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A PRELIMINARY MOUSE ABUNDANCE PREDICTION MODEL FOR THE CENTRAL QUEENSLAND GRAIN PRODUCING REGION

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ABSTRACT: A preliminary, mouse abundance model was constructed using artificial neural networks and data on trap success rates spanning a ten-year period in neighbouring catchments in Central Queensland. To predict trap success (percentage of traps that catch mice) in June, the model uses trap success rates in December and February, as well as rainfall in January/February and March/April. With a relatively small number of years in which all these data are available, there is a danger that the network may be ‘overtrained’, whereby the network ‘memorises the data’ rather than minimising the underlying dynamics. The preliminary model will be evaluated in coming seasons. In addition, the data used to construct the Cantrill model will be used to construct an artificial neural network to see if these provide any increased predictive power for southern Queensland.

INTRODUCTION

Mouse populations fluctuate widely in grain-producing areas within Queensland. Cantrill (1992) developed a plague prediction model for the central Darling Downs of southern Queensland. This is used to give advance warning of likely high mouse populations in that area. In Central Queensland, there are fewer data on mouse population indices as in southern Queensland, but there is the need for predictions of mouse abundance to enable grain-growers to plan their pest management programs effectively and efficiently.

The model of Cantrill (1992) is a rule-based model, built upon 12 years of regular trapping across the central Darling Downs. The original model has been slightly modified to take account of more recent data (up to 2002) and has a reasonably high success rate. There are not sufficient data for Central Queensland (Dawson and Callide valleys) to develop a similar, rule-based model.

Artificial neural networks have been used to estimate animal population changes using parental populations, rainfall and other climatic information (e.g. Obach et al. 2001). These models have advantages when the complexity and dynamic nature of the features being studied limit the development of simulation models (e.g. Schleiter et al. 1999). They are used for forecasting populations (e.g. incidence of cyanobacteria in the River Murray – Maier et al. (1998)). Ideally, these networks are developed using large data sets – for example, Maier et al. (1998) had 7 years of weekly data of eight variables.

We used trapping data for mice in Central Queensland to develop an artificial neural network that could predict mouse abundance in June, based on previous trap success rates and rainfall in preceding months.
METHODS

Monthly trapping data are available for two locations in Central Queensland (Dawson Valley and Callide Valley) for most years between 1990 and 2004, although trapping was conducted in only about half of the months with none at all in 5 years (giving a total of 60 trapping events in each catchment). The gaps in the data for years when data for most months were available were interpolated using spline estimation in TableCurve 2D. This enabled a data set of 6 years at each location where trap success for December, January and the following June was available for analysis. Rainfall data for January-February, and for March-April were obtained from records available on the Datadrill web site of Department of Natural Resources and Mines (http:\nrm.dnr.qld.gov.au\siloi)

An artificial neural network (using Neuralyst) was developed using trap success in December and February, and rainfall for the two 2-month periods to predict the trap success in June (which was generally the month of the highest mouse abundance). Other rainfall and trap success dates were tested, but did not improve the fit to observed data. There were insufficient data to divide the data set into a training set and a test set. Because of the relatively small number of data samples, there is an acknowledged potential for overtraining of the network, resulting in the network learning the individual data points rather than detecting the underlying patterns.

The network was then used to predict trap success for a range of conditions. There are insufficient data to test these predictions against field data.

RESULTS

Observed mouse abundance varied between locations and between months (Fig. 1). Care must be taken when examining these differences as sampling was conducted in less than half of the months and these were not always the same months at different locations.

![Traping result - Central Queensland](image)

Fig. 1. Mean trapping success (for 1990 to 2004) for the two locations in Central Queensland. (Note trapping not conducted in all months).
The network developed fitted all the observations used in its development, which should be the case given the small sample size. The factors used in the network were trap success in December and February as well as rainfall totals for Jan-Feb and Mar-Apr. This was the minimum set of variables required to give a relatively stable network when one data point was omitted. The data points with high trap success in June had a strong influence on the network weights, and therefore on its predictions.

Predictions were made using the network, for a range of trap success in December and February as well as a range of rainfall totals for Jan-Feb and Mar-Apr. The highest trap success in June was generally achieved when rainfall in Jan-Feb was 150mm and 5mm in Mar-Apr (data not shown). Under these conditions, the predicted trap success in June was predicted for a range of trap successes in Dec and Feb (range from 2% to 35%) that covered the range of conditions observed in the data used in development of the network. These results are shown in Fig. 2.

The highest predicted June trap success was observed when the December trap success was between 10 and 13%, irrespective of the February trap success. When December trap success was between 5 and 10% and February trap success was between 2 and 10, the predicted trap success in June was also high.

![Contour graph of predicted June trap success given December and February trap success, and given 150mm rainfall in Jan-Feb and 5 mm in Mar-Apr.](image)
DISCUSSION

Moderate mouse abundance in December, followed by high rainfall in January-February and then low rainfall in March-April produced the highest mouse abundance in June. The trap success in February was less important than trap success in December, when using the effect on June trap success as the criterion for importance.

The preliminary results shown here suggest that artificial neural networks have potential to be used to predict the likelihood of high mouse abundance in winter in Central Queensland. Neural networks have the advantage that they can be used when the relationships between environmental characteristics and trap success are not well developed. Also, there is scope for linking artificial neural networks and formal simulation models. This integration produces hybrid models that may improve model accuracy by incorporating alternative and complementary sources of knowledge (Oliveira 2004).

The reliability of predictions will be tested during future trapping events. This may enable predictions to be made on the basis of less information than was required to develop the model of Cantrill (1992) for the Darling Downs region of southern Queensland.

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REFERENCES


