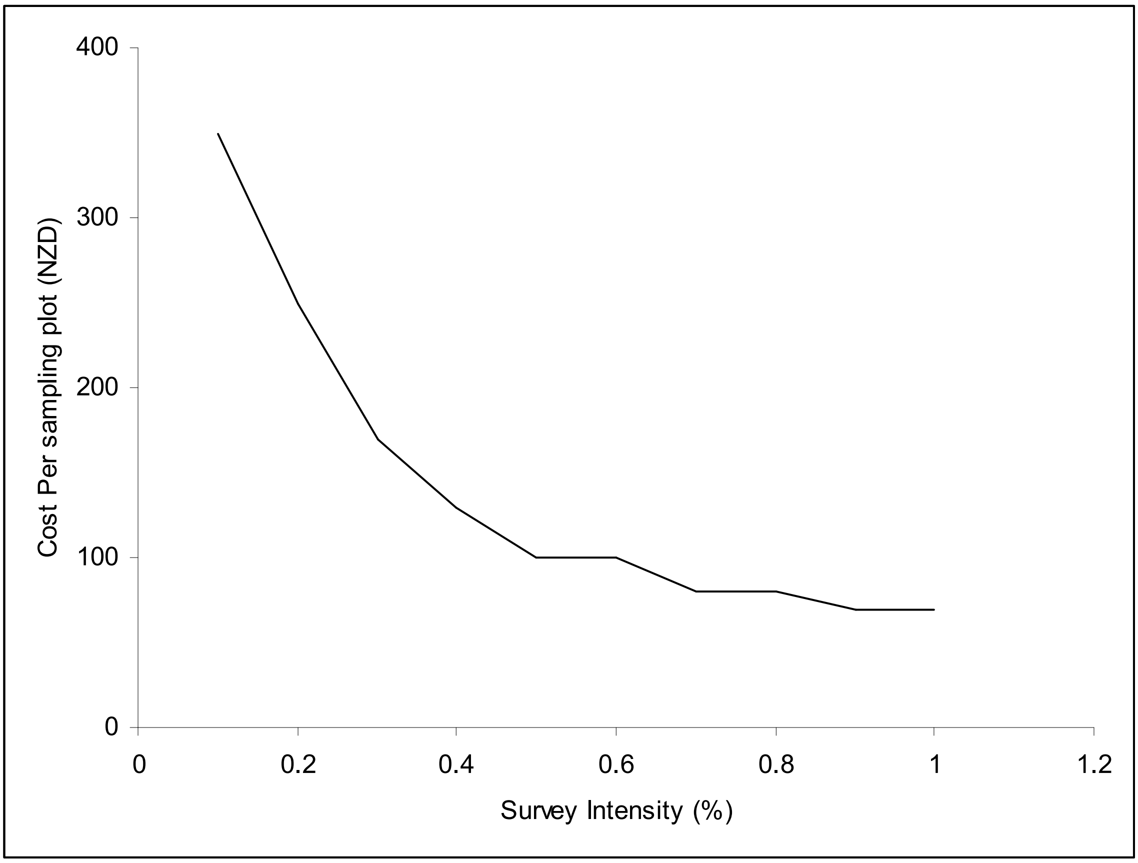


Figure 5. Survey costs per sampling plot as a function of survey intensity. Source Brent Rogan, SPS Biosecurity (pers. comm.).

RESULTS

Forest Health Condition Monitoring

Random sampling

Figure 6 gives an example for a single replicate of a randomly simulated sampling design for each intensity of sampling, for 1 year.

Figures 7a and 7b show the results of the 15 simulations of random sampling of Kaingaroa Forest for 2000 to 2005 with different sampling intensities, compared with the observed weighted disease levels (calculated from all sampled stands each year).

The random sampling strategy is not precise enough to reliably discriminate between most of the observed levels at 0.1% to 0.2% sampling effort. Whilst the simulated mean infestation rates across the fifteen samples almost perfectly matched observed mean disease levels at every sampling intensity, uncertainty remained high (≥2%) for some years up to a sampling intensity of 0.8%. Average uncertainty is 4.2 for the 0.1% sampling effort, and decreases to 1.2 for a sampling effort of 1%, with intermediate values of 2.7, 2.1, 1.3 and 1.2 for sampling effort of 0.2%, 0.4%, 0.6% and 0.8% respectively.

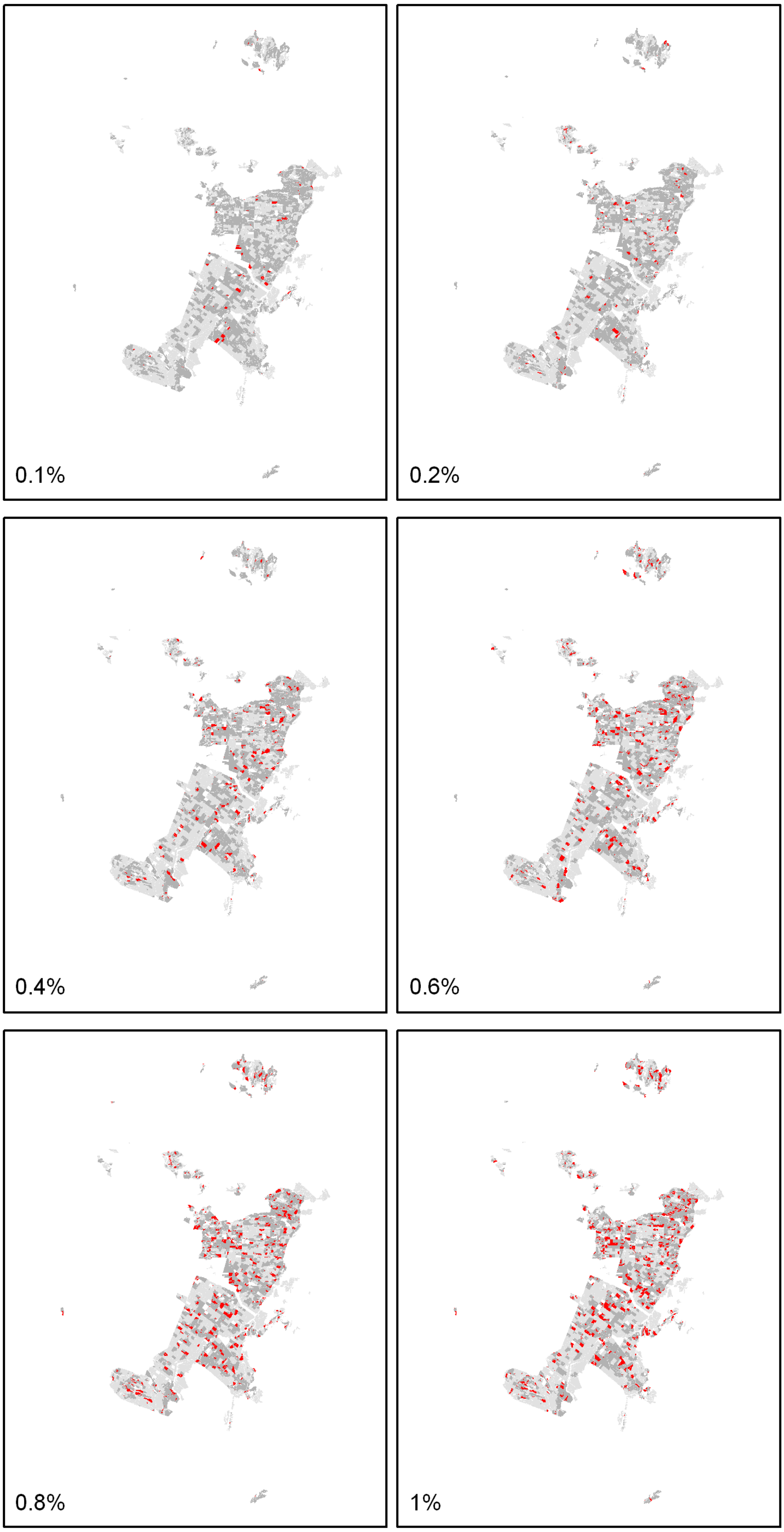
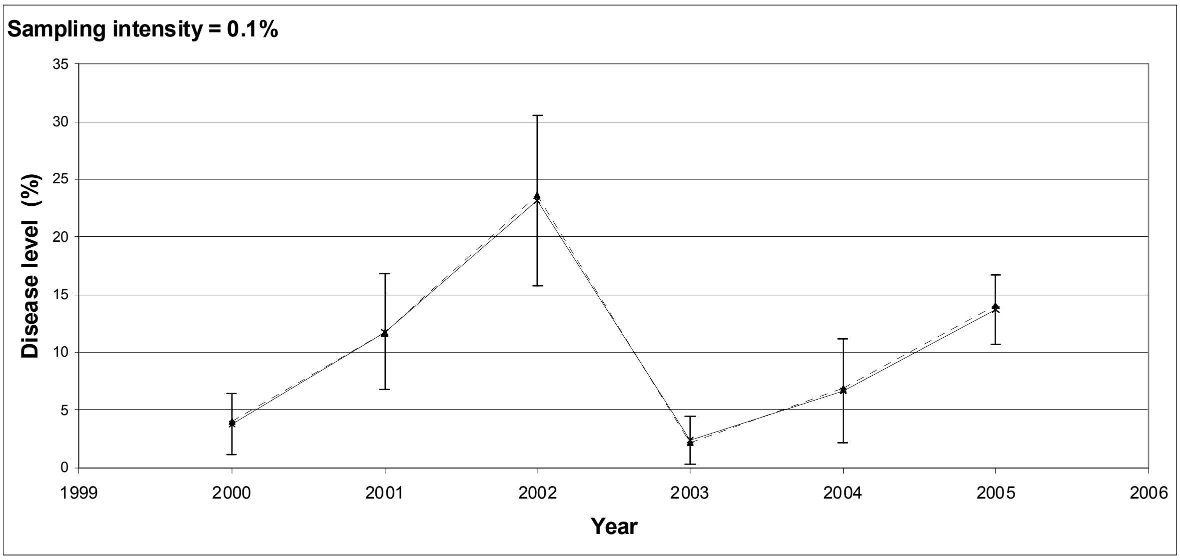
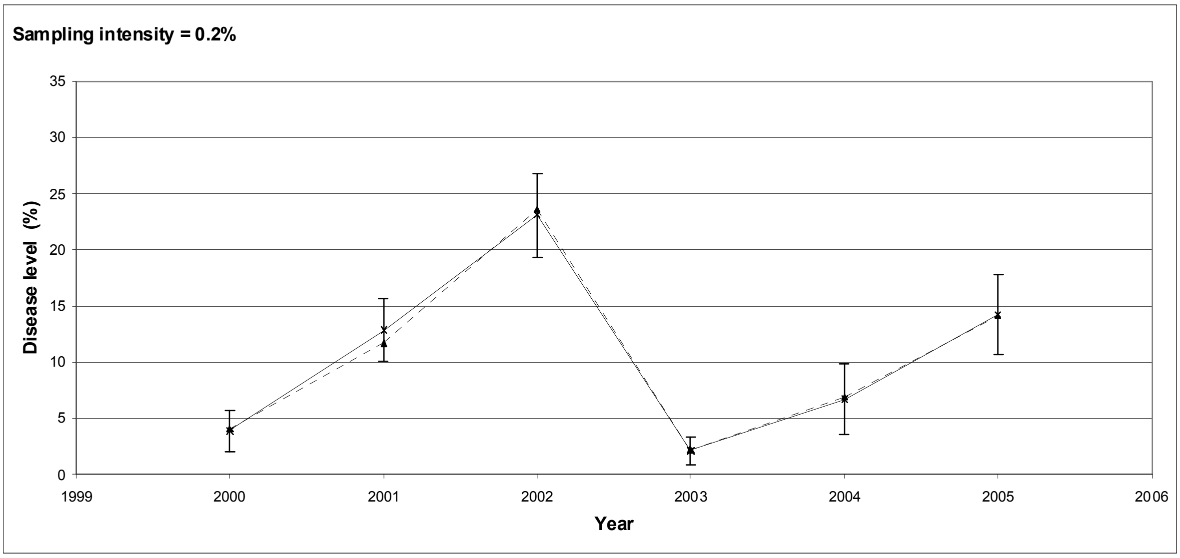


Figure 6. Example of simulation of a random sampling on Kaingaroa Forest in 2005; Stands without infestation data; Stands with infestation data; Stands sampled in simulation





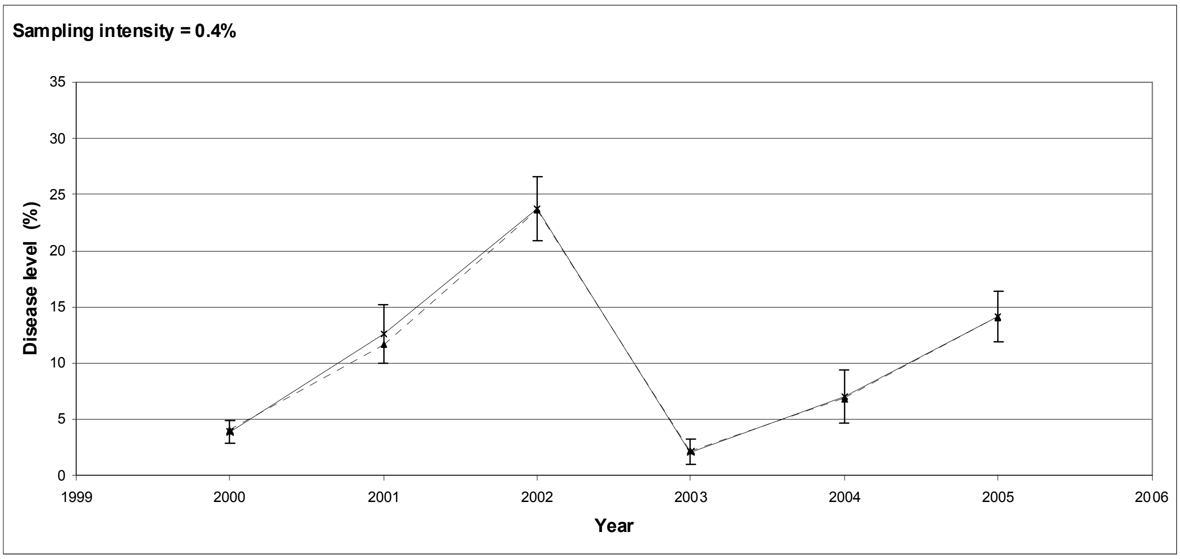


Figure 7a. Results of the fifteen simulations of random sampling on Kaingaroa Forest for 2000 to 2005 for sample intensity levels of 0.1 to 0.4%; [—×—] Simulated mean disease level; [- - ▲ - -] Observed mean disease level. Error bars represent uncertainty in the estimate of the mean, calculated as 1.96 * standard deviation.

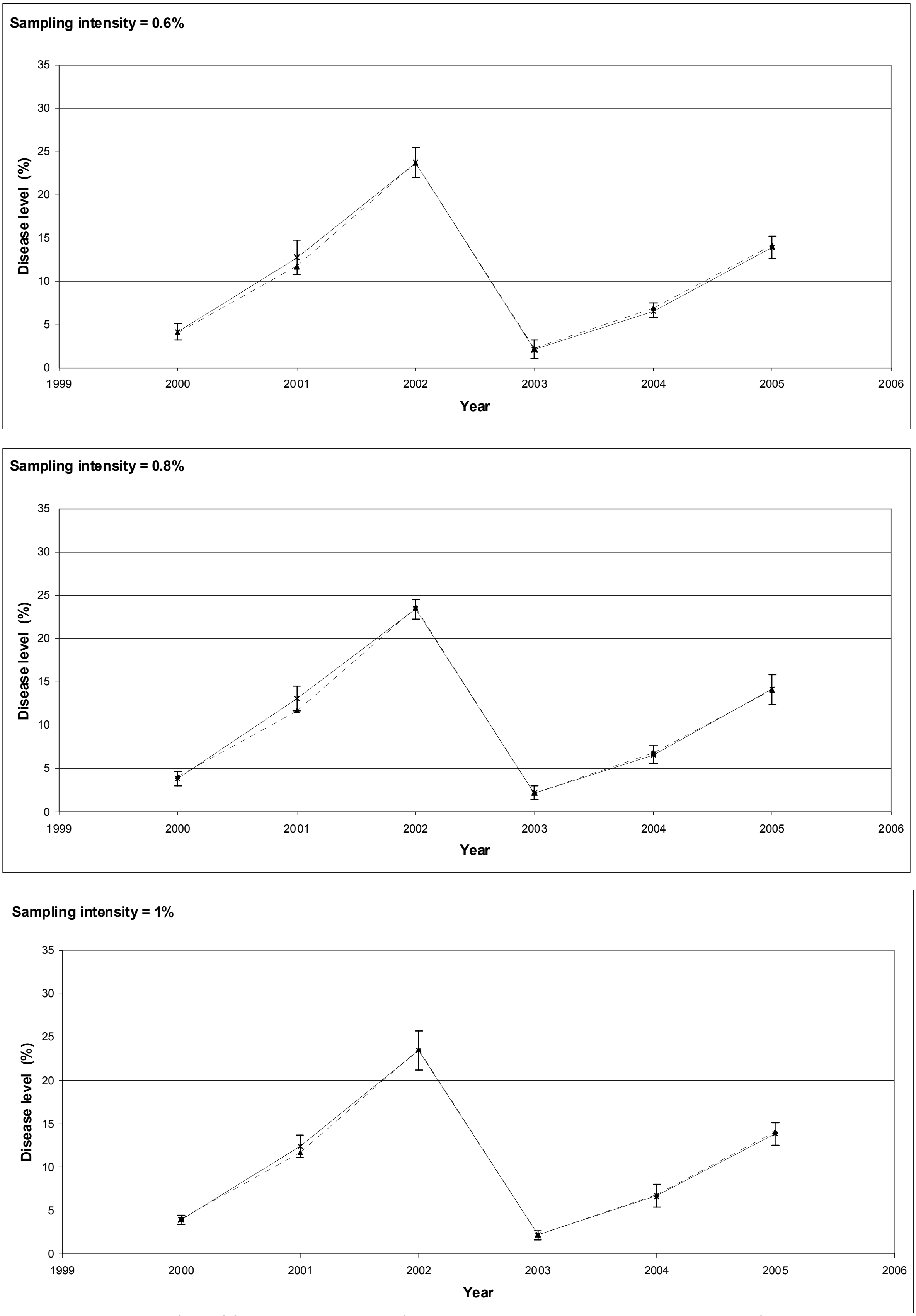


Figure 7b. Results of the fifteen simulations of random sampling on Kaingaroa Forest for 2000 to 2005 for sample intensity levels of 0.6 to 1%; [—×—] Simulated mean disease level; [- -▲- -] Observed mean disease level. Error bars represent uncertainty in the estimate of the mean, calculated as 1.96 * standard deviation.

Regular sampling

Figure 8 gives an example replicate for a simulation of a regular sample for each sampling intensity, for 1 year. Figures 8a and 8b show the results of the 15 simulations of a regular sample of Kaingaroa Forest for 2000 to 2005 with different sample intensities, compared to observed weighted rates of infestations (calculated from all sampled stands each year). The regular sampling strategy appears quite efficient. Using this method it is possible using a sample intensity of 0.2% to reliably (with 95% confidence) detect the difference between disease levels for 2003 and 2004.

Figures 9a and 9b show the results of the 15 simulations of regular sampling of Kaingaroa Forest for 2000 to 2005 with different sampling intensities, compared with the observed weighted disease levels (calculated from all sampled stands each year).

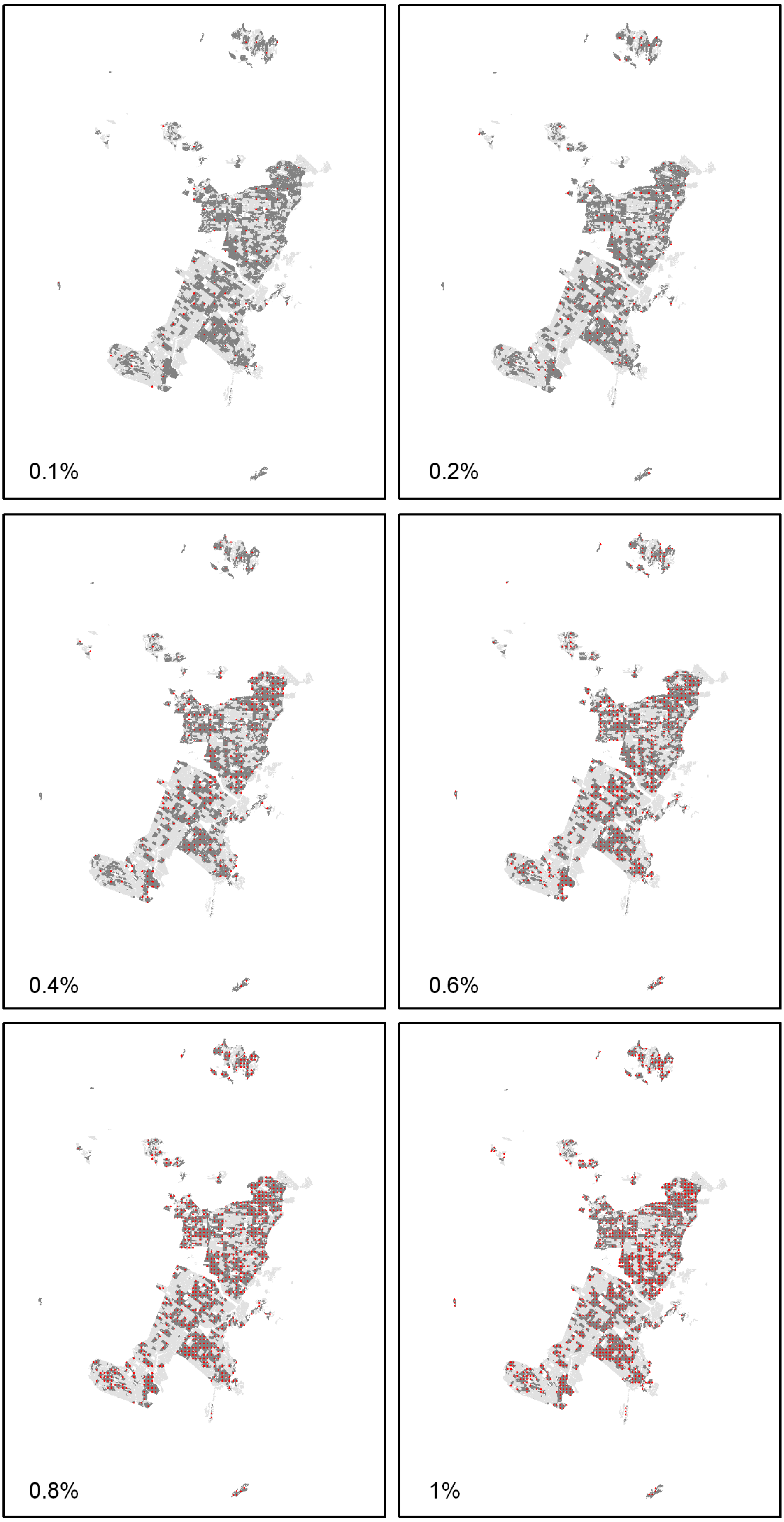


Figure 8. Example of simulation of a regular sampling on Kaingaroa Forest in 2005; Stands without infestation data; Stands with infestation data; sampled point.

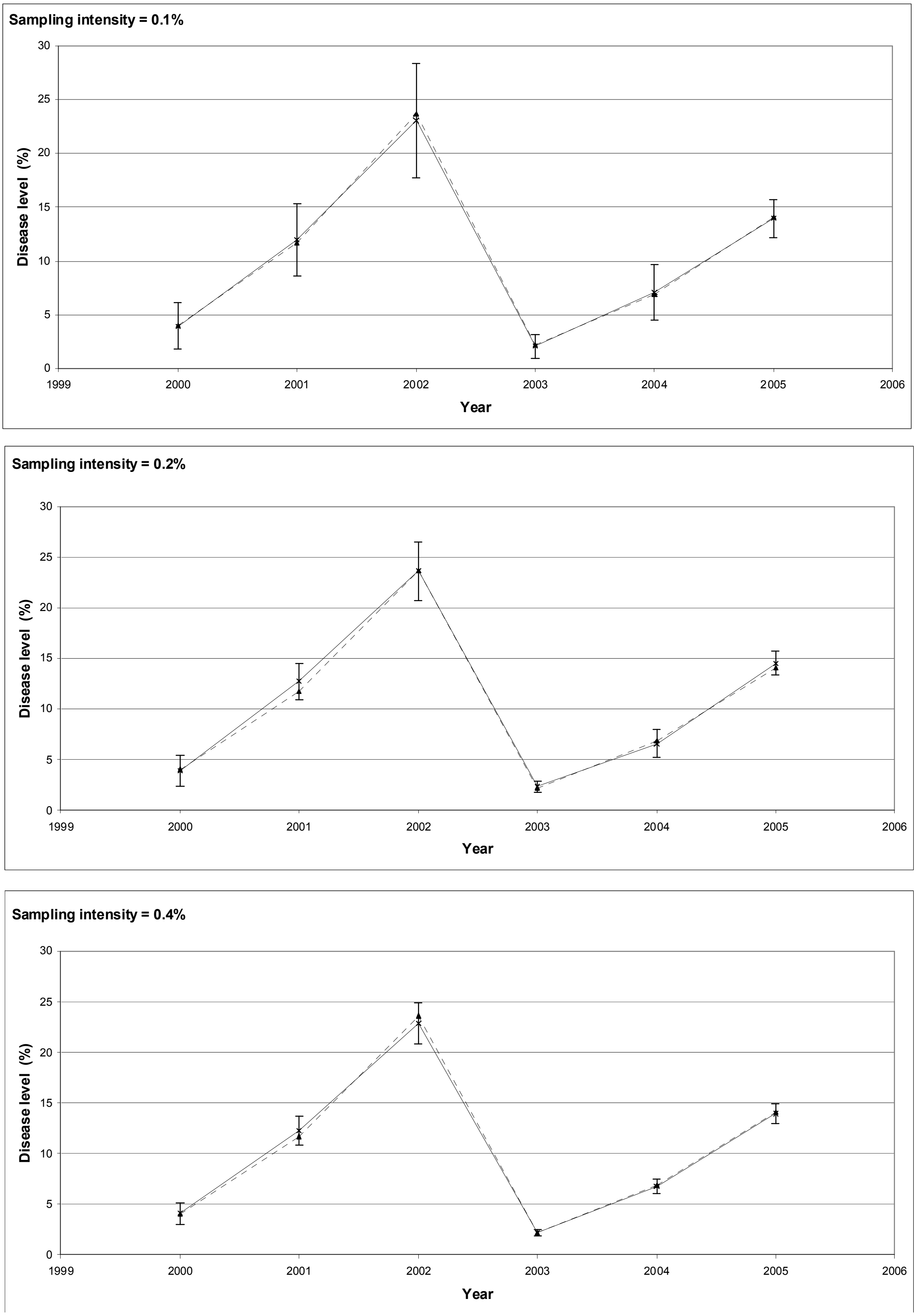


Figure 9a. Results of the fifteen simulations of regular sampling on Kaingaroa Forest for the 2000-2005 period for sample intensity levels 0.1 to 0.4%; [—×—] Simulated mean disease level; [- -▲- -] Observed mean disease level. Error bars represent uncertainty in the estimate of the mean, calculated as 1.96 * standard deviation.

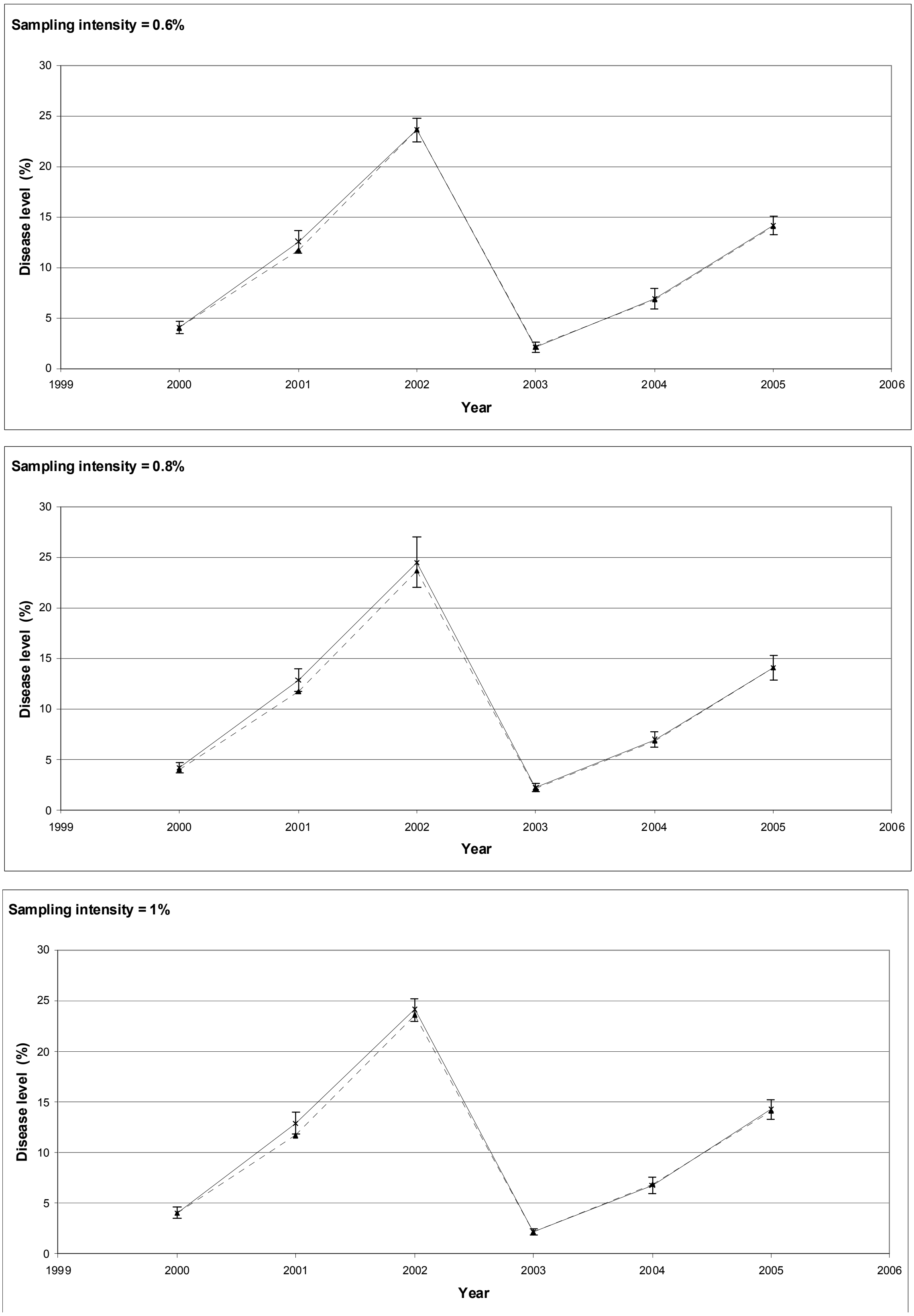


Figure 9b. Results of the fifteen simulations of regular sampling on Kaingaroa Forest for the 2000-2005 period for sample intensity levels 0.6 to 1%; [—×—] Simulated mean disease level; [- - ▲ - -] Observed mean disease level. Error bars represent uncertainty in the estimate of the mean, calculated as 1.96 * standard deviation.

Stratified random sampling

Figure 10 gives an example replicate for a simulation of a stratified random sample for each sampling intensity for 1 year. The number of sampled stands in the map corresponding to the sampling intensity of 0.1% (top left) is less than the number of stands sampled for the same intensity with other methods (Figures 6 and 8). Subdividing the forest landscape into 1 000 ha units for stratification purposes resulted in a large number of sample units (forest stands within a stratification cell) that were very small. Using the requirement that each field sample must consist of 1 ha resulted in the situation where for some years and/or some sampling intensity levels, the total sampled area of the sampled stands or their area was not big enough to meet the minimum area condition [(sampling intensity*area in cell/100)>1ha]. In fact $n_{r,y,i}$ is not equal to $\Sigma(b_{\text{cell}})$. As a result, the simulation of the stratified random sampling strategy at 0.1% could not be performed each year (area within a cell < 501 ha, n < 0.5 and round(n) = 0). This explains the pattern of results observed in Figures 10a and 10b. The stratified random sampling strategy performed poorly with uncertainty values greater than 2% up to a sampling intensity of 0.8%. Average uncertainty is 2.1 for the 0.1% sampling effort and decreases to 1.1 for a sampling effort of 1%, with intermediate values of 2.3, 1.6, 1.2 and 1.1 for sampling effort of 0.2%, 0.4%, 0.6% and 0.8% respectively.

When the requirement for a sample to include 1 ha of forest was relaxed, the resulting mean disease levels are similar to those from the stratified random strategy with the 1 ha size restriction retained, but with markedly lower levels of uncertainty, especially for low sampling intensities (Figure 11, Table 6). Figures 11a and 11b show the results of the 15 simulations of stratified random sampling of Kaingaroa Forest for 2000 to 2005 with different sampling intensities, compared with the observed weighted disease levels (calculated from all sampled stands each year).

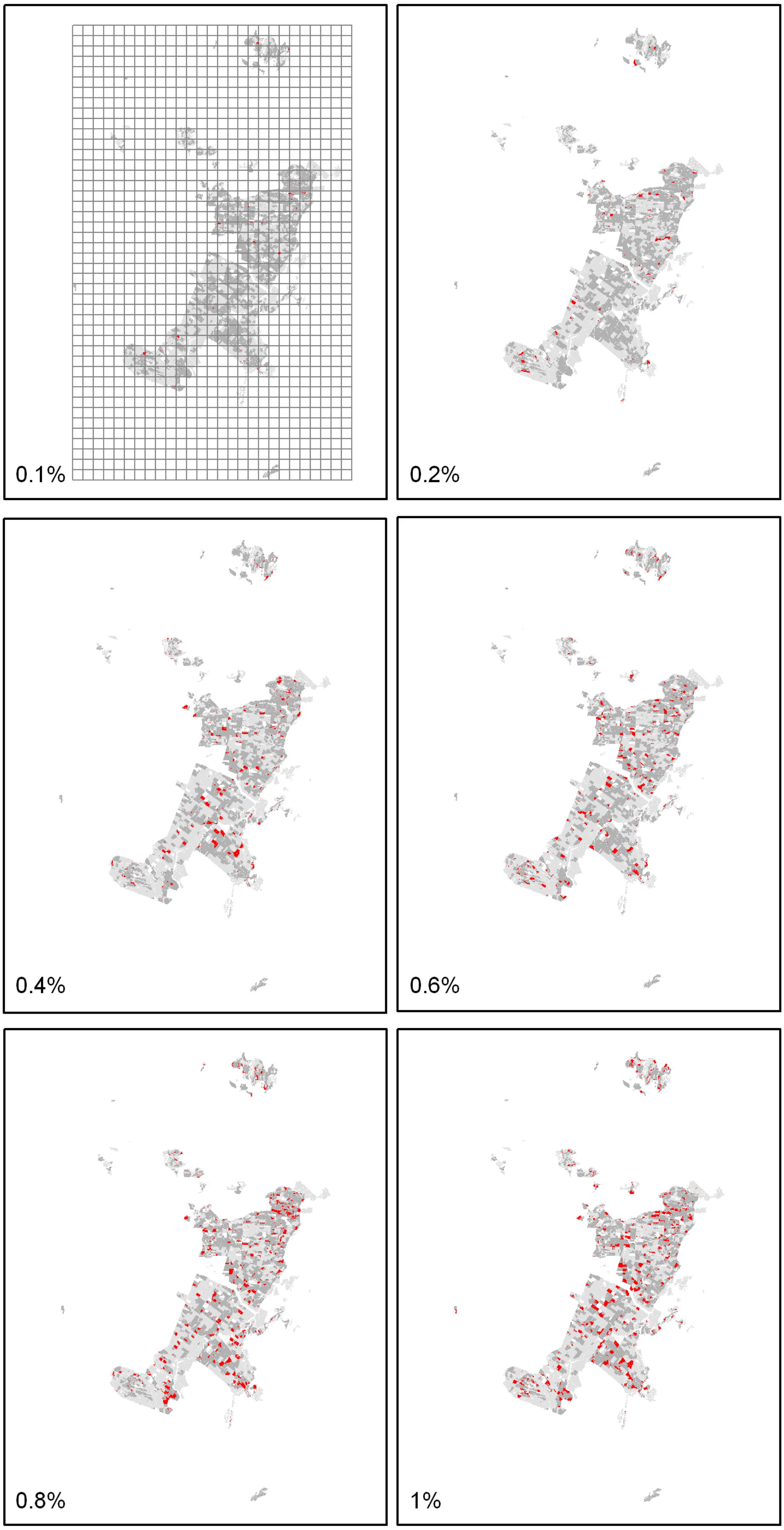


Figure 10. Example of simulation of a stratified sample of Kaingaroa Forest in 2005; Stands without infestation data; Stands with infestation data; Stands sampled in simulation; 1000ha fishnet

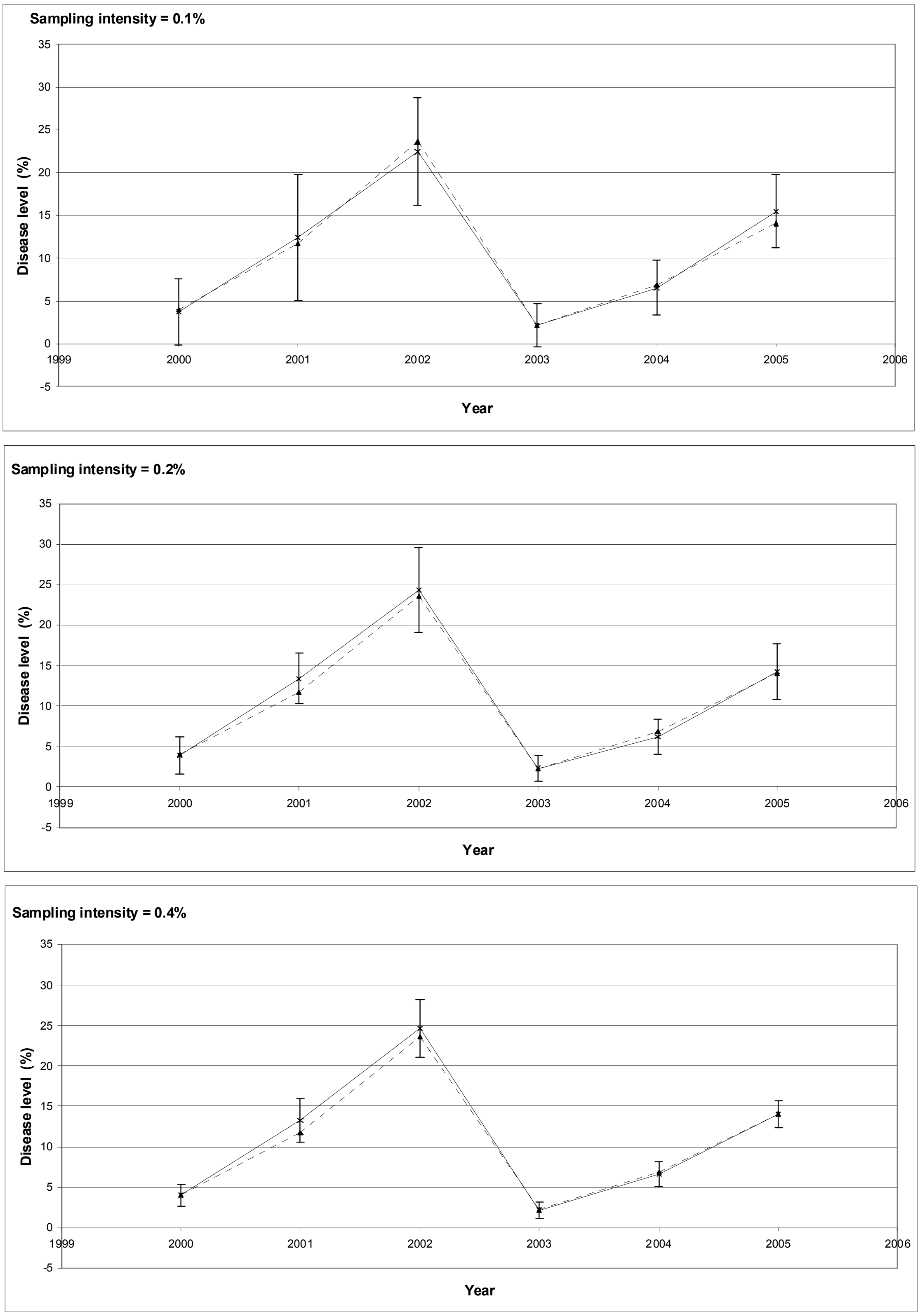
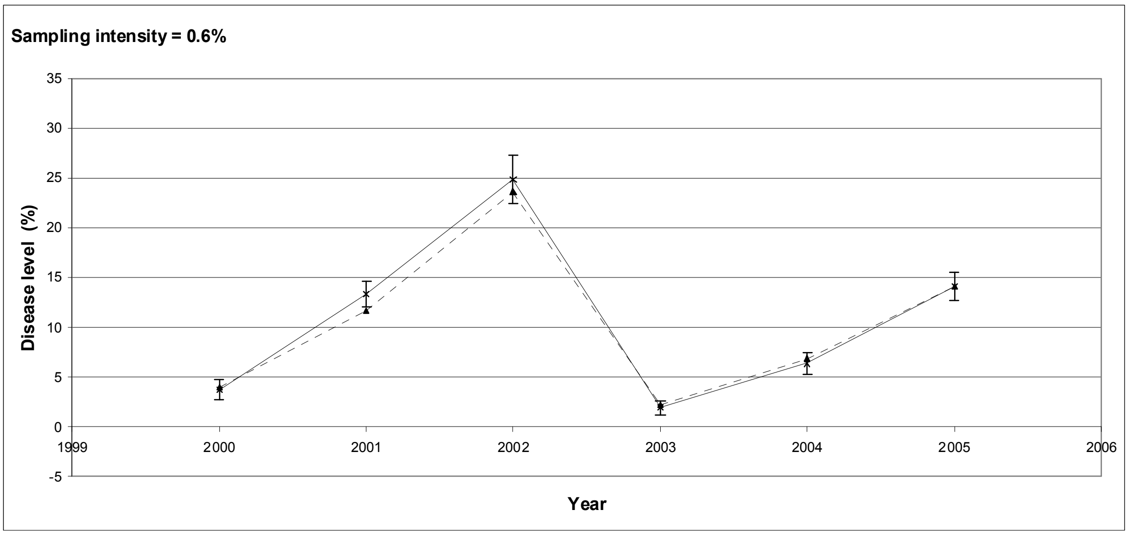
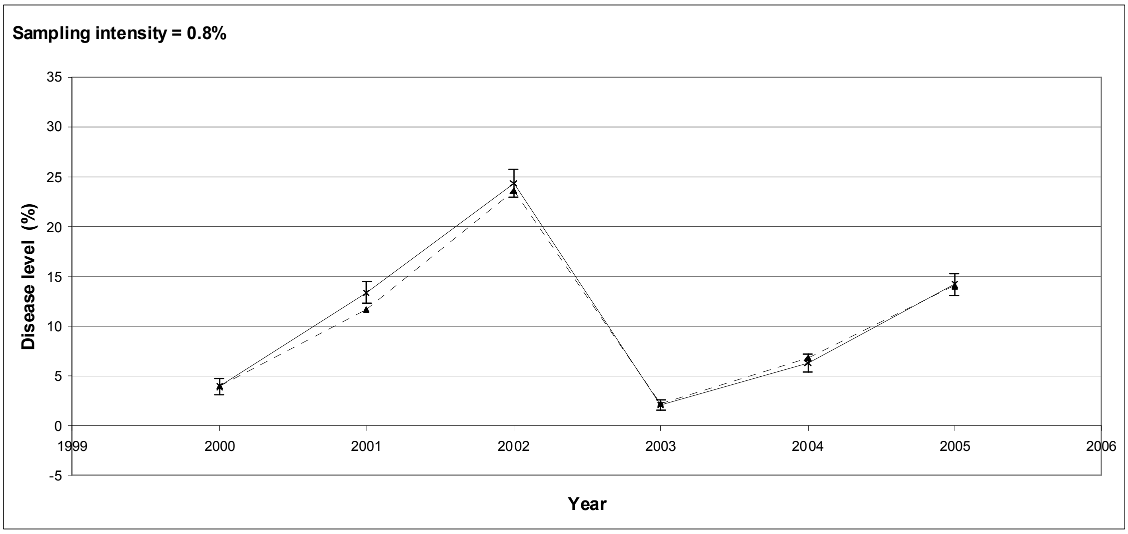


Figure 11a. Results of the fifteen simulations of stratified random sampling on Kaingaroa Forest for 2000 to 2005 for sample intensity levels 0.1 to 0.4%; [—×—] Simulated mean disease level; [- -▲- -] Observed mean disease level. Error bars represent uncertainty in the estimate of the mean, calculated as 1.96 * standard deviation.





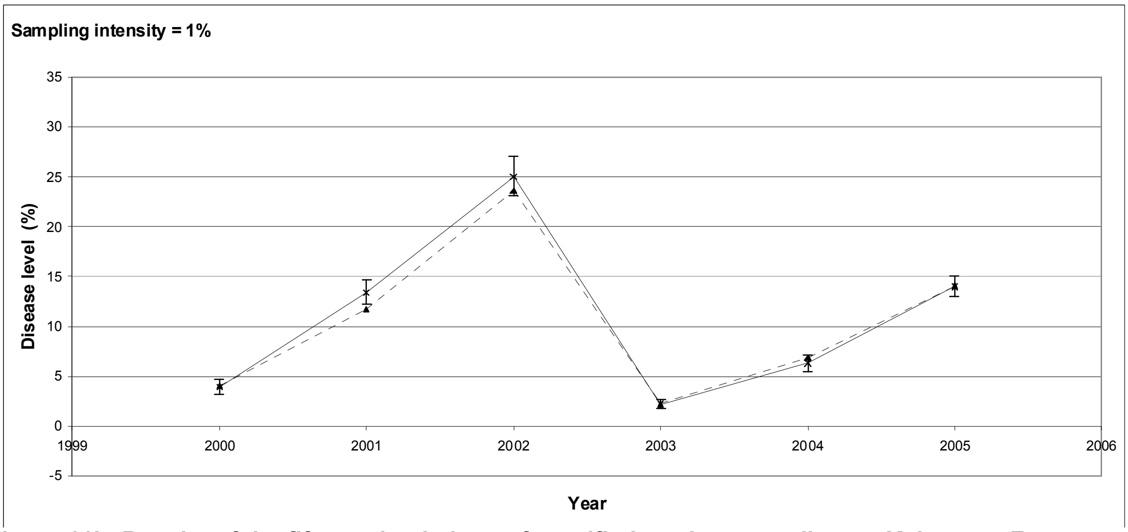


Figure 11b. Results of the fifteen simulations of stratified random sampling on Kaingaroa Forest for 2000 to 2005 for sample intensity levels 0.6 to 1%; [—×—] Simulated mean disease level; [- -▲- -] Observed mean disease level. Error bars represent uncertainty in the estimate of the mean, calculated as 1.96 * standard deviation.

Table 6. Comparison of uncertainty levels between stratified random sampling strategy with forced requirement for the sample to encompass 1 ha ("Enforced") and stratified random sample with relaxed requirement for the sample to encompass 1 ha ("Relaxed") for years 2000 to 2005.

	0.1%		0.2%		0.4%		0.6%		0.8%		1%	
Year	Forced	Relaxed	Forced	Relaxed	Forced	Relaxed	Forced	Relaxed	Forced	Relaxed	Forced	Relaxed
2000	3.83	1.17	2.25	1.14	1.38	1.46	1.08	0.72	0.84	0.97	0.79	0.84
2001	7.38	3.13	3.14	2.67	2.72	1.84	1.27	1.26	1.10	1.64	1.23	0.96
2002	6.29	3.52	5.21	3.71	3.55	2.71	2.45	2.44	1.44	1.91	1.99	1.75
2003	2.52	0.64	1.63	1.40	1.02	0.81	0.71	0.52	0.47	0.42	0.41	0.53
2004	3.22	1.97	2.21	1.67	1.51	1.26	1.07	1.53	0.92	0.83	0.89	0.96
2005	4.25	2.27	3.45	3.10	1.64	1.46	1.39	0.82	1.09	1.06	1.02	1.26

Comparison of the precision of the sampling strategies

Figure 12 indicates the precision of disease estimates (calculated from simulations on 6 years) of the four sampling strategies (random, regular and stratified random with and without restriction) for each level of sample intensity. The regular and stratified random without restriction sampling strategies appear to give the most precise results over the lower levels of sampling intensity. Whilst a sampling intensity of 1% give estimates with less uncertainty and less precision error, there is only a slight gain in precision between a sampling intensity of 0.4% and 1% with the regular and stratified random without restriction sampling strategies. The stratified random and random strategies have similar patterns of precision errors, decreasing as the intensity of sampling increases up to 0.8%, where all methods converge. It is interesting to note that despite the problem of "under-sampling" described above, the stratified random sampling strategy performed as well as random sampling. This under-sampling bias decreased with the increase of the area sampled in the source data. This result highlights the scale-dependent nature of this problem. The precision errors of the stratified strategy without size restriction are probably a better indication of how the stratified random sampling strategy can perform when the size of the stratification mesh is larger compared with the fraction of very small blocks. It appears that the stratified random sampling strategy without any size requirement performs better than the regular strategy at the 0.1% intensity, and as well as it at the other intensities tested.

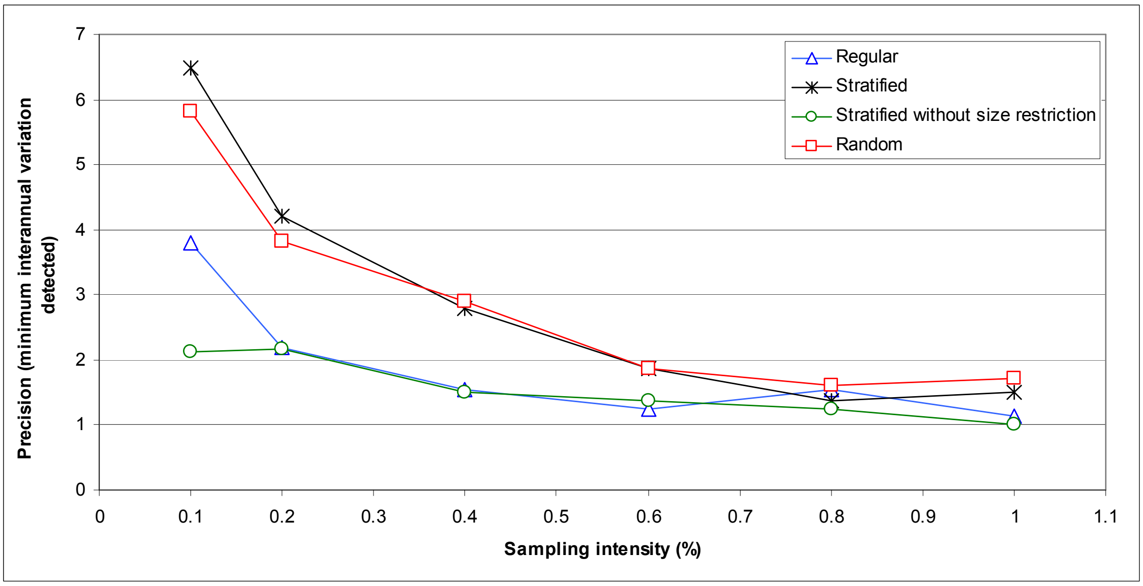


Figure 12. Relationship between the mean precision (6 years * 15 replicates) of the three sampling strategies (random, regular and stratified) and sampling intensity.

The costs of attaining a given level of precision of disease estimates are given in Figure 13. These costs are provided as an approximate indication of the total costs of surveying the plantation forest estate at each level of survey effort and the corresponding level of precision of the disease estimates.

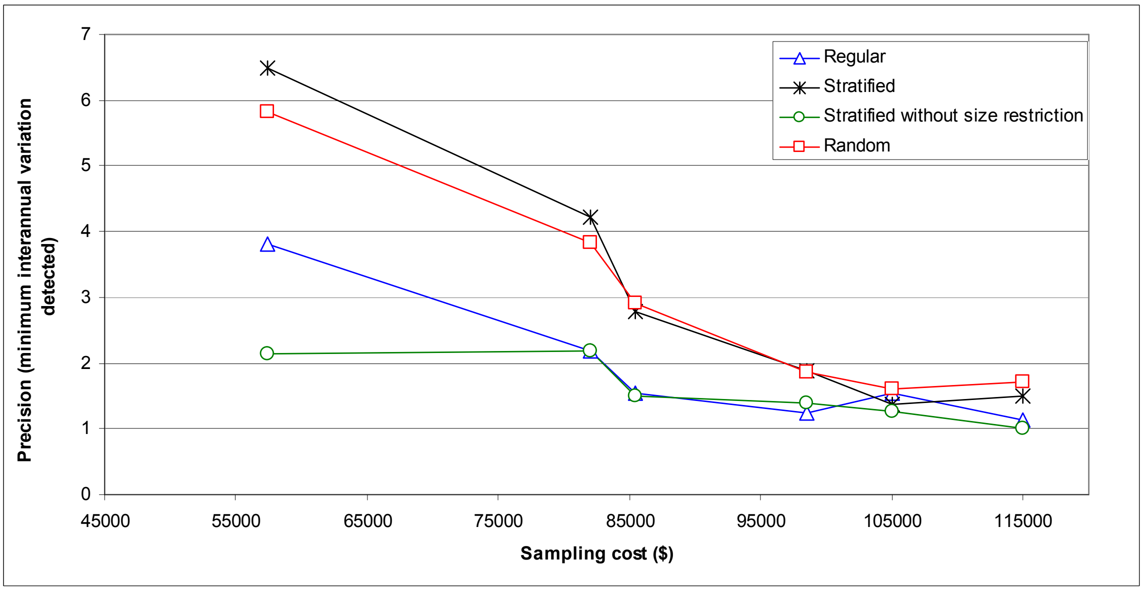


Figure 13. Average cost of survey *versus* mean precision (6 years * 15 replicates) of the three sampling strategies (random, regular and stratified)

Pest Spread Detection

Random sampling

Figure 14 gives an example replicate of a simulation of a random surveillance design, for each intensity of sampling, for 1 year (2000). If the pest is a species that is visible all year round, the total area colonised by the pest at first detection within the forest does not exceed 6 500ha for the lowest sampling intensity of 0.2% if the species state is obvious (Figure 15). There is a decrease in the area colonised before detection between a sampling intensity of 0.2 and 0.6% (3 200 ha for 0.4%; 2 050 for 0.6%); there is a decrease in the area colonised before detection of 150 ha between a sampling intensity of 0.6% and 1%. If the species is difficult to detect (cryptic), the area colonised before first detection reaches 52 280 ha for the lowest sampling intensity of 0.2% and largely decreases up to 0.6% of sampling intensity for which the area colonised is around 15 000 ha. The total area colonised before first detection decreases by 5 000 ha between 0.6 and 1% of sampling intensity.

Considering an obvious seasonal pest species, the total area colonised by the pest before it is first detected is around 28 600 ha for the lowest sampling intensity. The area colonised decreases to 14 000 ha and 9 200 ha for sampling intensity of 0.4% and 0.6% respectively. The area colonised before detection decreases by 4 300 ha between a sampling intensity of 0.6% and 1%. If the seasonal species is cryptic, the probability of detecting it early appears very low. The total area colonised before first detection reaches 91 000 ha at the lowest sampling intensity and decreases almost linearly to 38 900 ha colonised for the maximal sampling intensity of 1%.

The **plantation forest** area colonised by Argentine Ant before first detection is 86 ha when the largest sampling effort is applied in combination with the highest probability of detection (annual-obvious species/1% sampling effort) and it increases to 300 ha with a sampling intensity of 0.2% (Figure 15). The forest area colonised at the time of detection is higher for seasonal-obvious, annual-cryptic and seasonal-cryptic species (1 980 ha, 2 820 ha and 5 450 ha respectively for a sampling intensity of 0.2% and 270 ha, 490 ha and 2 140 ha for 1%).

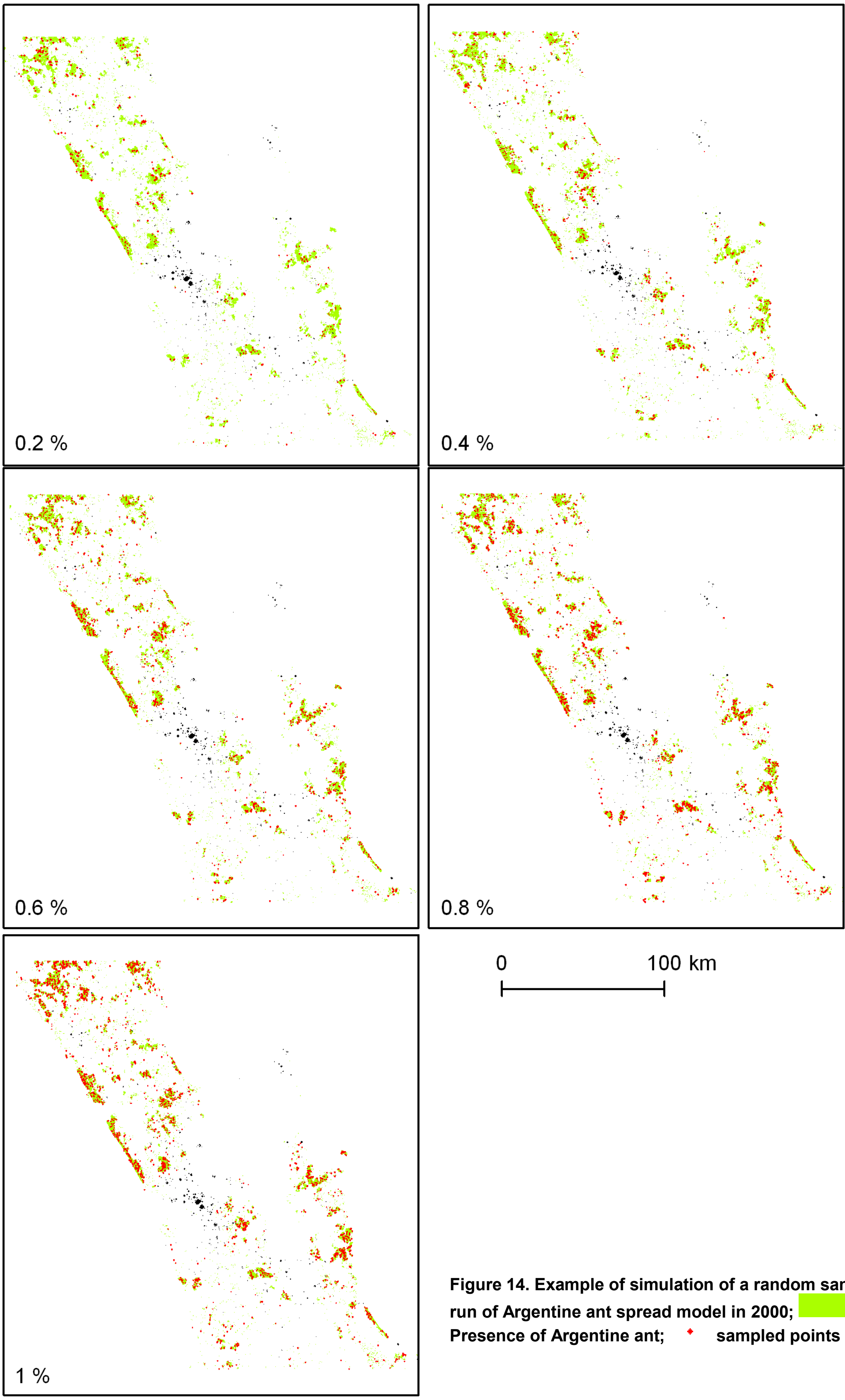


Figure 14. Example of simulation of a random sampling on a run of Argentine ant spread model in 2000; Forest; Presence of Argentine ant; sampled points

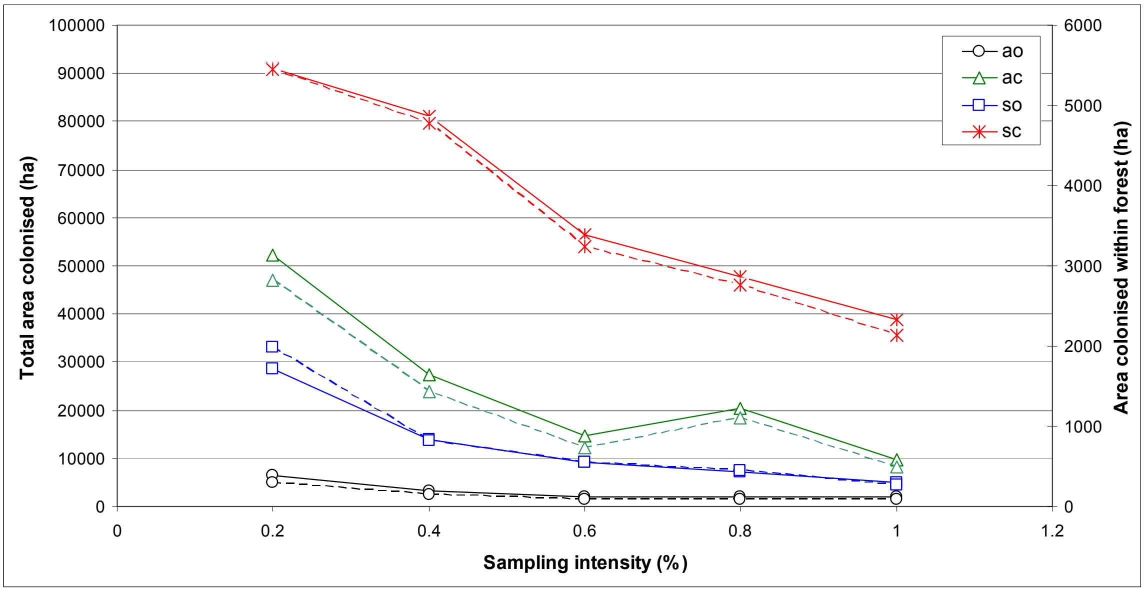


Figure 15. Results of ten simulations of random samples of 5 spread scenarios from the Argentine ant spread model: total area (hard line) and forest area (dashed line) covered by Argentine ant when first detected for different sample intensity levels; ao = annual obvious; ac = annual cryptic; so = seasonal obvious; sc = seasonal cryptic.

Regular sampling

Figure 16 gives an example replicate of a simulation of a regular surveillance design, for each sample intensity for 1 year (2000). Considering annual obvious, annual cryptic and seasonal obvious pest species, there is almost a linear decrease of the total area colonised by the pest when first detected (Figure 17). Total area colonised is around 2 500 ha when the largest sampling effort is applied in combination with the highest probability of detection (annual obvious species/1% sampling effort) and it increases up to 11 000 ha with a sampling intensity of 0.2%. The total area colonised is higher for seasonal obvious and annual cryptic species (27 300 ha and 46 450 ha respectively for a sampling intensity of 0.2% and 6 200 ha and 10 500 ha for 1%). The total area colonised by a seasonal cryptic pest before it is first detected dramatically decreases between sampling intensities of 0.2% and 0.4% (118 000 ha vs 64 800 ha) but increasing the sampling effort to 1% only decreases the area colonised slightly further (52 150 ha).

The average area of **plantation forest** colonised by Argentine Ant at the time of first detection is 114 ha when the greatest sampling effort (1%) is applied in combination with the highest probability of detection, and this area increases to 521 ha with a sampling intensity of 0.2% (Figure 17). These values are higher than with the same effort applied with a random sampling design. The forest area colonised is higher for seasonal-obvious, annual-cryptic and seasonal-cryptic species (1 475 ha, 2 731 ha and 7 382 ha respectively for a sampling intensity of 0.2% and 282 ha, 564 ha and 2 966 ha for 1%).

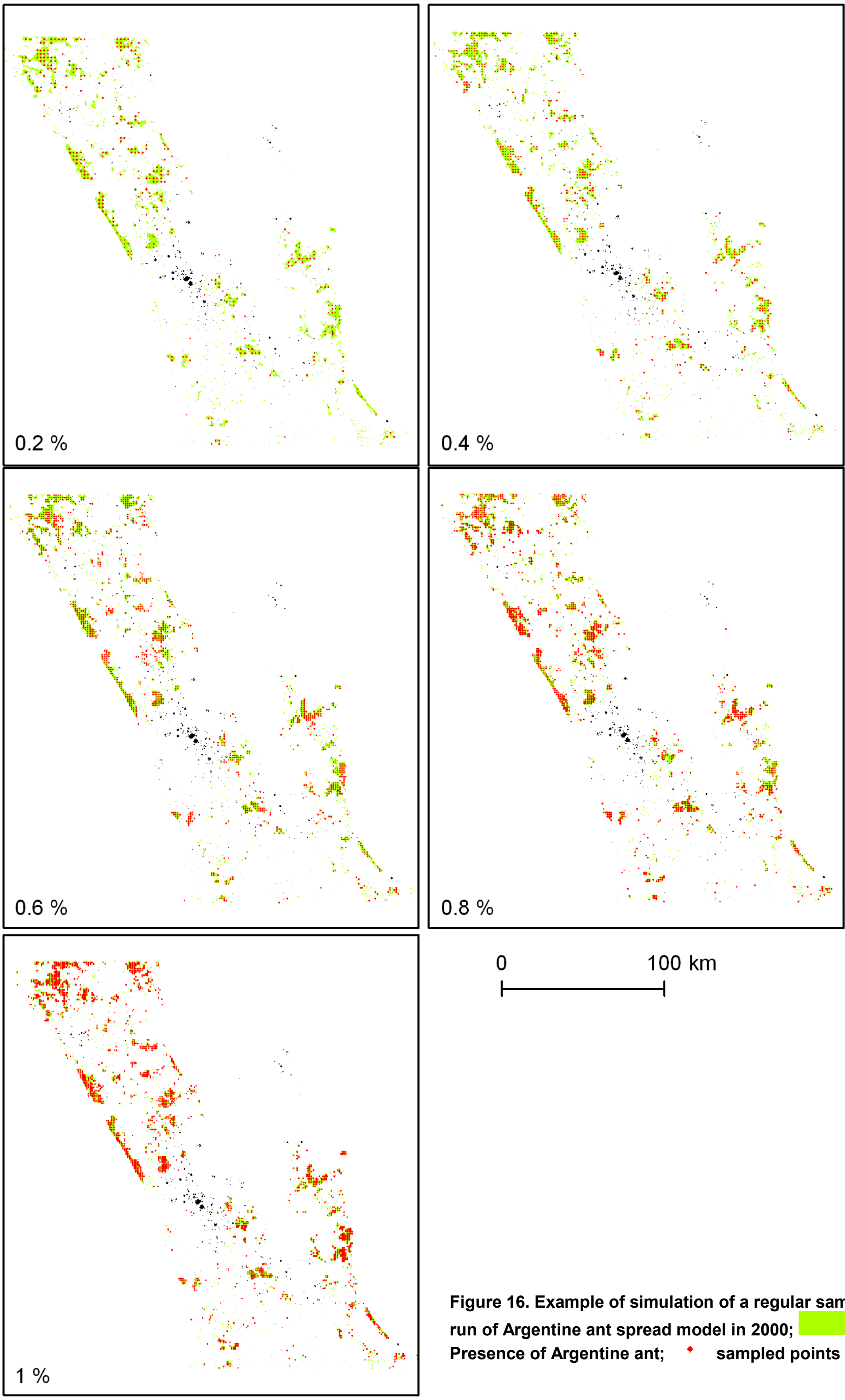


Figure 16. Example of simulation of a regular sampling on a run of Argentine ant spread model in 2000; Forest; Presence of Argentine ant; sampled points

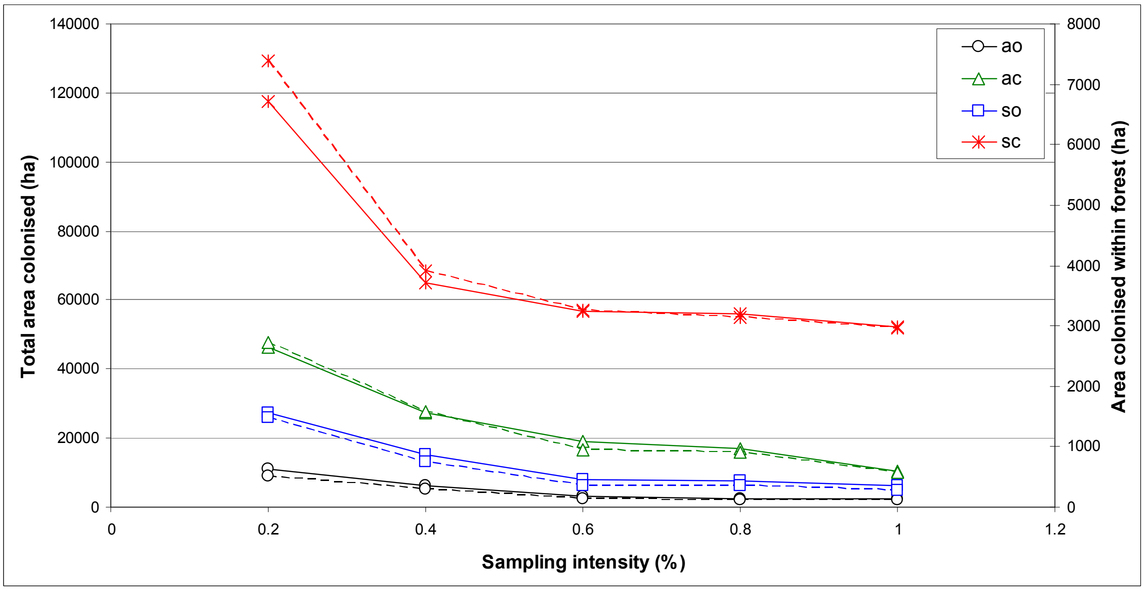


Figure 17. Average results of ten simulations of regular sampling on 5 spread scenarios from the Argentine ant spread model: total area (hard line) and forest area (dashed line) colonised by Argentine ant when first detected for different sample intensity levels; ao = annual obvious; ac = annual cryptic; so = seasonal obvious; sc = seasonal cryptic

Comparison of the effective costs of the sampling designs

The benefits of detecting a pest early can be gauged in terms of the amount of sampling effort by consulting Figure 18. Whilst the costs of surveying will change through time, the relationship between area colonised and the survey effort should remain constant. In this figure the infestation areas for the detectability classes have been averaged in order to provide a general indication of the areas involved across a range of species that vary in their detectability. It is unclear however what proportion of the invasive fauna would fall into each of the detectability classes.

To assist in gauging the costs and benefits of surveying effort, sampling intensity has been translated into present values (2008) for New Zealand dollars (Figure 19). The costs per survey site used here are indicative, and necessarily approximate, and should not be used for detailed planning purposes.

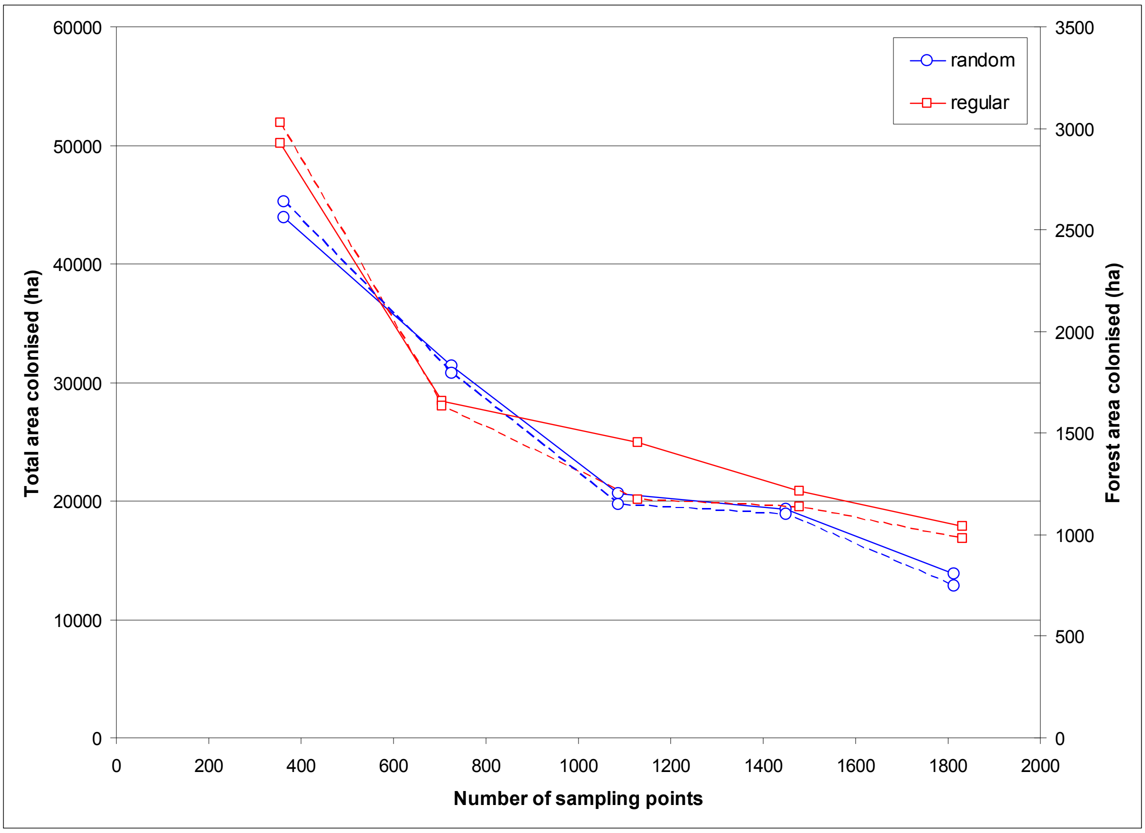


Figure 18. Average number of sample points vs total area (hard line, left-hand axis) and forest area (dashed line, right-hand axis) colonised by Argentine ant at the time of detection for the random and stratified sampling strategies. Values have been averaged across the detectability classes.

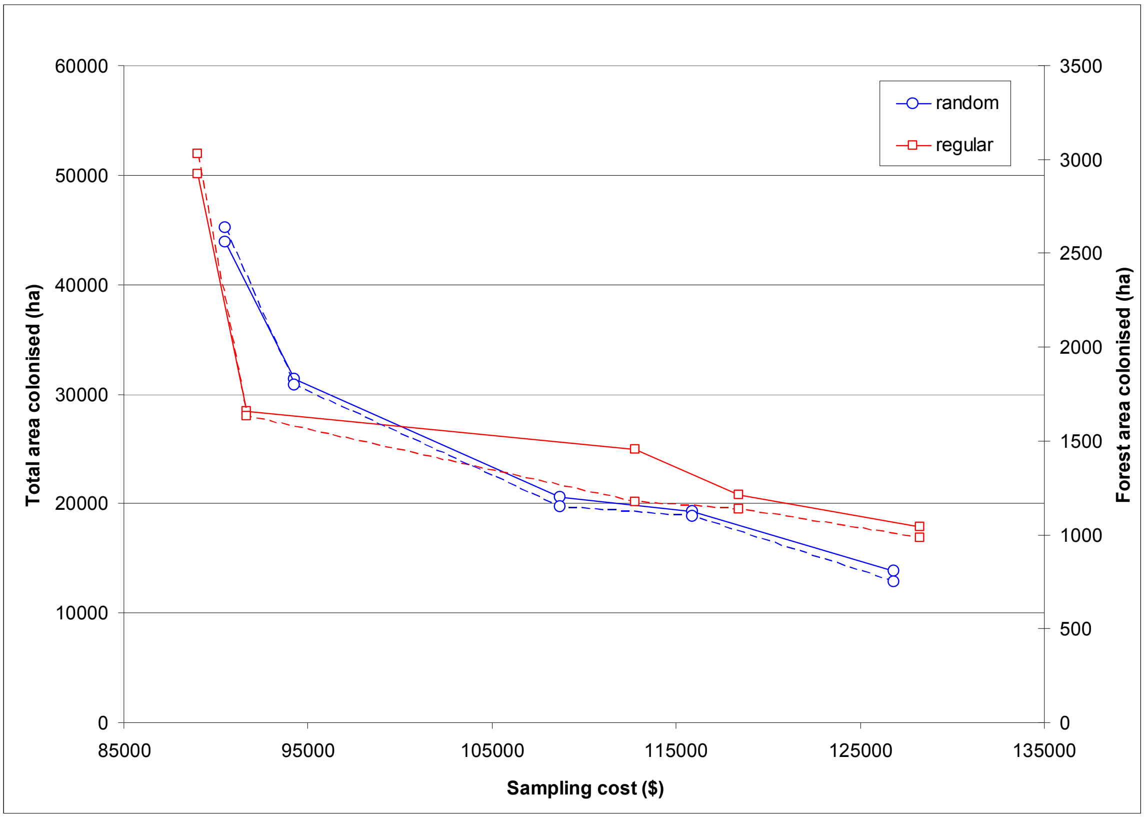


Figure 19. Average cost of survey *versus* total area (hard line, left-hand axis) and forest area (dashed line, right-hand axis) colonised by Argentine ant at the time of detection for the random and stratified sampling strategies. Values have been averaged across the detectability classes.

DISCUSSION

Forest Health Condition Monitoring

The precision associated with each sampling technique clearly varies in a non-linear manner (Figure 12). This precision estimate indicates the minimum inter-annual variation in average disease levels that could be reliably detected using each of the assessed techniques. It is possible therefore to consider the decisions that hinge upon the annual estimates that will be derived using this scheme, and to assess the impacts of different precision levels on those decisions. These impacts can then be traded off against the costs of undertaking sampling at each level of intensity.

The regular sampling strategy appears to be the best performing strategy for estimating forest health status, particularly at lower sample intensity levels, with little improvement at intensities above 0.4%. The regular sampling approach would also capture some internal variation within moderate to large stands.

The effectiveness of random and stratified random sampling of stands *with replacement* could not be tested using the present sampling framework. Because the source data included only a single value per stand, no spatial variation *within* a stand is available. A simulation of random or stratified sampling *with replacement* would not therefore provide relevant evidence of the performance of a “with replacement” strategy under all field conditions because there is no fine scale spatial information in our dataset available to be sampled. A *with replacement* strategy could decrease the breadth of the forest sampled, slightly increasing the risk of missing special patterns in the distribution of health problems (e.g. outliers or rare phenomena) but it could provide valuable information about finer scale patterns within stands.

The present results are limited by the nature of the underlying baseline data. Because it was sampled at a stand level means that the advantages of random sampling for generating unbiased estimates of mean values may be under-represented.

Despite the comparatively poor performance of the stratified random strategy due to the source data on which simulations were run, the mean precision of this strategy is as good as the random strategy with a sampling intensity > 0.4%. The stratified random sampling strategy without any size requirement indicates that the stratified strategy performs better than the regular strategy at very low sample intensities, and as well as it at higher intensities. In practice, the stratified random sampling approach is likely to cause difficulties due to the splitting of stands into four or even more sub-units based on the stratification cells. In addition, it is more time consuming to establish the sampling maps.

Although not explored in this project, status and trend monitoring techniques may also be of more value for this system (e.g., US EPA Statistical Primer, http://www.epa.gov/bioiweb1/statprimer/sampling.html). This technique has also been described as sampling with partial replacement (Patterson 1950). The s*tatus* of a forest is generally best sampled using a set of sites that are randomly selected each period (year). However the *trend* in a resource such as a forest is best assessed by selecting a set of sites using a random or regular system in the first period, and then revisiting those sites each year. In order to capture the best attributes of each of these approaches, it is possible to combine them, selecting some sites randomly each year, whilst maintaining a set of trend sites. In fact, this was an element of the surveillance system proposed by Bulman and Kimberley (2005). The statistical methods developed for status and trend monitoring draw on the strengths of each of the status and trend sub-datasets to provide an efficient means of estimating each of the attributes. Scott (1998) describes the development of the status and trend methods, and how they can be applied to forest monitoring.

Pest spread detection

The extent of a biological invasion before the unwanted organism is detected has a critical effect on the probability of success of an eradication programme. In the case of the Argentine ant simulations, it is apparent that the forest health surveys would be wholly inadequate to detect an invasive pest prior to it reaching population levels that preclude eradication. This is because the point of origin of the Argentine ant population was in Auckland, where there are no commercial forests that would be surveyed under the system being discussed here. Given the geographical isolation of New Zealand, the most likely pathway for pests to arrive is via sea or air transport into the international or regional ports and devanning sites. These areas have been identified by MAF Biosecurity New Zealand as the high risk areas. Whilst these areas may not have commercial forests immediately adjacent, they do have a wide variety of suitable hosts for forest pests in the form of amenity plantings of either commercial forest species or closely related species. It seems clear from this study that adequate pest detection for forest pests will require complimentary survey effort in the high risk zones.

The partitioning of the area invaded into forest and non-forest regions (Figure 17) indicates the value of pest detection surveillance conducted in the forests. This indicates the extent to which the forests would be directly affected prior to the detection of the forest pests. From these figures, given estimates of per tree pest damage it is possible to estimate the immediate direct costs of a pest incursion into the forests.

In the analyses where we considered only the area of forest infested by the pest at the time of first detection, the relationship between the area infested and survey intensity is likely to apply in the event where a pest arrives in a plantation forest via air currents. Under these circumstances, the high risk site surveillance system would most likely miss detecting the pest. From Figure 17 it appears that at a sample intensity of 0.6% it is possible to detect such pests when their infestation areas are sufficiently small that it may be technically possible to eradicate them, or at least respond with a set of management controls before severe economic damage is inflicted. Nonetheless, the probability of a pest first establishing in a forest is very much less than that of establishing near ports and devanning sites. This is borne out by the fact that between 1 January 2003 to 31 December 2007, most new to New Zealand pests have been detected firstly in high risk site surveillance or special surveys (14) compared with just 2 within forests (Lindsay Bulman, Scion, Forest Health Database, unpub. data). The relative amount of effort spent detecting pests in forests and high risk sites should probably reflect this pattern, with the majority of effort being expended in the high risk site surveillance. The historical pattern of invasion indicates that the human-mediated transport of pests is a more potent route for invasive alien organisms to establish in New Zealand. However, the potential for aerial dispersal of pests from southeastern Australia is a direct threat to the plantation forests of New Zealand. A complete reliance upon the high risk site surveillance system to detect newly arrived pests would leave the plantation estate more vulnerable to invasion by aerially dispersed organisms.

CONCLUSIONS

Considering both the forest health estimate and pest detection purposes of the forest health surveillance system, it would appear that there are marked increases in performance of the system up to a survey intensity to 0.5%. Beyond 0.5% the increased benefits of increased search efforts are marginal. There is little difference between the performance of regular or stratified random survey (without size restriction) methods for forest health condition monitoring. Within the timeframe available for this project, we were unable to assess the performance of the stratified random sampling effort as a system for pest detection. It is likely that the stratified random system would perform similarly to the regular system for pest detection. The main difference would appear to be the significant extra effort required to stratify the survey at a resolution of 1 000 ha. It may also be the case that the regular surveying system is more efficient for field application insofar as the pattern of points to be surveyed lends itself clearly to a sampling route composed of a series of parallel transects. A regular survey also lends itself to taking on longitudinal study objectives, which may be an attractive property as we seek to address climate change issues, and we need to track changes in forest properties through time.

ACKNOWLEDGEMENT

Mr Joel Pitt generously allowed us to utilise modelled spread data for Argentine ant from his PhD study. Dr Mike Watt made useful comments on a draft of the report.

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