Estimation of the spread-rate of epidemics*

The case of African Swine Fever in wild boar populations from Belgium

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Introduction

The speed at which an infectious disease outbreak progresses can be influenced by a number of factors, including host density and environmental conditions. However, it cannot be directly observed or measured. It needs to be derived from the locations and dates of the observed outbreaks, which is typically a sparse and partial observation of the real progress of the epidemic.

Tisseuil et al. (2016) proposed to estimate the local spread-rate from the surface of dates of first invasion, which is in turn estimated from the observed cases. They compared several competing approaches and concluded that the inverse slope of a Thin-plate spline regression of the earliest observed cases worked best in most cases. This approach has been applied for Bluetonge in Tisseuil et al. (2016) and for Lumpy Skin Disease in Mercier et al. (2017).

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We adopted their methodology and adapted it to the epidemic of African Swine Fever that is affecting wild boar populations in Belgium since September 2018. The source data are records of outbreak locations and dates from the European Commission's Animal Disease Notification System (ADNS)[1].

Several factors influence the precision and reliability of the resulting estimates of spread-rate. First, only a fraction the diseased animals are actually detected. Experts consulted in personal communications estimate this fraction roughly between 10 and 15%. Furthermore, the probability of detection is not uniform in the space nor in time, introducing spurious variations in the observed dates of first invasions. Finally, locations and dates are recorded at a finite resolution, not always constant. For instance, some observations could have been recorded with a GPS device, thus with a precision of a few metres, while others could have been more vaguely referenced at the village or commune level.

In order to assess the precision of our results we adopted a Monte Carlo approach to *Uncertainty Quantification*. This involves introducing random perturbations in the original data and the input parameters within reasonable bounds and performing the estimations of spread-rate for multiple instances of the generated datasets and parameters. The resulting Monte Carlo estimates of spread-rate yield a reliable description of the expected variation in the estimated values with respect to the known sources of error.

The estimated spread-rates range from about 0.5 to 7.7 km/month, depending on the location. Although the largest estimations are also the most imprecise. The average spread-rate is of approximately 2.9 km/month, with a 89% Monte Carlo interval of (2.2, 3.4) km/month.

Materials and methods

Locations and dates of the observed cases of African Swine Fever were retrieved from the Animal Disease Notification System (ADNS) of the European Commission on April 30, 2019. The dataset included 580 cases from September 13, 2018 to April 19, 2019 and extended over a region of more than 32 km in diameter (Figure 1).

For the purpose of the estimation of the spread-rate, only the cases that invade for the first time a vicinity are of interest. Cases that occur at a later date than a previously observed case within a *tolerance radius* are then discarded. This tolerance parameter depends both on the expected resolution of the recorded

[1] https://ec.europa.eu/food/animals/animal-diseases/not-system_en

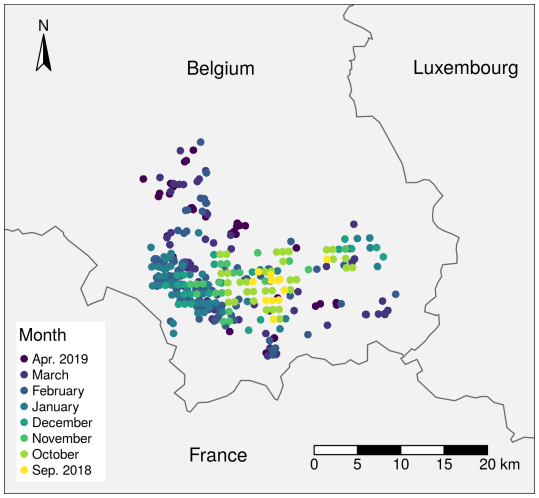

Figure 1: Location of cases by month. Earlier cases on top.

data and epidemiological considerations about the nature of the disease and the animal density.

A Thin-plate spline regression model was then fit to the resulting set of observations and interpolated into a raster surface covering the convex-hull of the whole dataset extended by 4% of the diameter.

The local spread-rate estimates were computed as the inverted-slopes of the surface of date of first invasion.

We generated 999 Monte Carlo samples of datasets and neighbouring-tolerance radius parameters and reproduced the computation of the spread-rate estimates for each combination.

In each Monte Carlo sample, the coordinates of the original cases were sampled uniformly from an interval of 1 km around the true value and the recorded dates were shifted in plus or minus 1 day with probability 0.25 each.

Finally, for the neighbouring-tolerance radius parameter we randomly sampled values from a Normal distribution with 99.9 % of its support between 400 and 1200 m.

Results

The average spread-rate estimate across all of the observed locations is of 2.9 km/month, with a 89% Monte Carlo interval of (2.2, 3.4). However, the local

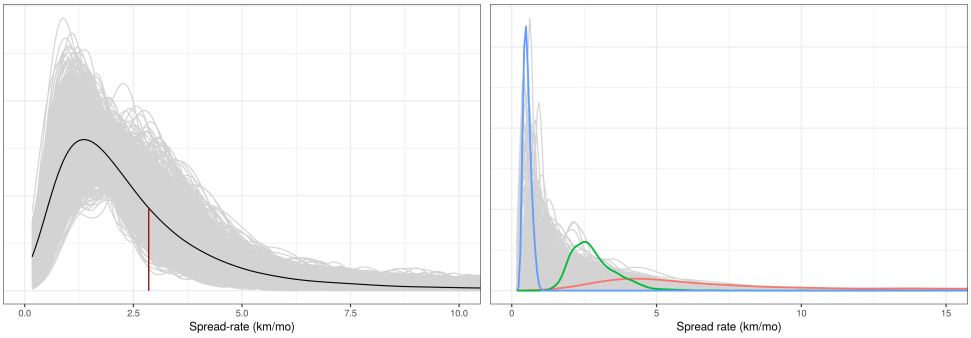

Figure 2: **Left:** average spread-rate estimate across observation locations (red vertical line), mean Monte Carlo density of spread-rate across observation locations (black curve), Monte Carlo samples (grey curves). **Right:** densities of point-wise Monte Carlo spread-rate samples. The locations with smallest and largest uncertainty are highlighted in black.

estimates vary considerably from site to site, ranging from about 0.5 up to 7.7 km/month (Figure 2, left).

However, there is a positive correlation of 93% (result not shown) between the magnitude of the estimated spread-rate and its standard error. The locations with highest spread-rate estimates also carry the highest estimation error (Figure 2, right). For instance, the highest spread-rate estimate of 7.7 km/month has a 89% Monte Carlo interval in between 2.4 and 17.6 km/h.

Figure 3 displays the estimated map of local spread-rate averaged across all the Monte Carlo samples and the corresponding map of standard error.

Conclusions

The average spread rate of African Swine Fever in wild boar populations in Belgium has been between 2.2 and 3.4 km/month. This figure is higher than the previously reported values in Latvia and Estonia (2 km/month) and in Lithuania and Poland (1 km/month) (European Food Safety Authority (EFSA) et al. 2017). However, to the best of our knowledge, no assessments of the estimation accuracy are available from previously published estimates.

The local spread rate vary considerably around this average value, with a right-skewed distribution. Furthermore, higher estimates imply more uncertainty and should be considered with care.

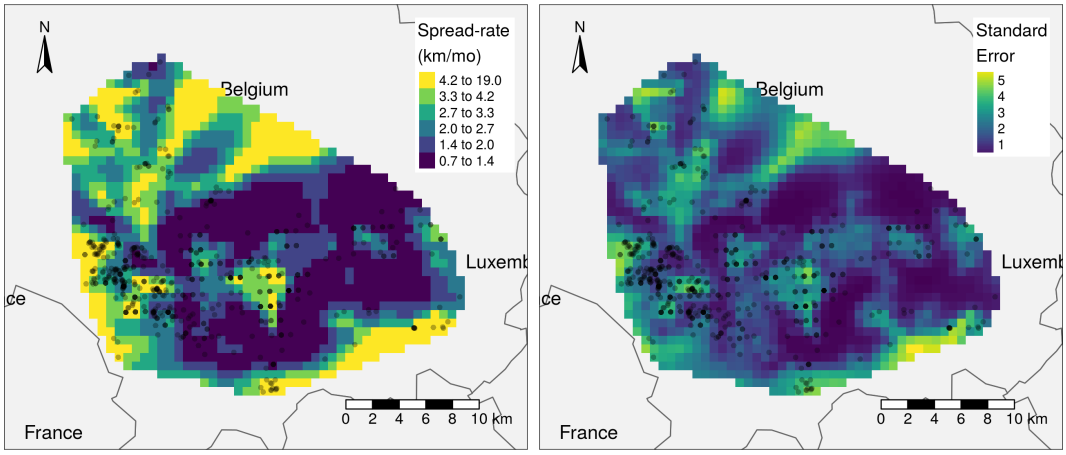

Figure 3: Estimate and standard error of local spread-rates.

References

European Food Safety Authority (EFSA), José Cortiñas Abrahantes, Andrey Gogin, Jane Richardson, and Andrea Gervelmeyer. 2017. "Epidemiological Analyses on African Swine Fever in the Baltic Countries and Poland." *EFSA Journal* 15 (3). https://doi.org/10.2903/j.efsa.2017.4732.

Mercier, A., E. Arsevska, L. Bournez, A. Bronner, D. Calavas, J. Cauchard, S. Falala, et al. 2017. "Spread Rate of Lumpy Skin Disease in the Balkans, 2015-2016." *Transboundary and Emerging Diseases*, February. https://doi.org/10.1111/tbed.12624.

Tisseuil, Clément, Aiko Gryspeirt, Renaud Lancelot, Maryline Pioz, Andrew Liebhold, and Marius Gilbert. 2016. "Evaluating Methods to Quantify Spatial Variation in the Velocity of Biological Invasions." *Ecography* 39 (5): 409–18. https://doi.org/10.1111/ecog.01393.