Transferability of Plant Pest Models

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Box 1: Introduction

- The Food and Agricultural Organisation estimates 40% of global crop production is lost to plant disease annually. With climate shifts and increased global movement, there is immense pressure for plant health managers to protect themselves against novel plant disease threats [1][2][3].
- There is a need for standardised yet robust strategies for the detection and eradication of novel plant disease using a risk based approach that best informs plant health managers to how much surveillance is necessary in limiting disease progression whilst not over extending resources [4][5].
- Modelling provides an excellent opportunity to explore the dynamics of an epidemic in the context of disease surveillance. The use of parameters relevant to plant disease are very informative to modelling disease in this regard. This informative approach is a critical component of testing disease management theories before being widely accepting by National Plant Protection Organisations (NPPOS) such as Defra in the UK.[5]

Box 2: Research Questions

- Can we use a spatially stochastic epidemiological model to confirm the accuracy of early stage epidemic prediction equations (see Box 3)? [5]
- How do parameters such as the dispersal ability and landscape pattern influence our ability to predict early stage epidemic spread?
- Can we use simple equations to estimate appropriate surveillance effort in realistic but complex host landscapes?

Box 3: Methodology—Predicting incidence at detection with a "rule of thumb" equation (Parnell et al., 2015)

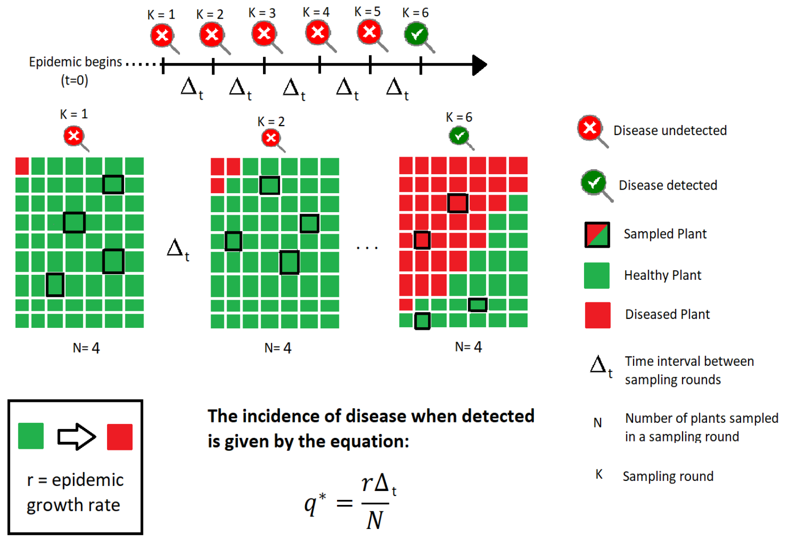


Figure 1, a visual representation of Parnell et al.'s "rule of thumb", a useful tool for determining epidemic incidence early on given a particular surveillance structure.

- 1000 spatially stochastic epidemic simulations were run per parameter combination to estimate the growth rate r (see Box 4.a). Parameters that defined r were the dispersal distance parameter ϑ, the shape of the kernel, the transmission coefficient β and the host distribution.
- The use of the τ-leap algorithm [6], based on the poisson distribution, was necessary to reduce computational time. Surveillance structure was fixed, but the plants selected for sampling was randomised every round.
- Using the "rule of thumb" equation (see Figure 1) [5], we estimate the incidence of disease when it is detected for the first time, and compare this estimation against our 1000 simulated epidemics (see Box 4.b).

Box 4.a: Preliminary results—epidemic growth curves (*r*)

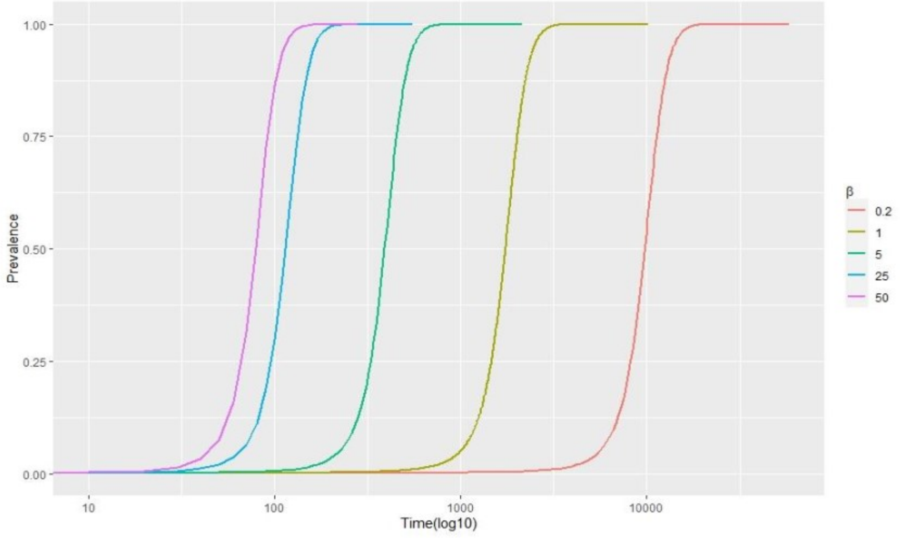
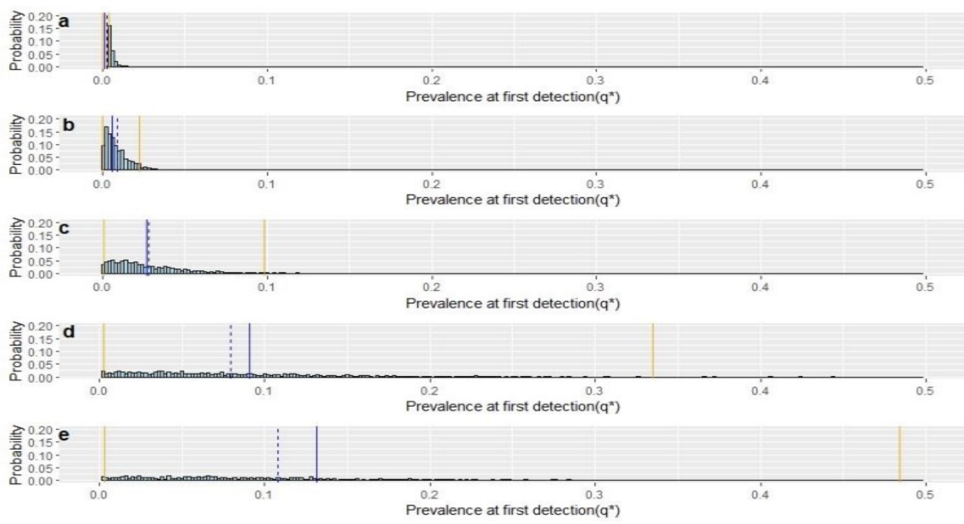


Figure 2, as the likelihood of infection given contact (β) increases, the epidemic growth rate (r) increases and time taken to reach maximum prevalence (incidence) decreases. Estimations of r being 0.001, 0.004, 0.017, 0.060 and 0.087 respectively.

- The transmission coefficient (β) directly relates to the epidemic growth rate. The landscape was homogenous, that is totally randomly distributed hosts. The shape of the kernel was gaussian, so long distance dispersal events are likely and dispersal distance (ϑ) was fixed.
- Even though our models are stochastic, we can "fit" a logistic growth curve to estimate r, which is the important parameter in Parnell et al.'s "rule of thumb".
- Given the time taken for β= 0.2 and 1, the parameters need adjusting to develop better representations of biologically feasible plant epidemics.

Box 4.b: Preliminary results—comparative outcome between predicted incidence and actual incidence



β	± Δ	% Δ
0.2	0.001	50
1	0.002	25
5	0.002	7.14
25	0.010	12.5
50	0.023	21.3

Figure 3, showing the average incidence at first detection (dotted blue) and the predicted incidence at first detection (completed blue) for respective values of β (see Figure 2). The orange lines are the 95% confidence intervals. The blue box represents this difference in absolute and relative terms (±Δ and %Δ respectively).

- The accuracy of the "rule of thumb" is measured as a comparison between simulated prevalence at detection (1000 sims) and prediction provided by the "rule of thumb" equation (see Figure 1)[5].
- Absolute prediction accuracy (±Δ) generally decreased as β increased, which could indicate a threshold where the mathematical assumptions of our model (continual exponential growth) do not fit.

Box 6: Next Steps

- The next objective is to generate a more biologically feasible set of simulation results by modifying our parameters β and ϑ. Furthermore, we are modifying our gaussian kernel to a fixed exponential kernel.
- Once our parameter space has been well defined, we will inductively explore different landscape configurations to test "rule of thumb's" in complex landscape patterns.
- We will validate these models against real data sets; providing NPPOs with the confidence needed to develop strategies based on models validated by our research.

Box 7: References

[1] New standards to curb the global spread of plant pests and diseases. Retrieved from http://www.fao.org/news/story/en/item/1187738/ [2] Bebber DP. 2019 .Climate change effects on Black Sigatoka disease of banana. Phil. Trans. R. Soc. B374: 20180269 [3] Bebber, D., Ramotowski, M. & Gurr, S. 2013. Crop pests and pathogens move polewards in a warming world. *Nature Clim Change* **3,** 985–988. [4] Spence, N., Hill, L., Morris, J., 2020. How the global threat of pests and diseases impacts plants, people, and the planet. PLANTS, PEOPLE, PLANET 2, 5–13.. doi:10.1002/ppp3.10088 [5] Parnell S, Gottwald TR,Cunniffe NJ, Alonso Chavez V, van den Bosch F.2015. Early detection surveillance for anemerging plant pathogen: a rule of thumb to predict prevalence at first discovery.Proc. R. Soc. B [6] Keeling, M.K., Rohani, P. 2008 Modeling Infectious Diseases In Humans and Animals. Princeton University Press.