Chilean needle grass impact network analysis

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## Introduction

Here we focus on the farm to farm spread of *Nassella neesiana* (Trin. & Rupr.) Barkworth Chilean needle grass (CNG) in the Hawkes Bay. We source data and suggest some methods for modeling its spread under current and future climates. Distribution data for CNG was sourced from Hawkes Bay Regional Council and should be presented confidentially, though the data set is large the methods to collect it appear to be ad-hoc. Estimates of the eco-climatic range of CNG in New Zealand were sourced for current and future climates from Shona Lamoureaux (Bourdôt et al. 2012).

CNG was introduced in 1962 to a Waipawa farm (-39.949371, 176.582344) in the Hawkes Bay region formerly owned by a “Mr Hornblow” but introduced prior to his ownership, he was told nothing of the problem when he bought the property (Mrs. Hornblow pers. comm.) Apparently it was introduced after cultivation and seeding using seed sent from the South Island Connor, Edgar, and Bourdôt 1993). The rate of local spread was estimated at approximately 120-140 metres per year, since the seed has no major features for long distance dispersal other than being able to penetrate animal hides and furs. Its unclear how its ability to survive at low numbers <3% after passage through Angus steer guts could contribute to spread (Gardener, Whalley, and Sindel 2003). Longer distance dispersal is believed to be primarily human mediated, via farm equipment, hay, and farm to farm movement of livestock. Once the plant colonizes riverbeds, it can spread downstream, and has infested most of the lower reaches of the Tukituki and Waipawa Rivers, it may also be spread in gravels harvested from the river. Another farm in Puketapu was planted with contaminated seed in 1976 (both cases from seed provided from Marlborough farms). Now approximately 135 farms are infested.

We use Impact Network Analysis (INA) to model spread (Garrett 2021), an attractive feature is that it can account for the interacting influence of dispersal, socio-economic networks, which in term influence adoption rates and ultimately plant establishment. Here the INA combines a stochastic network model of spread between nodes for a bio-entity, with establishment probability being impacted by simulated levels of management (including variability in effectiveness), but the simulated adoption rate for the management is contingent upon whether the node/farm has received information about the management technology. The spread of this information is modelled in a separate socio-economic network (unless you set it up so that every node starts with information).

## Methods

Data provided:

1. Hawkes Bay Farms from Agribase. (HB\_wgs84.shp)
2. Climex model outputs for CNG under current (NZ\_fine\_scale\_fishnet\_join.shp) and future climates.
3. Known records of CNG in Hawkes Bay (HBRC\_CNG\_points.xlsx)

R-code provided:

1. Farm selection and querying Agribase. (AgribaseClimexDistMatrix.R)
2. Grouping of farm units into multipart units based on Farm ID. Get centroids. (AgribaseClimexDistMatrix.R)
3. Selection of vulnerable farms with high climatic fit in Climex model. (AgribaseClimexDistMatrix.R)
4. Mapping farms to weed occurrences (on or near the farm). (AgribaseClimexDistMatrix.R)
5. Creating a distance matrix from polygons (farms sharing a boundary have zero distance). (AgribaseClimexDistMatrix.R)
6. Setting up an adjacency matrix of dispersal probabilities based on a dispersal kernel.
7. Determining optimal nodes for surveillance using the Impact Network Analysis package. (file: “Set up adjacency matrix.R”)
8. An example for running an Impact Network Analysis scenario. (file: “INA\_only.R”)
9. Graphs of the output from the scenario analysis.

Farm location data was sourced from Agribase (Sanson 2000) for the Hawkes Bay Region, where CNG is targeted in the [Hawkes Bay Regional Council’s Pest Plan](https://www.hbrc.govt.nz/environment/pest-control/biosecurity/regional-pest-management-plan/). Since farms in the database contain multiple land parcels, farms with the same farm ID were merged into multipart shapes with a single ID. Then only sheep and and beef farms selected as vulnerable – as was done in previous analyses (ref#). An ecoclimatic index for CNG of >5 was also used to further reduce the number of farms to be used in an adjacency matrix. The selected farms are shown in Figure 1.

Chart, scatter chart

Description automatically generated

**Figure 1)** Map of Agribase farms showing ecoclimatic-index average per farm and known points where CNG has been recorded.

Stochastic network models of spread require an adjacency matrix that document the probability of node-to-node spread. I used a Pareto dispersal kernel with a threshold for adjacent farms of 1/20. This produces a fat-tailed distribution similar to negative exponential, Weibull or power-law distributions. I also made an arbitrary cut-off of 1/10,000 as the lowest probability of dispersal that is interesting (truncating the fat tail). This is to simplify the network because running the INAscene function is quite memory intensive on large matrices.

Chart, histogram

Description automatically generated

2) The dispersal kernel for setting the node-to-node spread probabilities uses the Pareto distribution and a threshold of 1/20 for adjacent farms.