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Simulation to investigate site-based monitoring of pest insect species for trade

Rieks D. van Klinken[1,*], Daniel W. Gladish[2], Nicholas C. Manoukis[3], Peter Caley[4], Matthew P. Hill[5]

[1]CSIRO Health and Biosecurity, GPO Box 2583, Brisbane, QLD 4001, Australia, [2]CSIRO Data61, GPO Box 2583, Brisbane, QLD 4001, Australia, [3]Tropical Crop and Commodity Protection Research Unit, Daniel K. Inouye U.S. Pacific Basin Agricultural Research Centre, Hilo, HI, USA, [4]CSIRO Data61, GPO Box 1700 Canberra, ACT 2601, Australia, [5]CSIRO Health and Biosecurity, GPO Box 1700, Black Mountain, ACT 2601, Australia *Corresponding author, mail: Rieks.vanKlinken@csiro.au

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Pest insect surveillance using lures is widely used to support market access requirements for traded articles that are hosts or carriers of quarantine pests. Modeling has been used extensively to guide the design of surveillance to support pest free area claims but is less commonly applied to provide confidence in pest freedom or low pest prevalence within sites registered for trade. Site-based surveillance typically needs to detect pests that are already present in the site or that may be entering the site from surrounding areas. We assessed the ability of site-based surveillance strategies to detect pests originating from within or outside the registered site using a probabilistic trapping network simulation model with random-walk insect movement and biologically realistic parameters. For a given release size, time-dependent detection probability was primarily determined by trap density and lure attractiveness, whereas mean step size (daily dispersal) had limited effect. Results were robust to site shape and size. For pests already within the site, detection was most sensitive using regularly spaced traps. Perimeter traps performed best for detecting pests moving into the site, although the importance of trap arrangement decreased with time from release, and random trap placement performed relatively well compared to regularly spaced traps. High detection probabilities were achievable within 7 days using realistic values for lure attractiveness and trap density. These findings, together with the modeling approach, can guide the development of internationally agreed principles for designing site-based surveillance of lure-attractant pests that is calibrated against the risk of non-detection.

Key words: trapping, market access, quarantine pest, survey and detection

Introduction

Global trade provides substantial economic benefit to participating countries, but also provides potential pathways for numerous plant pests and pathogens (MacLachlan et al. 2021, Turner et al. 2021). A wide range of measures can be applied to manage the risk of pests entering and establishing via trade pathways (van Klinken et al. 2023, 2022). A commonly applied measure uses surveillance to provide confidence that pests are rare or absent on the registered site on which the traded article occurs (van Klinken et al. 2020, 2023). Here we refer to registered sites as production or post-production businesses that are registered for trade such as orchards, farms, transport hubs, or sites on which packing, treatment, or storage facilities are located (see van Klinken et al. 2023). These can include pest free production sites and pest free places of production as defined in ISPM 10 (IPPC Secretariat 2016a). This "registered site" measure typically requires pest surveillance (e.g., trapping), with a corrective action imposed if pest detection exceeds a corrective action threshold, and suspension of the business if it exceeds a rejection threshold (van Klinken et al. 2021). Site-based monitoring also reflects the level at which management decisions, that are often required rapidly, are undertaken (Lasa et al. 2015, IPPC Secretariat 2016a). Alternatively, an "area wide" measure can provide confidence in pest freedom or low pest prevalence across the designated area (Jang et al. 2014, IPPC Secretariat 2016b, 2017, 2018, FAO/IAEA 2018). Here, surveillance is typically undertaken across diverse land uses, and all businesses registered to trade within that area are impacted if response thresholds are exceeded.

Surveillance design is an important element of pest freedom or low pest prevalence measures applied area-wide or within a registered site as it influences detection efficacy and cost. Area-wide surveillance generally focuses on providing confidence that pests are not present within the area, or do not exceed an accepted threshold (van Klinken et al. 2023), or on the detection and delimitation of nascent populations (Caton et al. 2021). In contrast, surveillance at the scale of the registered site needs to provide confidence that both pests already in the site and pests entering the site will be detected at sufficient sensitivity, even if there is no information available on adjacent source pest populations. Evaluating the effectiveness of a given surveillance design in the field is often not practical (Venette et al. 2002, Caton et al. 2021), and results may not be transferable. Modeling has been used to support area-wide surveillance (Manoukis et al. 2014, Berec et al. 2015, Caton et al. 2021), but site-based pest modeling has focused on integrated pest management (Lux 2014) or the detection of new or emerging pests (Triska and Renton 2018), not surveillance of established pests to support market access.

Traps containing a pest-attractant lure are often the sole or a key component of surveillance (Gut et al. 2004, Jang et al. 2014, Weldon et al. 2014, FAO/IAEA 2018). Such traps only detect individuals within a population that are attracted to the trap at that point in time, and subsequently captured (Bau and Cardé 2016). The proportion of the population that is in an attractive state ("trappable") will depend on factors such as physiological status of the pest or whether the lure is sex-specific (Weldon et al. 2014, Bau and Cardé 2016). Our focus in this paper is on detection of the trappable component of pest populations within a registered site. Typically, specified pest thresholds are low when trapping is used as part of a measure to provide confidence in pest freedom or low pest prevalence. For quarantine pests that are considered high-risk, even a single pest detection can trigger a response. This contrasts with integrated pest management aimed at limiting production losses from pests where pest management action thresholds can be less stringent (Lance 2014, Drummond and Collins 2020a). The ability of surveillance to detect pests, or to estimate pest densities, can be sensitive to trapping density, and trap placement (Lance 2014, Suckling et al. 2015, Drummond and Collins 2020a). Setting standardized pest thresholds for corrective action or suspension thresholds to support trade therefore requires a consistently applied surveillance design based on an understanding of the relationship between surveillance design and pest detection sensitivity.

Other factors besides trapping density and placement also impact surveillance network sensitivity. These include the dispersal ability of the pest and lure attractiveness (Gut et al. 2004, Lance 2014, Weldon et al. 2014, Caton et al 2021). These processes therefore need to be modeled. Dispersal ability influences the probability that an individual pest will enter the attractive range of a trap. Models of pest dispersal processes are either diffusion-based or individual-based. Modeling using diffusion processes describes the daily rate of spread of a population from a central point (Manoukis et al 2014, Caton et al. 2022) and is mathematically tractable at large spatial and temporal scales relevant to modeling area-wide pest surveillance (Caton et al. 2022). However, it is not as appropriate for modeling movement of small populations into or within a site, and where pests respond to encountering suitable habitat such as an orchard. Simplification of movement means that diffusion does not represent individual trajectories, the center of the population remains the same (Caton et al. 2021), and the population continues to disperse ad infinitum so individuals are unable to respond to suitable landscape habitats. Surveillance strategies at smaller spatial scales are therefore commonly simulated by modeling pest movement as a random walk, parameterized to include responses to landscape and other environmental cues (Lux 2014, Triska and Renton 2018). An additional critical factor is lure attractiveness, which is generally parameterized to decay with distance from trap using a probability model (e.g., Manoukis et al. 2014). Both pest movement (Caton et al. 2022) and lure attractiveness (Manoukis and Gayle 2016) can be parameterized or inferred through empirical studies. However, these parameters can vary with pest and environment, so when modeling it is important to capture the likely range.

Providing confidence that pest abundance within a registered site does not exceed an acceptable threshold (e.g., pests per trap) is a key requirement for trade for many commodities (van Klinken et al. 2023). Here we test how pest detection sensitivity is affected by surveillance design when all traps can only be placed within the registered site of interest. This reflects a common constraint of site-based measures where surveillance and management can only legally or practically be undertaken within the registered site. We were particularly interested in how trap density and trap placement (random, regular, or perimeter) affected the ability to detect pests that were already present in the site versus pests that are dispersing into the site. We took a simulation approach, with lure attractiveness and dispersal parameters selected to represent a diverse range of pests that are attracted to lures, and to test the robustness of conclusions with respect to the size and shape of the site. Because our focus was on surveillance to support market access we modeled the ability to detect very low pest numbers (1, 10, and 100 individuals). We finish by discussing the implications of our study for the development of standardized principles that can be used to design surveillance as part of a measure aimed at providing trading partners confidence in pest freedom or low pest prevalence within a registered site.

Materials and Methods

Here we describe the model we used to run the simulations, and the simulations that we ran.

Pest Dispersion Model

We developed a target-trap simulation model with a probability detection function. It drew heavily on TrapGrid, a simulation model that uses trap attractiveness, the spatial position of traps, and insect movement to quantify detection probability over time at a user specified scale (Manoukis et al. 2014). Simulations allow the effect of different target–trap interactions on detection probabilities to be evaluated. An advantage of the TrapGrid approach is that the single "lure attraction" parameter in the detection function (λ) is readily interpreted and can be estimated through empirical studies of capture probability with distance (Manoukis et al. 2014, Manoukis and Gayle 2016). The instantaneous probability of capture as a function of distance (d) from a trap, defined as $p(d)$, takes the form of a hyperbolic secant function (Eq. 1).

$$p(d) = \frac{2}{e^{-\lambda d} + e^{\lambda d}} \tag{1}$$

Here, λ determines how fast trap attractiveness declines with increasing distance, with smaller values indicating a higher trap attractiveness and hence probability of capture. In practice, the model is parameterized using the reciprocal, $1/\lambda$, which represents the distance, in meters, where we expect about 0.65 probability of capture (Manoukis et al. 2014).

Our interest lies in pest detection and monitoring at the typically smaller site-based scale rather than area wide, and accommodating situations of low pest abundance. We developed a pest simulation spread and detection model using the statistical programming language R (R Core Team 2020), incorporating detection probabilities from TrapGrid where possible (e.g., Eq. 1). To accommodate low pest prevalence, we incorporated the alternative summary measure of surveillance sensitivity for probability of grid detection from Manoukis and Hill (2021). Instead of using a diffusion dispersal process which has been used with TrapGrid to date (e.g., Manoukis et al. 2014, Caton et al. 2021), we used a more flexible pest movement mechanism which can incorporate simple pest responses to the landscape. Below is a brief description of our model.

Calculating Grid Detection Probabilities

We were interested in the detection of very low pest populations as typically required for market access. Considering this, TrapGrid was recently updated so that it is possible to select a "one or more capture probability" output (Manoukis and Hill 2021). Briefly, this changed the way the model calculates escape probability from the *average escape probability* in the original implementation, to one that considers the *probability that all insects escape detection*.

We took this approach to calculate the probability of a trapping array detecting at least 1 pest as the complement of detecting none of the pests residing in the site at any stage during the trapping period. Let p_{ijk} be the probability of the ith pest being captured in jth trap on kth day following Eq. (1). Then the surveillance sensitivity of the trap grid to detect at least 1 pest is calculated as:

$$P\,(\textit{At least one pest detected}) = 1 - P\,(\textit{No pests detected in any traps on any day}) = 1 - \prod_i \prod_j \prod_k (1 - p_{ijk}) \tag{2}$$

Dispersal process. We implemented a random walk process for insect movement using a daily time step. Noting that insect pests may make several movements in a day, we assumed a position jump process is valid on the daily time scale (Othmer et al. 1988) and thus an uncorrelated random walk is valid (Codling et al. 2008). We implemented a 2D modified simple random walk with the added condition that the pest cannot leave the registered site as we were interested in pest detection within the site. Specifically for a pest at position $s_t = (x_t, y_t)$ at time t, the position at the next daily time step s_{t+1} was determined by:

$$\begin{aligned} x_{t+1} &= x_t + r_{t+1}\cos(\theta_{t+1}) \\ y_{t+1} &= y_t + r_{t+1}\sin(\theta_{t+1}), \end{aligned} \tag{3}$$

where r is the step length simulated from a uniform distribution from 0 to $2R$ with R the mean step size for a given pest (see Pest Parameters Section below), and θ the turning angle generated from a uniform distribution from 0 to 2π. Pest outbreak locations were started either inside or outside the site. We note that Eq. (3) is 1 parameterization of an uncorrelated random walk. However, we also allowed pest movement to respond to the landscape (see below), and so our implementation was not completely unbiased.

We included a simple landscape level response to ensure that pests released outside of the site would quickly enter the site, and that any pests already in the site could not leave. Pests seeded outside the site were only seeded at most R meters away from the site boundary. To ensure pests entered the site, if the resulting s_{t+1} location from Eq. (3) was more than R meters away from the site, a new location was generated. For pests inside the site, if the resulting s_{t+1} location led the pest outside the site boundary, a new location was also generated until s_{t+1} resided inside the site. This is similar to the method employed in Drummond and Collins (2020b) and simulates a site that is highly suitable to the pest and is surrounded by poor habitat.

Pest Detection Simulation

To investigate pest detection sensitivity of trap arrangements, we created multiple scenarios for simulation. Critically, we investigated the pest detection of three different trap arrangements within scenarios that vary the number and attractiveness of traps, shape and size of the site, location and size of the pest outbreak, and movement of the pest insect. Table 1 shows the associated parameter values considered for our simulations. We describe more details of the individual parameters below.

Trap parameters.

Three parameters are related to traps: trap arrangement, lure attractiveness, and trap density.

We compared three trapping arrangements: random, regular, and perimeter (Fig. 1). The "random" trap arrangement placed traps randomly around the site with the only constraint being that traps are not within 1 m from each other to ensure they are not placed over one another. The "regular" trap arrangement placed traps in a grid formation throughout the site, by rasterizing the site with a resolution such that the number of cells within the boundary equals the desired number of traps that are located at the center point of each cell. In doing so, traps are placed in an equidistant grid arrangement. Note that this meant no constraint was used on closeness to the perimeter. For the "perimeter" trap arrangement, traps were placed equidistantly on the perimeter of the site, and would be expected to be more efficient at detecting pests entering the site (Mangel et al. 1984).

Estimates of lure attractiveness (1\λ) have been made through field experiments. In the examples we are aware of, Manoukis et al. (2015) estimate 14 m for lure attractiveness of Tri-medlure to *C. capitata* and 36 m for methyl eugenol to Oriental fruit fly (*Bactrocera dorsalis*), and Manoukis and Gayle (2016) estimate lure attractiveness of cuelure to melon fly (*B. cucurbitae*) at 27 m. For our analysis, we consider lure attractiveness of 14 m and 36 m as well as the midpoint between 2 of 25 m (representing an approximation of cuelure). We also included 5 m which corresponds to very low attractiveness (Caton et al. 2021) and 50 m to represent a hypothetical, extremely attractive lure (Table 1).

Table 1. Parameters and parameter values included in simulations

Simulation scenario settings		
Object	Parameter variable	Values
Site	Size	10, 20, 50, 100 ha
	Shape	Square, triangular, quadrilateral, pentagonal
Traps	Arrangement	Regular, random, perimeter
	Number	0.1, 0.2, 0.5, and 1 trap per ha
	Lure attractiveness (1/λ)	5, 14, 25, 36, and 50 m
Pests	Outbreak origin	Inside site, outside site
	Mean step length (R)	20 m, 43 m, 63 m
	Number	1, 10, 100 pests

This resulted in 17,280 unique combinations of parameters.

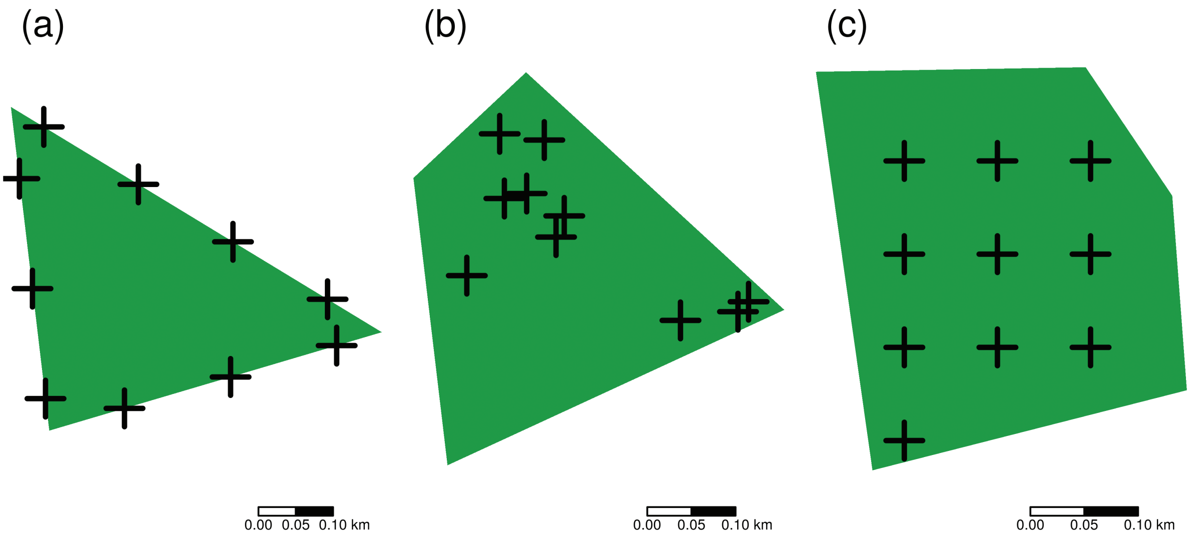

Fig. 1. Examples showing different site shapes and trap arrangements for a 10-ha block with 1 trap/ha. a) Shows a perimeter trap arrangement on a triangular site, b) shows random trap arrangement on a quadrilateral site, and c) shows regular trap arrangement on a pentagonal site. Not shown is the square site shape.

Increasing trap density generally results in higher probabilities of pest detection (Caton et al. 2021), but can also be more costly. We investigated 4 trap densities, from 0.1 to 1 trap ha^{-1} (Table 1).

Site parameters.

The shape and size of sites are expected to vary considerably between registered sites. Thus we considered 4 different site shapes: triangular, square, quadrilateral (non-square), and pentagonal; and 4 sizes (10–100 ha) (Table 1). For a given shape and size, we then generated a random boundary. This was done first by determining the radius of a circumscribed circle of a regular polygon of the shape along with the associated angles of the vertices of that regular polygon. We then generated random distances and angles (for all except the square) from a Gaussian distribution with means of the initial radius and angle. Finally, we scaled the vertexes in space to achieve the desired area. Note that for different combinations of parameters, a new shape was generated, resulting in multiple forms for the non-square shapes.

Pest parameters.

We examined 3 parameters that are directly related to the pest: origin of outbreak, mean daily dispersal step size (which in turn informs r in Eq. (3)), and number of pests released (Table 1).

Origin of outbreak was used to test how surveillance design affected the probability of detecting outbreaks initiated within and outside the site. Outbreaks inside the site were initiated by choosing a random release location inside the site. Initiation outside the site was done by releasing within a distance R from the boundary (see Dispersal Process above).

To test the effect of mean daily dispersal (R) on probability of detection we used values estimated from trapping data over a 30-day period for the European grapevine moth *Lobesia botrana* (20 m), *C. capitata* (43 m), and *B. dorsalis* (63 m) (Caton et al. 2022). Actual step size for a given day was determined using Eq. (3).

The effect of release size on detection probability was tested by comparing releases of 1, 10, and 100 individuals to represent the presence of very low pest numbers.

Simulation and analysis.

For the 8 variables described above, we ran 1 simulation for all possible specified parameter combinations, resulting in 17,280 pest simulation scenarios. For each of the 17,280 scenarios, 50 simulations were run that started at a random point either inside or outside the site (a total of 864,000 simulation runs). Each simulation stepped through 21 days.

To explore the impact of each parameter on the probability of detection, we utilized a random forest model (Breiman 2001) fit using the "ranger" package (Wright and Ziegler 2017) in R. We used all 8 simulation parameters described above as input values predicting the probability of pest detection. Because our simulation incorporated a temporal component, we fitted random forest models on simulation results at weekly intervals (Day 0, 7, 14, and 21), which is a common trap-servicing interval, and for the combined output from Days 0, 7, 14, and 21. The combined model incorporated a ninth predictor which we refer to as "Day", accounting for the day of the simulation. In addition, for inferential analysis, we fitted a generalized linear model, the details of which are found in the Supplementary Material.

Results

The fitted random forest models explained 69.1%, 64.3%, 64.3%, 64.0%, and 73.3% of the variation in probability of pest detection for Day 0, Day 7, Day 14, Day 21, and combined Days 0, 7, 14, and 21.

The variable importance plot of the resulting random forest models showed general agreement between models (Fig. 2). Lure attractiveness, release size, and trap density were the most important variables, and site shape, mean step size, and site size the least important, irrespective of time since release.

Time since release was the second most important variable in the combined model (0.076). This was reflected in the changing importance of individual variables through time. The importance of lure attractiveness, outbreak origin, and trap arrangement was greatest at Day 0, prior to dispersal being initiated in the model, and then reduced through time. This reflects the instantaneous probability of the pest being released within an attractive radius of a trap. Mean step size was the least important variable for Day 0 unlike the other random forest models.

Site Size and Shape

The shape and size of sites had little effect on detection probability (Fig. 2). Probability of detection after 7 days did show more variability over site sizes, particularly when trapping density was low (0.1–0.2 traps per ha) (Supplementary Figure S1). Site shape had little effect on probability of pest detection regardless of lure attractiveness or trap density. Neither variable was considered further in the following analyses.

Number of Pests Released

Individuals released outside the site quickly entered as expected (Supplementary Figure S2), with 89.9% of pest individuals in all simulations entering the site by Day 7. Unsurprisingly the number of pests had a large effect on probability of detection, irrespective of time since release (Fig. 3). When a single pest was released, median detection was 69.1% (5th quantile = 3.8%; 95th quantile = 100.0%) compared to 99.7% (24.3–100%) for 10 pests and 100% (58.8–100%) for 100 pests. However, there was an interaction with pest origin and trap arrangement. The probability of detection after the release of 1 or 10 pests was most sensitive to pest origin and trap location, with greatest detection rates of pests released within the site using a regular trapping array and pests released outside the site with a perimeter array. When 100 pests were released, there was always a high probability of detection by Day 7, irrespective of whether pests were released within or outside the site, or how traps were placed. The 10-pest scenarios are examined more closely below.

Step Size, Lure Attractiveness, and Trapping Density

The time-dependent probability of detection increased with lure attractiveness, mean step size, and trapping density (Fig. 4).

As expected from the parameter importance (Fig. 2), lure attractiveness and trapping density had the greatest effect on pest detection. At Day 0 detection probability ranged from at or close to zero when lure attractiveness was very low (5 m), irrespective of trap density, to almost 100% when lure attractiveness was very high (50 m) and trap density was high. That is, only a small part of the site is within the attractive radius of a trap when lure attractiveness is very low, resulting in a very low probability that an individual will be detected without subsequent dispersal. Conversely, when lure attractiveness and trapping density is high then a pest was almost always within the attractive range of a trap, even before step-dispersal was initiated in the model.

After 21 days the mean probability of detection only reached 77% at the highest trapping density when lure attractiveness was very low (5 m), but always approached or reached 100% when lure attractiveness was very high (50 m) (Fig. 4). At intermediate lure attractiveness (14, 25, or 36 m) detection probability approached 100% provided trap density was sufficiently high.

Detection probabilities did increase with mean step size after pest release, but this was most apparent when lure attractiveness and trap densities were low. Furthermore, the biggest increase in detection probability was between mean step sizes of 20 and 43, with little further increase in mean step size to 62.5 even after 21 days (Fig. 4). Mean step size above 20 m had no effect when lure attractiveness reached 25 m and trap density reached 0.5 traps/ha (Fig. 4).

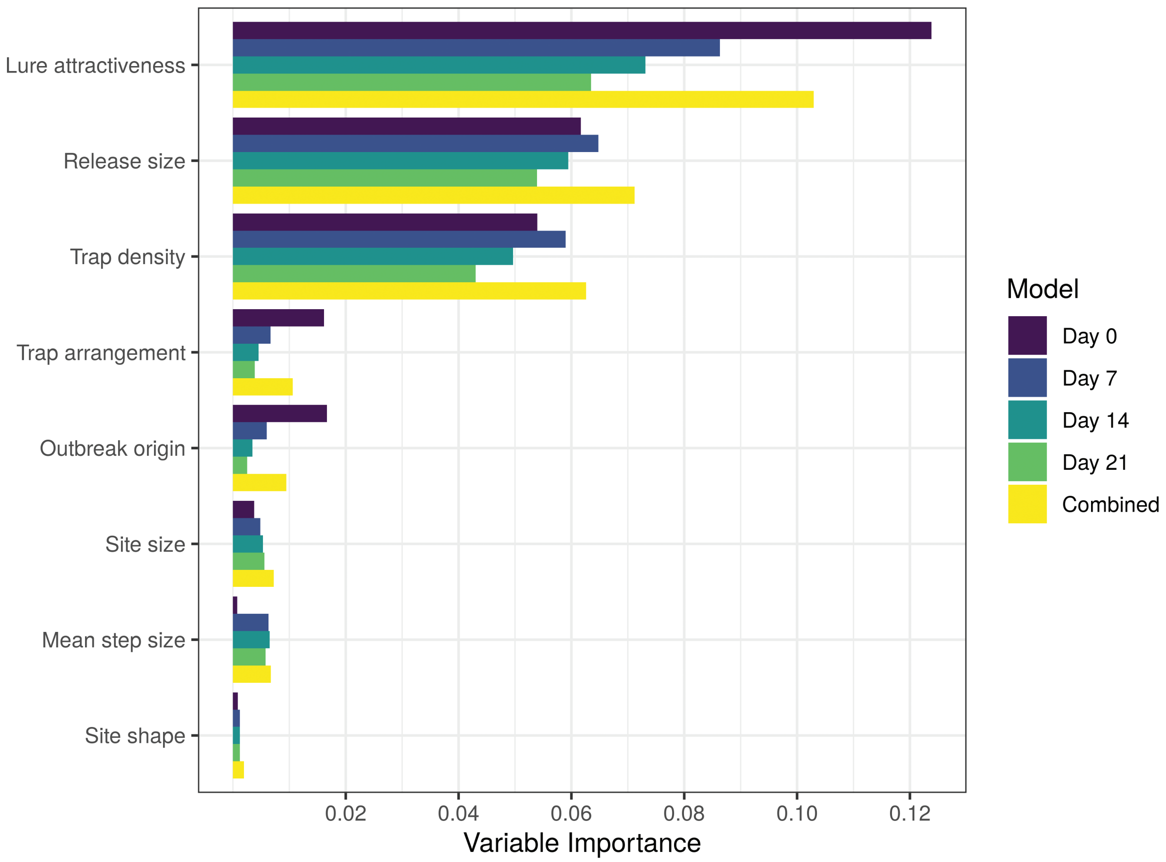

Fig. 2. Variable importance plot of the 8 simulation parameters by mean squared error for the random forest models using Days 0, 7, 14, 21 and combined Days 0, 7, 14, and 21 simulation output. Parameters are ordered based on combined random forest model. The added "Day" parameter for the combined random forest model is not included in this plot.

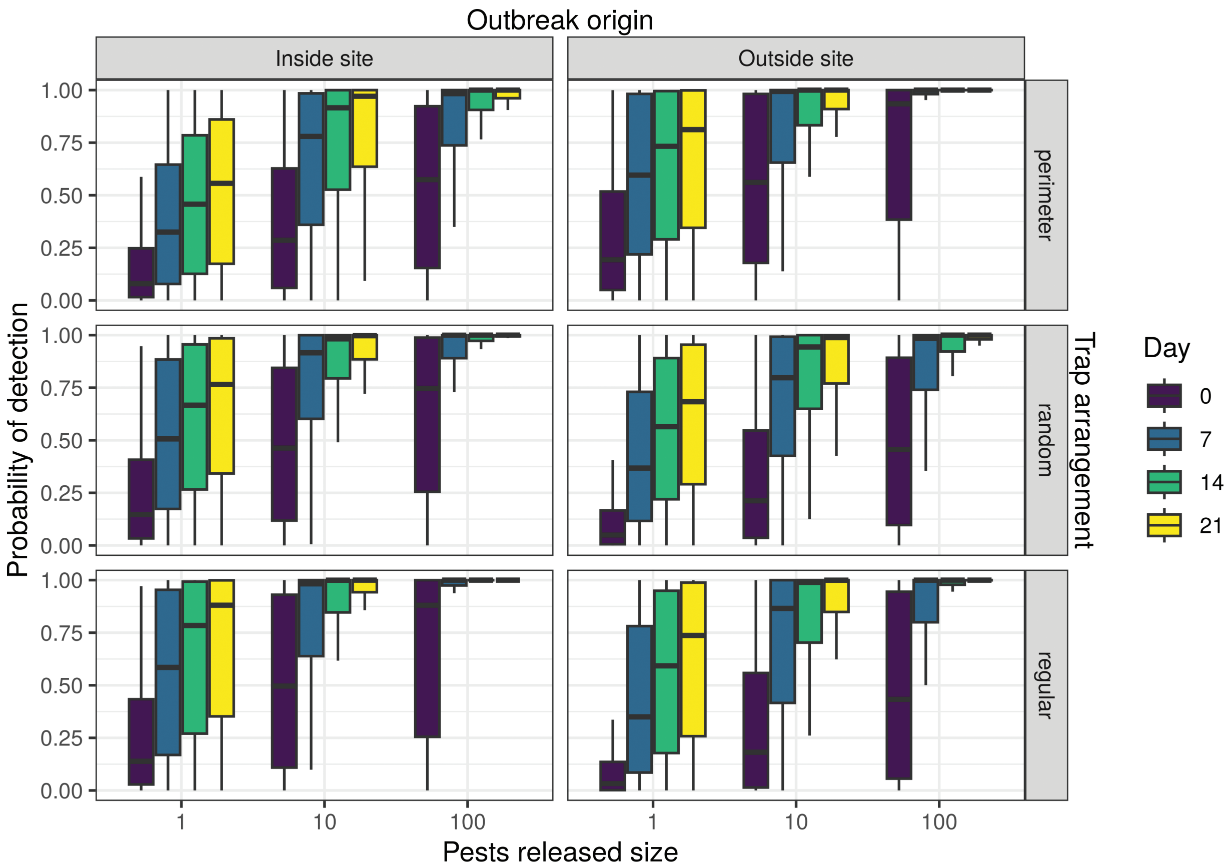

Fig. 3. The effect of pest release size and time since release (0 to 21 days) on mean probability of pest detection, grouped by outbreak origin (inside site left, outside site right) and trap arrangement (perimeter top row, random middle row, regular bottom row). Boxplots show the 25th, 50th, and 75th percentiles in the box and 1.5 times the interquartile range.

Surveillance Design, Lure Attractiveness, and Probability of Detecting Pests based on Outbreak Origin

Here we examine the effect of surveillance design (trap placement and density) and lure attractiveness on the probability of detecting pests released within or outside of the site at Day 0 (Fig. 5) and Day 7 (Fig. 6). We only included a release size of 10 pest individuals as pest detection showed the greatest range (see above). Trap arrangement, lure attractiveness and outbreak origin all significantly affected pest detection at both Day 0 and Day 7 (Supplementary Table S1).

Detection probability at Day 0 was calculated before any step-dispersal takes place, and so reflects the proportion of the site that is within an attractive distance of a trap. When lure attractiveness was very low (5 m) then detection probabilities at Day 0 were also very low even under high trapping densities (Fig. 5). When pests were released within the registered site a regular trap arrangement was more sensitive than a random arrangement, which also out-performed perimeter trapping (Supplementary Table S1). In contrast, when pests were entering the registered site then perimeter trapping out-performed both random and regular trap arrays, which performed similarly to each other (Supplementary Table S1). The most sensitive trapping strategy for detecting pests already inside or moving into the registered site performed similarly well for each lure attractiveness level (Fig. 5).

Detection probability at Day 7 occurs after pests have had the opportunity to disperse within the registered site. As a result, probability of detection was significant, even when lure attractiveness was very low (Fig. 6). Regular trapping remained the best option for detecting pests already within the registered site, and perimeter trapping the best for pests moving into the site (Supplementary Table S1). Detection of pests within or moving into the site was also similar under these optimal trap arrangements. After 7 days detection probabilities approached 100% even when lure attractiveness was very low (5 m), provided trap density was high and they were optimally placed (Fig. 6). Similarly, detection probabilities approached 100% when lure attractiveness was low (14 m) if trap density was high and optimally placed. Only a trapping density of 0.2 traps/ha was required when lure attractiveness was moderate (lambda = 25) and traps optimally placed, and 0.1 traps per ha was sufficient when lure attractiveness was very high (50 m).

Discussion

Site-based surveillance of quarantine pests using lures is frequently used to support market access by providing confidence that the pest is rare or absent within the registered site (van Klinken et al. 2021, 2023). To be an effective measure, surveillance needs to be able to detect both pests that may already be present within the registered site, and any pests that disperse into the site from undocumented sources. Here we used simulation modeling to determine how the probability of detecting pests already in or entering the site is affected by surveillance design (trap density and arrangement), lure attractiveness, pest dispersal, and release size. Pest detection was most sensitive to lure attractiveness, trap density, and pest abundance, with step size (daily

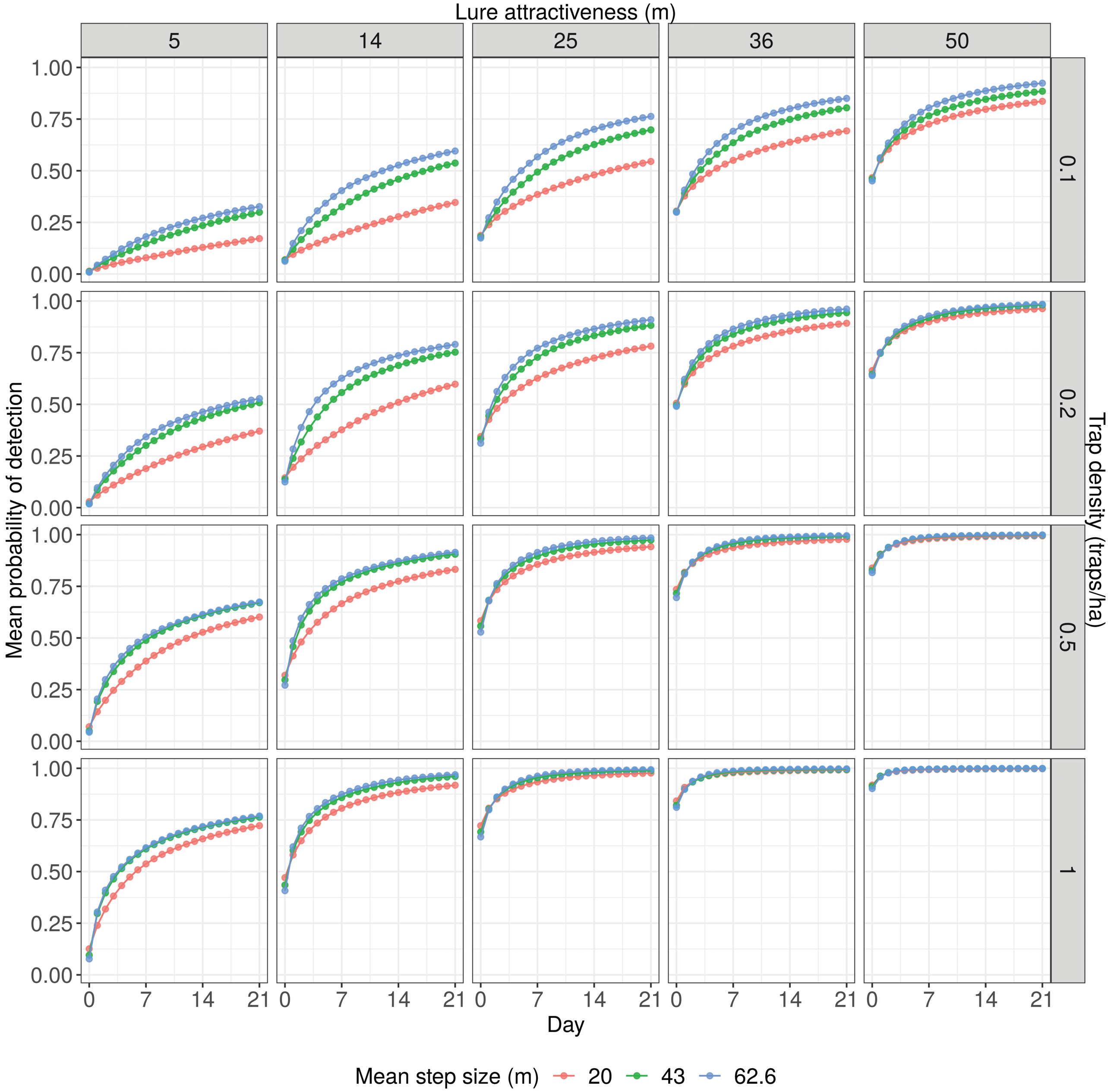

Fig. 4. Line plots of the mean probability of detection over days, grouped by mean step size (line color), lure attractiveness (columns), and trap density per ha (rows). Note that uncertainty bounds are not included.

dispersal) having surprisingly little influence. These results were robust to the size and shape of the site which suggests that the probability of pest detection will be comparable between sites when using a standard surveillance design and common lure performance. For the alternatives tested, detection of pests released within the site was best achieved using a regular trap array, and pests entering the site using perimeter trapping, although the effect of trapping arrangement reduced with time since release and was of limited importance when lure attractiveness and trap density was high. Also, regular trap arrays were not substantially more sensitive than random. This agrees with similar studies (Berec et al. 2015) and suggests that in practice the exact trap placement may not be critical within homogenous sites we studied here. The model used here can provide guidance for optimizing the design of site-based surveillance. This will be especially critical where lure attractiveness is low, and there is a requirement to rapidly detect very low pest numbers.

Lure attractiveness and trap density were the most influential parameters affecting pest detection probabilities for a given pest release size. The greater the lure attractiveness and trap density the greater the proportion of the site in which a pest would be attracted to a trap and therefore the higher the "instantaneous capture probability" (Manoukis et al. 2016). Higher lure attractiveness combined with higher trap density increases the probability of immediately detecting a pest, even if traps are not optimally placed. The importance of lure attractiveness in maximizing survey efficacy is consistent with other modeling studies, including for area-wide surveillance and delimitation of pest incursions (Manoukis et al. 2014, Caton et al. 2021).

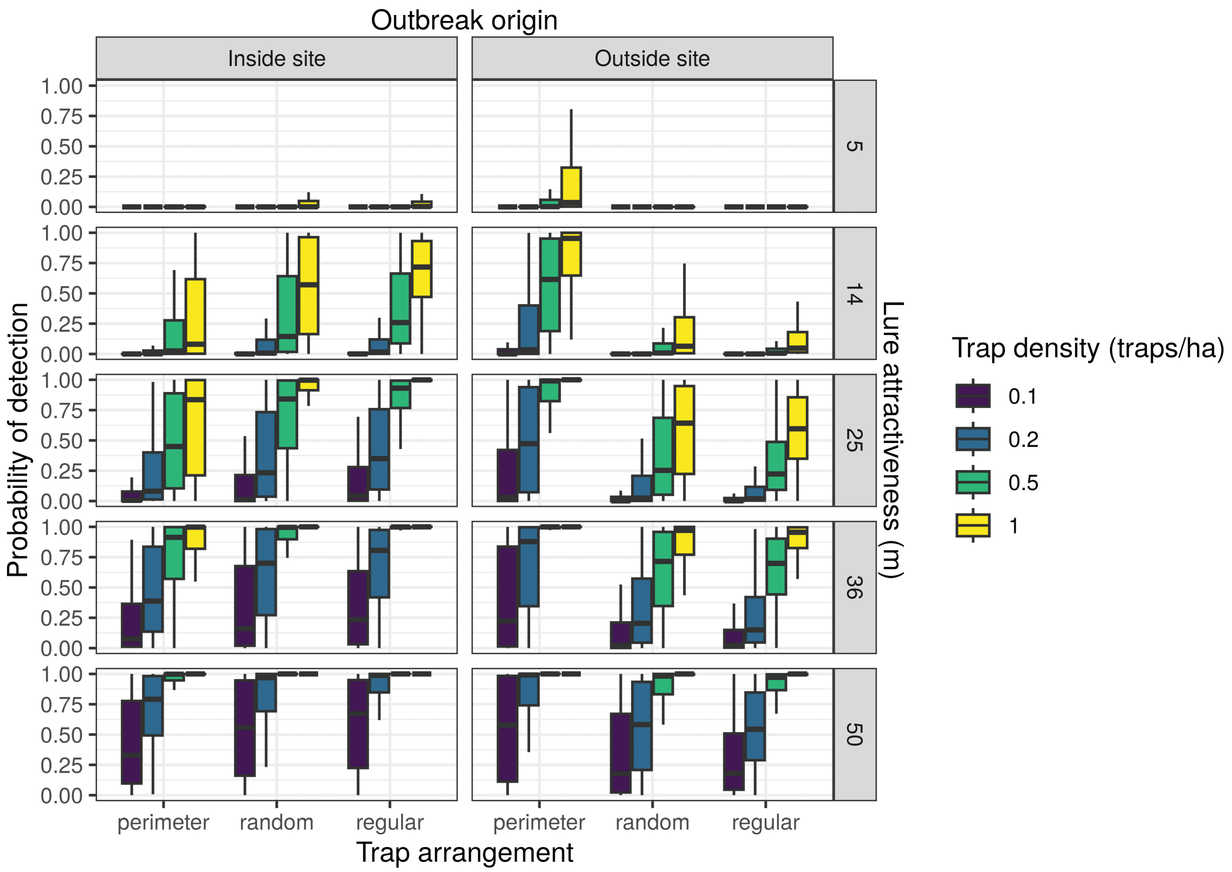

Fig. 5. Boxplots of the mean probability of pest detection by trap arrangement on Day 0, grouped by trap density (see legend), outbreak origin (columns) and lure attractiveness (rows). Release size was 10 pests. Boxplots show the 25th, 50th, and 75th percentiles in the box and 1.5 times the interquartile range.

If lure attractiveness or trap density decreases then pest dispersal, and therefore time, is needed to ensure that a released pest will enter the attractive radius of a trap. Although dispersal is important when trap coverage of the site is incomplete, in our study a mean daily dispersal distance of 20 m was often sufficient, and the time-dependent probability of pest detection did not increase greatly above 43 m. Thus, the same surveillance design (assuming equivalent lure attractiveness) will give similar detection probabilities for relatively poor dispersers such as European grapevine moth (mean step length of 20 m, Caton et al. 2022) and Mediterranean fruit fly (43 m, Caton et al. 2022) as for better dispersers. It also suggests that our results should not be overly sensitive to variability in daily dispersal distance that might be affected by a range of physiological and environmental factors (Lance 2014); for example, when mean dispersal ranges from 40.5 to 77.3 m across regions for Oriental fruit fly (Caton et al. 2022). Dispersal distance is likely to be more important for area-wide surveillance as trap densities are by necessity much lower, and the acceptable time to first detection greater (Manoukis et al. 2014). These findings emphasize the value of developing attractive lures for site-based surveillance, as is the case for area-wide surveillance (Manoukis et al. 2014).

Site-based surveillance may aim to detect pests that are already present in the registered site as well as pests entering the site from outside. Seasonal pest movement into orchards can be significant, and the placement of high densities of traps around the perimeter of fields has been shown to be an effective pest management tool (Cohen and Yuval 2000, Prokopy et al. 2003, Drummond and Collins 2020b). We compared the ability of three trap arrangements (regular, random, and perimeter) to detect pests either already in the site or entering the site from an external source. For a given trap density and lure attractiveness, a regular arrangement performed best overall for detecting pests already in the site due to superior site coverage, and perimeter traps for pests entering the site, resulting in similar detection probabilities. Trap arrangement was most important at lower trap densities and lure attractiveness levels as it affected trap coverage. More work is needed to determine what the optimal trap arrangement would be for detecting both pests already in the site and pests entering the site, within the required time frame. However, it is likely to require an approximately regular trap arrangement that is perimeter biased. Alternatively, although more costly, the trapping density of a regular trap array could be increased throughout the block to achieve the same effect.

Optimal surveillance design will depend on the purpose of the surveillance. Site-based surveillance can be used to support market access by giving confidence that the site is pest-free or has acceptably low pest numbers (low pest prevalence), possibly as part of a systems approach (van Klinken et al. 2020). In the latter case a non-zero threshold (pests/trap/week) may be acceptable. When site-based surveillance is used to support the management of production pests then action thresholds can be quite high (Drummond and Collins 2020a). As our interest was in quarantine pests we focussed on the time-dependent probability of detecting very low numbers (1, 10, and 100) of a pest released from a single point within or immediately adjacent to the registered site. Our results suggest that rapid detection of even such low numbers is possible, thereby allowing a rapid response. However, our simulations only considered individuals

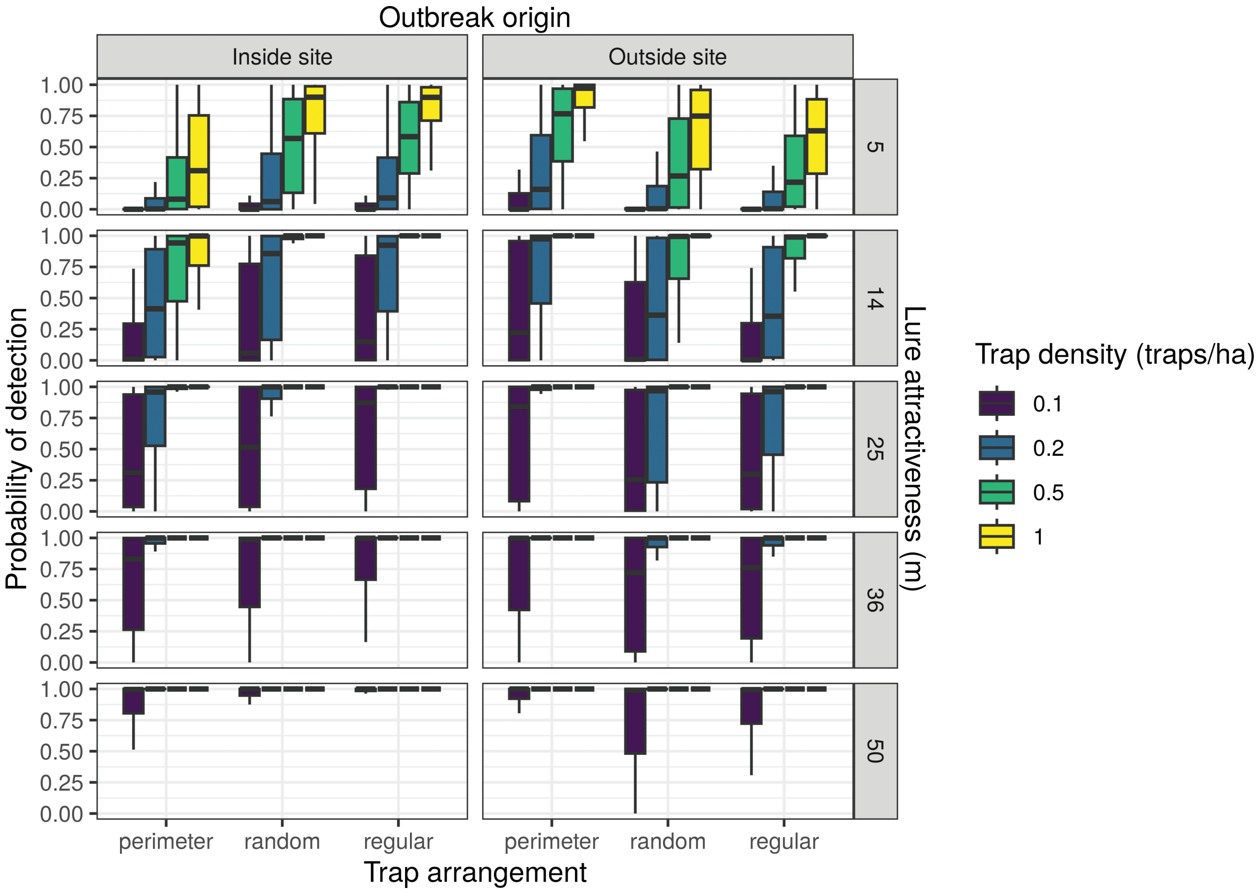

Fig. 6. Boxplots of the mean probability of pest detection by trap arrangement on Day 7, grouped by trap density (see legend), outbreak origin (columns), and lure attractiveness (rows). Release size was 10 pests. Boxplots show the 25th, 50th, and 75th percentiles in the box and 1.5 times the interquartile range.

within the population that are responsive to lures and are successfully trapped once attracted (Weldon et al. 2014, Bau and Cardé 2016). Our model could be extended to consider trap efficiency (following Bau and Cardé 2016) and the likelihood that individuals are in a lure-attractive state. Furthermore, understanding the relationship between probability of detection and absolute population size in the site (Lance 2014), or infestation rate of the commodity, would be needed to support the setting of non-zero action thresholds based on trap catch metrics (such as pests per trap per day: FAO/IAEA 2018).

Our modeling approach, while similar to many area-wide trap simulations, provides added flexibility when assessing site-based surveillance. Specifically, it allows one to determine the effect of trap coverage (including trap density, arrangement, and lure attractiveness) on the probability of detecting a small pest incursions initiating from either inside or outside the site. Our approach was inspired by the TrapGrid model and its method of estimating pest detection (Manoukis et al. 2014, Manoukis and Hill 2021). However, we simulated dispersal using a random walk model rather than a diffusion model as it better captures the dynamics of small populations at spatial scales relevant to site-based surveillance. This is relevant given recent results from experiments to measure movement by pests in the real world (Drummond et al. 2020a, Miller et al. 2022). We tested only a small number of the possible scenarios that could have been investigated. However, this model could be readily adapted to investigate diverse surveillance strategies for both site-based and area-wide applications, and across multiple pests, dispersal distributions (e.g., alternative distributions for the step size and correlated random walk) and environments, with greater realism and flexibility compared with simpler calculations (e.g., Lance and Gates 1994).

Although widely used to support market access, the design of site-based surveillance using lures to give confidence that pests are sufficiently rare in, or absent from, a registered site has received little attention when compared to area-wide surveillance to support pest free claims. Agreed principles are important for international trade as they help standardize surveillance methodologies, quantify the contribution site-based surveillance makes to reducing risk, and simplify the development, negotiation, and application of surveillance protocols. ISPM 10 (IPPC Secretariat 2016a) is an important reference point, although it is limited to pest free places of production and pest free production sites, and provides little guidance on surveillance design. Our results, combined with empirical methodologies developed by others (e.g., Caton et al. 2022), suggest that it should be possible to develop a set of guiding principles that support the development of site-based surveillance. Namely, principles for optimizing the density and placement of traps given attractiveness of available lures, the biology of the pest, and the desired level of detection sensitivity.

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Author Contributions

Rieks van Klinken (Conceptualization-Supporting, Formal analysis-Supporting, Funding acquisition-Lead, Investigation-Supporting, Methodology-Supporting, Project administration-Lead, Resources-Lead, Supervision-Supporting, Validation-Supporting, Visualization-Lead, Writing – original draft-Supporting, Writing – review & editing-Lead), Daniel Gladish (Formal analysis-Equal, Methodology-Equal, Software-Equal, Validation-Equal, Visualization-Lead, Writing – review & editing-Supporting), Nicholas Manoukis (Methodology-Supporting, Software-Supporting, Writing – original draft-Supporting, Writing – review & editing-Supporting), Peter Caley (Conceptualization-Supporting, Formal analysis-Supporting, Methodology-Supporting, Software-Supporting, Supervision-Supporting, Writing – original draft-Supporting, Writing – review & editing-Supporting), Matthew Hill (Conceptualization-Lead, Formal analysis-Equal, Investigation-Equal, Methodology-Lead, Software-Lead, Visualization-Equal, Writing – original draft-Lead, Writing – review & editing-Supporting).

Supplementary Material

Supplementary material is available at *Journal of Economic Entomology* online.

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