Predicting spatial patterns of animal pest abundance: a case study of the brushtail possum (*Trichosurus vulpecula*)

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ABSTRACT

Methods for modelling and predicting abundances of animal pest species throughout New Zealand were developed, using brushtail possum (*Trichosurus vulpecula*) data in generalised regression analysis and spatial prediction (GRASP) techniques to develop models describing the statistical relationships between trap-catch indices (TCIs) of possum abundance and key environmental factors (e.g. land cover, climate). TCI data from monitoring surveys of uncontrolled possum populations were tested as predictors of relative possum abundance at 'equilibrium' (with estimated uncertainties) throughout New Zealand. The GRASP model accounted for 50% of the variation in TCIs and identified seven spatial variables significantly correlated with TCI. This model also produced 'correction graphs' for converting between TCI values in January and June, and between raised-set and ground-set trapping. Post-control trap-catch data, together with control history information, were then used to predict the relative abundance of possums under different control scenarios. These models accounted for 1–30% of the variation in post-control TCIs, suggesting that a statistical modelling approach to predicting spatial patterns of abundance can provide important and useful information for pest/conservation management. However, priority should be given to improving the uncontrolled population model. The greatest improvement in the GRASP models will come from including recent historic and newly collected data from surveys in presently poorly sampled regions or environments. Guidelines and standards for collecting and recording population monitoring data, and for their collation and storage, must be developed and implemented in liaison with the Animal Health Board. Common standards for possum population monitoring and control operations will allow integration of such information from both agencies. The Department of Conservation's new standard operating procedure for operational reporting of animal pest operations largely fulfils the control operation information requirements for our GRASP models.

Keywords: brushtail possum (*Trichosurus vulpecula*), pest control, relative abundance, trap-catch index, generalised regression analysis and spatial predication (GRASP), geographic information systems (GIS), measuring conservation achievement.

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1. Introduction

The Department of Conservation (DOC) is developing a system to optimise its allocation of resources to manage conservation assets. Briefly, this prioritisation system requires that managers be able to predict the condition of the conservation assets at particular sites with and without management of the various threats that impose pressures to degrade these assets (Anonymous 2001). One part of this system requires a national assessment of the changes in the extent or intensity of the threatening agents or processes as they are managed or as they disperse into new areas. In 2000, the Science & Research Unit of DOC commissioned Landcare Research to develop a system to do this assessment for one important threat to conservation, the brushtail possum (*Trichosurus vulpecula*).

2. Background

DOC is developing systems to manage New Zealand's natural habitats and ecosystems as though they are assets in a business management portfolio. In part, this requires that managers measure changes in these habitats and ecosystems as they are subjected to natural processes, manageable pressures such as threats from weeds and pests, and unmanageable perturbations. Measuring differences in the condition of the natural assets with and without management of unnatural (human-induced) changes is a key element of this system and will also provide an audit for the Biodiversity Strategy of the effectiveness of particular threat management (Anonymous 2001).

Brushtail possums are one major threat to conservation assets in New Zealand (Payton 2000; Sadleir 2000) and are also the main wildlife vector of bovine tuberculosis (Tb) (Coleman & Caley 2000). They are present over most of the three main islands of New Zealand (Clout & Ericksen 2000) and can be found in most habitats, where they have usually been present for sufficient time to have reached carrying capacity (Cowan 2001).

Within conservation lands, possums are currently controlled for conservation purposes over about one million hectares (c. 10% of the total area) and for bovine Tb eradication over about a further one million hectares (J.P. Parkes, Landcare Research, pers. comm.). The effectiveness of control operations is routinely measured using a standard trap-catch index (TCI) (NPCA 2001), sometimes also taken before control is applied but more usually taken only after control. The latter provides an index of the residual possum density and is commonly used as a performance measure for assessing the contractors who undertake the control.

Spatial modelling of pest abundance can provide useful information for pest management, including a better understanding of the habitat requirements and environmental limits of the pest species, more detailed and area-specific estimates of densities that could be expected in the absence of control, and estimates of how long previously controlled pest populations might take to reach such densities. When control history is incorporated into the models, it then becomes possible to investigate the efficacy of various control strategies, including predictions of post-control pest abundance under a range of control scenarios. Combined with information on the presumed or known impacts of the pest species, such results can then form the basis for predicting the difference (i.e. benefits) made by control.

Possums are an ideal species to test the predictive capability of a spatial modelling approach. They are virtually ubiquitous, so any models do not have to predict or factor in future dispersal. Their density varies with habitat type (Cowan 2001), but is nevertheless relatively stable about equilibrium densities (at least compared with *r*-strategy pests such as rodents). They are subject to widespread control, and the results of this management both on possum densities and (less commonly) on their impacts on conservation values are often measured, providing the empirical data with which to test the various models in the literature that predict possum population dynamics and impacts (e.g. Efford 2000; Choquenot & Parkes 2001).

Spatially explicit estimates of the relative abundance of possums when close to or at carrying capacity (i.e. uncontrolled) or following control, combined with the results of research and ongoing monitoring of possum impacts on conservation values, will assist DOC in the Measuring Conservation Achievement (MCA) process (Stephens 1999; Overton et al. 2002). The estimates will also ultimately be of use in developing and co-ordinating a national control strategy for possums. At the area-specific level, spatial predictions of possum abundance could be integrated with spatial data on possum impacts and key conservation values under threat within the Natural Heritage Management System (NHMS) to enable more effective identification of conservation-related control priorities and to determine where future control should be targeted. At the operational level, the spatial models developed in this project will assist local and regional managers to compare the relative abundance of possums in managed and unmanaged areas, identify priorities and determine where control should be targeted, and determine if more or less control is required or if alternative control strategies might be more effective.

The principal outputs for this project are: a spatial database containing possum population monitoring data and control operation information; several models describing the statistical relationships between an index of possum relative abundance and key environmental factors; predictions of the relative abundance of possums in uncontrolled and controlled possum populations; and a set of explicit guidelines and standards for collecting and recording population monitoring data and control-history information, and for the collation and storage of these data. The best-practice procedures and data standards developed here will help to ensure that all new data are collected in a consistent and readily usable form, and stored in such a way that they are easily accessible.

We envisage that the possum database and the generalised regression analysis and spatial prediction (GRASP) analyses developed in this project will provide a model and analytical framework for a comprehensive national database covering most or all animal pest species, which would then be available for a range of operational, management, and research purposes. This extension to all pest species recognises that controlling suites of animal pests is often more important and more effective than focusing on a single species (Cowan 2001).

3. Objectives

The objectives of this study were to:

- Predict indices of uncontrolled possum densities in all habitats nationwide by extrapolation from empirical indices of uncontrolled or pre-control densities from recent population monitoring surveys.
- Predict post-control possum densities and recovery rates across different habitats under different control strategies.
- Determine the key spatial predictors of the relative abundance of possums and the effects of spatial and other predictor variables on TCIs.
- Develop best-practice guidelines for the collection, collation, and storage of possum population monitoring data and control operation information.

4. Methods

4.1 GENERALISED REGRESSION ANALYSIS AND SPATIAL PREDICTION (GRASP)

GRASP techniques (Lehmann et al. 2002, 2003) can be used to develop models for describing the statistical relationships between indices of the relative abundance of possums (e.g. TCI) and key environmental (e.g. land cover, climate) and other (e.g. control history) factors. Applying such models to TCI data from uncontrolled[1] populations from a range of locations will enable the estimation of the relative abundance of possums (together with estimated uncertainties) at carrying capacity for specific areas and, by extrapolation, throughout New Zealand (for those habitats where possums occur). Post-control data from the same or similar areas, together with control-history information, can then be used to further develop the models so that they can be applied to predict the relative abundance of possums under different control scenarios. The results of this work, in terms of the applicability and relevance of the most promising model(s), will enable an assessment of whether a statistical

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[1] In effect, many of the possum populations where pre-control or trend monitoring percentage trap-catch data have been collected have been harvested to some extent for fur. Therefore, possum densities are likely to be somewhat below those that could be expected at carrying capacity, the actual difference being dependent primarily on the intensity and timing of previous harvesting. Pre-control percentage trap-catch data from remote and/or inaccessible areas (where possum populations are unlikely to have been harvested) are more likely to represent truly uncontrolled (approximately carrying capacity) densities.

modelling approach to spatial density prediction can provide a useful management tool for possums (and potentially other pest species).

GRASP is both an analytical concept and a specific implementation and graphical user interface (GUI) in S-plus (Lehmann et al. 2002, 2003). The GRASP process can be described as a means of defining the patterns of the response variable (here, TCI) in relation to climatic, landform, or other spatial variables, and management history, and using these patterns to make the best estimates of the response variable across the landscape. GRASP can use both continuous and categorical predictor variables.

This process can be illustrated with a single response variable and a single continuous spatial predictor variable. Consider using mean annual temperature as the spatial predictor variable to make a prediction of TCI (the response variable) for a region. Here, GRASP is a simple regression technique, using the TCI observed on each trap line to produce a regression model of TCI as a function of temperature. The spatial prediction of TCI as a 2-D map for the region is then made by using the regression model to predict TCI from a geographic information system (GIS) surface of mean annual temperature.

The GRASP process can also use categorical predictor variables such as land-cover type. Consider a model of TCI as a function of land cover, such as in the Land Cover Database (LCDB). Here, the GRASP model would be an analysis of variance, consisting of the mean TCI for each category of the LCDB. The spatial prediction of TCI across the region then would be the average TCI for each land-cover class, applied to every area mapped in the GIS as having that particular land cover. Hence the overall TCI for any region would then be simply the average of the land-cover-class TCIs weighted by the distribution (i.e. relative proportions) of each land-cover class.

Most models in GRASP are more complex than either of the two previous examples (i.e. they incorporate a number of spatial predictor variables). The regression models used by GRASP are generalised additive models (GAMs), a modern non-parametric regression technique with a number of advantages for ecological modelling. However, GRASP is still relatively new and continued refinements and improvements are being developed. GAMs are multiple regression models that can include a combination of continuous predictor variables and categorical predictor variables. GRASP takes each predictor variable of interest and attempts to find the spatial pattern or relationship for this variable across the landscape, relative to environmental, land-cover, fragmentation, or spectral characteristics. It then uses this relationship to predict a pattern for the response variable for the entire landscape. In this study, the values for the TCIs observed on the trap lines were regressed against environmental variables such as climate, landform, and land cover (the spatial predictors; see Table 1), as well as variables that relate to the survey, such as survey month or trap-set type (see Table 2). These regression relationships can then be used to predict TCIs from the surfaces of the environmental variables stored in the GIS.

The graphs of the GAMs presented below (for example, see Fig. 4) show the partial contribution of each predictor variable that was included in the final model. GAMs are additive models, and the overall model is obtained by summing the partial contribution of each predictor variable. As discussed

TABLE 1. SPATIAL PREDICTORS DEVELOPED FOR THIS STUDY. NOT ALL SPATIAL PREDICTORS WERE USED IN GRASP, FOR A VARIETY OF REASONS (SEE TEXT). Climate and landform variables are more fully explained in Leathwick et al. (2003) and neighbourhood land-cover and historical variables are discussed in the text.

NAME	ABBREVIATION	UNITS	DEFINITION	CATEGORY
Mean annual temperature	MAT	°C	Mean annual temperature	Climate
Minimum winter temperature	TMIN	°C	Relative deviation of the minimum temperature relative to MAT	Climate
Mean annual solar radiation	MAS	MJ m^{-2} d^{-1}	Mean annual solar radiation	Climate
June solar radiation	JUNESR	MJ m^{-2} d^{-1}	Relative deviation of the winter solar radiation relative to MAT	Climate
Rainfall to potential evapotranspiration	R2PET	ratio	Ratio of annual rainfall to the annual potential evapotranspiration	Climate
Annual water deficit	H2ODEF	mm	Rainfall minus evapotranspiration	Climate
Vapour pressure deficit	VPD	KPa	October vapour pressure deficit	Climate
Mean annual rainfall	MEANRAIN	mm	Mean annual rainfall	Climate
Slope	SLOPE	degrees	Slope estimated from Digital elevation model	Landform
Elevation	ELEVAT	m	Elevation above sea level	Landform
Land cover	LANDCOV	n.a.	Land- cover categories from the Land Cover Database	Land cover
Major land cover	MAJLANDCOV	n.a.	Most common land cover in 300 m radius	Neighbourhood land cover
Percent woody vegetation in 300-m radius	WOOD300	%	Mean percentage woody vegetation in a 300 m radius around each pixel, derived from LCDB categories	Neighbourhood land cover
Distance to pasture	DISTPAST	m	Distance of each pixel to the nearest pasture pixel	Neighbourhood land cover
Distance to indigenous forest	DISTIFOR	m	Distance of each pixel to the nearest indigenous forest pixel	Neighbourhood land cover
Distance to plantation forest	DISTPFOR	m	Distance of each pixel to the nearest plantation forest pixel	Neighbourhood land cover
Distance to scrub	DISTSCRUB	m	Distance of each pixel to the nearest scrub pixel	Neighbourhood land cover
Distance to woody vegetation	DISTWOOD	m	Distance of each pixel to the nearest scrub or forest pixel	Neighbourhood land cover
Time since colonisation	TCOLONISE	years	Time in years since colonisation of an area by possums	Historical
January trap catch	JANTC	%	January trap catch predicted from uncontrolled model	Possum habitat suitability
June trap catch	JUNETC	%	June trap catch predicted from uncontrolled model	Possum habitat suitability
Time to previous control	TPREVCONT	years	Time in years since the previous control	Spatio-temporal control
Distance to edge of previous control	DISTPREVCON	m	Distance of each pixel to the nearest edge of previous control operation	Spatio-temporal control

TABLE 2. VARIABLES DESCRIBING ASPECTS OF THE SURVEY OR CONTROL OPERATIONS.

NAME	ABBREVIATION	DEFINITION	CATEGORY
Survey start month	SSMONTH	Month in which survey began	Survey variable
Set type for trapping	SETTYPE	Raised- or ground-set traps	Survey variable
Regional organisation	REGORG	Regional organisation responsible for control	Control variable
Aerial or ground control	AERIALGND	Aerial- or ground-based control	Control variable

above, the form of the partial contribution depends on whether the predictor variable is a continuous variable (e.g. MAT—mean annual temperature) or a categorical variable (e.g. SETTYPE—trap-set type). For continuous predictor variables, GAMs use a scatter plot smoother to estimate a non-linear curve for the partial contribution. Sometimes statistical tests indicate that a curve is not justified and a linear regression is used. The curves or lines are shown as solid lines, with point-wise standard errors indicated by the dashed lines above and below. For categorical predictor variables, the graph shows what is essentially an ANOVA for that variable, giving the mean contribution of each variable (the wide bars) with standard errors (SEs) indicated with dashed lines (upper and lower SE limits denoted by the narrow bars). The width of each mean bar is proportional to the number of samples in that category. Overall, the graphs of the GAMs show the regressions and ANOVAs that are added together to make the overall model.

The GRASP implementation (Lehmann et al. 2002, 2003) is a collection of functions and a user interface in S-plus that is designed to facilitate the GRASP process and the analyses needed to check the models and predictions. The GRASP implementation provides a toolbox for quick and easy data checking, model building and evaluation, and calculation of predictions. In addition to making the GRASP process easier, this implementation also standardises the modelling process and makes it more consistent and less subjective, while preserving analytical flexibility.

GRASP (the implementation and process) was used to model the relative densities of possums and predict TCIs for four 'scenarios' (see Section 4.4). Models were constructed usually by backwards stepwise selection, with significance tests for variable removal that varied with model family. For each variable, the following outputs were produced:

- Graphs of the modelled variable against each candidate spatial predictor variable.
- Final GAM, with the curve of the partial contribution of each predictor variable to the overall model.
- Model validation and cross-validation results, showing the plots of the observed versus the predicted values for each. The correlation between predicted and observed values was used to assess the model.
- Estimates of the relative contributions of each spatial predictor variable to the model. These were done both as drop and alone contributions[2] to the model. The drop contribution of a spatial predictor variable is the difference in explained deviance between the final full model and a model with that

variable excluded. If the variable in question is not in the final model, the drop contribution is defined as zero. The alone contribution of a spatial predictor variable shows the deviance explained by a model with only that variable in the model.

Once the final model was constructed, it was used to make spatial predictions for the response variable. Predictions were made by exporting lookup tables from S-plus into Arcview and using programs (scripts) written in Avenue (the Arcview programming language) to produce spatial predictions using the lookup tables and the grid layers of the spatial predictor variables. Since the post-control deviance model essentially failed, it was not used to predict TCIs.

Predictions were masked to avoid predicting outside the range of the data. Masks were defined by finding the range of each spatial predictor variable spanned by the data. Pixels in the prediction grid that fell outside the range of the data on any of the axes were masked out. While it might be possible to predict slightly outside the ranges of the observed data, this was not done here because sample densities tend to decrease towards the edge of the distributions, increasing model uncertainty at the edges of the range and, therefore, making further extrapolation unwise.

4.2 DATA COLLECTION—TRAP-CATCH INDICES

Standardised leg-hold trap-catch monitoring data are routinely collected by DOC conservancies, regional and district councils, the Animal Health Board, and research organisations as the basis for estimating indices of uncontrolled or pre-control and, more commonly, residual possum population densities following control. Indices of mean residual population densities are typically used to determine whether control agencies or private contractors have reduced possum populations to below some specified TCI target density and are frequently used as a basis for determining whether performance-based payments for control operations should be made. Some monitoring of possum populations is not conducted in association with control, but rather as trend monitoring over a period of years.

All DOC conservancies and Wellington, West Coast, Canterbury, and Southland Regional Councils were sent a form letter requesting data from any possum monitoring surveys carried out since 1990[3] where the trapping practice was in accordance with the National Possum Control Agencies Trap-Catch Protocol (NPCA 2001). Potential respondents were specifically asked to indicate one of the following:

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[2] The drop and alone contributions are graphed on axes of explained variance (e.g. see Fig. 5). Since the total deviance differs between models (depending upon sample size and model family), the graphs of drop and alone contributions should only be used to compare the relative importance between the different predictor variables.

[3] Although the Protocol was first applied in 1996, the trap-catch methodology was in reasonably common use before this time and data from some pre-1996 surveys have been included where the trapping practices used were sufficiently similar to the Protocol.

- Data cannot be made available.
- Data are available, but DOC (or the regional council) cannot collate and supply it, but a staff member from Landcare Research can visit and retrieve as much as possible.
- Data are available and DOC (or the regional council) can supply it.

Subsequent follow-ups to the initial mail-out were done by telephone and email. Electronic template files (in either MS Access or MS Excel format) were provided to those agencies that responded with the third option above. Potential respondents were also asked to supply information on any control operations (both ground- and aerial-based, and both initial and maintenance control) since the mid-1990s.

4.3 SPATIAL AND OTHER PREDICTORS OF POSSUM DENSITY

4.3.1 Climate and habitat variables

Spatial predictor variables used or developed for this study included a number of climatic, landform, and land-cover variables (Table 1). Land-cover variables included both the point measurement of the land cover (LANDCOV) derived from the LCDB, as well as a number of neighbourhood land-cover variables. These neighbourhood land-cover variables were developed for each 100 × 100-m pixel of the grid layer in the GIS, and describe the land cover in the area around each pixel rather than just within the pixel itself. This was done for two reasons: while the trap lines are depicted as points, they are actually 200 or 400 m long, and hence cross at least two (and sometimes up to seven) of the pixels used for the analyses; and possums are mobile, therefore each trap line effectively samples a wider area around its actual location.

4.3.2 Management variables

A number of other (non-spatial) variables were also developed or derived from the data for use in the analyses (Table 2).

4.3.3 Colonisation history

Colonisation history was also used as a spatial predictor in our models. This was developed first as a polygon coverage in the GIS and then converted to a GIS grid layer for compatibility with other spatial predictors. The polygon coverage showed a crude ‘reconstruction’ of the time of first colonisation, and was based on maps of possum distribution at various stages of colonisation (Wodzicki 1950; Pracy 1974; Cowan 1990; Clout & Ericksen 2000). These maps are simplistic interpretations of historic views of possum distribution at various times (including 1946, 1963, 1974, 1980, 1986, 1990, 1998) since colonisation. In addition, DOC offices in the few localities where possums are still expanding their distribution were asked to provide more detailed and recent colonisation information. The localities from which we received information on recent colonisation are the northernmost parts of Northland (D. McKenzie pers. comm.), south Westland (T. Farrell pers. comm.), western Otago (P. Hondelink pers. comm.), and Fiordland (P. Willemse pers. comm.), and this information was supplied in map form. The overall combined polygon coverage was then converted to a grid layer (at 100 m resolution) that predicted the time of possum colonisation throughout the country. The estimated year of colonisation (for each grid) was then subtracted from the year 2000 to provide an estimated time since colonisation.

4.4 TRAP-CATCH MODELS

Four different models for quantifying and predicting TCIs were developed, each with a different objective.

4.4.1 Uncontrolled model (for predicting TCIs in uncontrolled populations)

This model was developed to quantify and predict the TCIs that could be expected if possum populations were not controlled (and presumably at, or close to, carrying-capacity densities). All that needed to be known about the trap-catch lines were the trap-set type used, the location, and the TCI value for each line. In addition, 250 'pseudo' trap lines with a TCI of 0.0% were generated on bare ground and ice at high elevations. The TCI for each line was then regressed against environmental and land-cover variables, as well as survey variables, such as survey month and set type.

4.4.2 Pre-maintenance control model (for predicting TCIs 1–6 years after control)

This model is required to predict the TCI values from 1 to several years following control. This model requires a relatively complex spatio-temporal analysis, since not only is it required to know how long it has been since control occurred, but also of interest is the spatial relationship of the trap line from the edge of the control area. The additional variables used in this model that were not present in the uncontrolled model include time since previous control and distance to edge of previous control area.

4.4.3 Post-control model (for predicting TCIs following control operations)

This model was developed to predict the TCI values that could be expected *immediately* following control operations. This analysis was quite similar to the analysis of uncontrolled populations, but also included variables that described the control operation (e.g. survey organisation, aerial or ground).

4.4.4 Post-control deviance model (for predicting the residual deviance of individual post-control trap lines from the survey mean)

This model was designed to predict the degree of variation within a post-control survey that could be explained by the environmental and other spatial variables used in this study. To test this, the mean TCI of each post-control survey was subtracted from the TCI for each individual trap line in that survey. This indicated whether each trap line was above (positive values) or below (negative values) the overall survey mean TCI. The predictor variables tested were the same as those for the two other post-control models.

In addition to the above, GRASP was also used to model the distribution and density of the trap lines used in the model for predicting TCIs in uncontrolled populations. The density of trap lines was modelled in relation to environmental and land-cover variables. This was expressed as the probability of a trap line being present, using the locations of the trap lines as presences and a 2% systematic sample of a 100 × 100 m nationwide grid which was treated as absences. This model estimates the probability that any pixel of the 100 × 100 m grid contains a trap line and, therefore, provides a spatial prediction of trap-line density (i.e. trap lines per unit area). While this model was developed on 100 × 100-m pixels, the results were converted to trap lines/km^2 to make the numbers more tractable. Since this model indicates the distribution and density of the data used to generate the uncontrolled population model, it also provides one indication of the reliability of the predictions for that model.

4.5 DATA STANDARDS AND BEST-PRACTICE GUIDELINES

The guidelines and standards for collecting and recording population monitoring data and control-history information, and for the collation and storage of these data, builds upon previous (e.g. the NPCA Protocol; Warburton & McGlinchy 2000) and ongoing work (e.g. DOC's standard operating procedure (SOP) for Animal Pests: Operational Reporting; Lawless 2002) in this area. However, the guidelines and standards we propose also evolved as the project progressed and, in part, reflect some of the issues and problems that were experienced. We assumed that, ideally, data standards and related issues should be applicable to all agencies, not just DOC.

5. Results and Discussion

5.1 DATA COLLECTION AND COLLATION

Landcare staff visited and retrieved data from the West Coast Conservancy and the Canterbury and West Coast Regional Councils. For the remainder of the data, we relied on those conservancies and regional councils that could readily access and provide the required data themselves. The quantity of data subsequently collected was disappointing, and its quality was extremely variable. Currently, the database holds records of 174 pre-control surveys, 230 possum control operations, and 325 post-control surveys (also see Table 3).

Clearly, the data collected to date represent only a small fraction of the data available. For example, in the 2000/01 year alone, 272 possum population monitoring surveys (mostly post-control but also including a few trend surveys, and comprising 10 720 actual trap-catch lines) were undertaken in relation to

TABLE 3. NUMBERS OF SURVEYS AND ACTUAL TRAP LINES* FOR UNCONTROLLED POSSUM POPULATIONS, ACCORDING TO DOC CONSERVANCY.

CONSERVANCY	NO. OF SURVEYS OBTAINED†	NO. OF LINES OBTAINED	NO. OF SURVEYS USED	NO. OF LINES USED
Northland	2	10	1	5
Auckland	0	0	0	0
Waikato	19	136	18	128
Bay of Plenty	11	97	10	88
East Coast/Hawke's Bay	0	0	0	0
Tongariro/Taupo	5	22	4	12
Wanganui	1	30	0	0
Wellington	8	48	8	48
Nelson-Marlborough	4	29	4	29
Canterbury	0	0	0	0
West Coast	25	160	25	160
Otago	0	0	0	0
Southland	31	135	29	122
Totals	106	667	99	592

* These data only record those obtained from DOC; the total numbers of surveys and lines used for the analyses include lines from regional councils also.

† Some of these numbers are estimated since data were often supplied without clear identification of the survey (i.e. some data were supplied in simple files with line locations and trap-catch index (TCI) data, but with no survey variables; some of these were able to be sorted out but c. 5% remained uncertain).

Animal Health Board-funded possum control (J. McInnes, Animal Health Board, pers. comm.). Although the number of these surveys that were on conservation land is unknown, it is likely to be considerable.

Several DOC conservancies supplied data in a format other than that requested. This highlights the lack of standard practices for the collection and storage of possum population monitoring data and control operation information. Furthermore, in at least one field centre, only the summarised results of monitoring surveys were retained (with the original forms containing trap-line data being discarded). Similar problems or inadequacies were also noted in relation to the smaller amount of regional council data obtained.

AgriQuality provided digital coverage of AHB-funded control operational areas. West Coast and Canterbury Regional Councils provided trap-catch information in hard copy form. The West Coast Regional Council also provided maps of control areas. Areas not already in the AgriQuality control layers were digitised and added to the GIS control polygons. Southland Regional Council provided trap-catch data, mostly from post-control surveys, and Wellington Regional Council provided a considerable amount of pre- and post-control survey data as well as GIS polygons of control operation areas. However, since post-control analyses were only performed for the West Coast and Canterbury regions, only the data relating to pre-control surveys in uncontrolled possum populations were used in the Wellington and Southland Regions.

Possum relative abundance data (i.e. TCIs) and control operation information were imported into an MS Access database in a series of linked tables (Fig. 1).

Trap-line locations were stored in various ways in the database, depending on their source. Trap lines that had locations supplied as text typically had a New

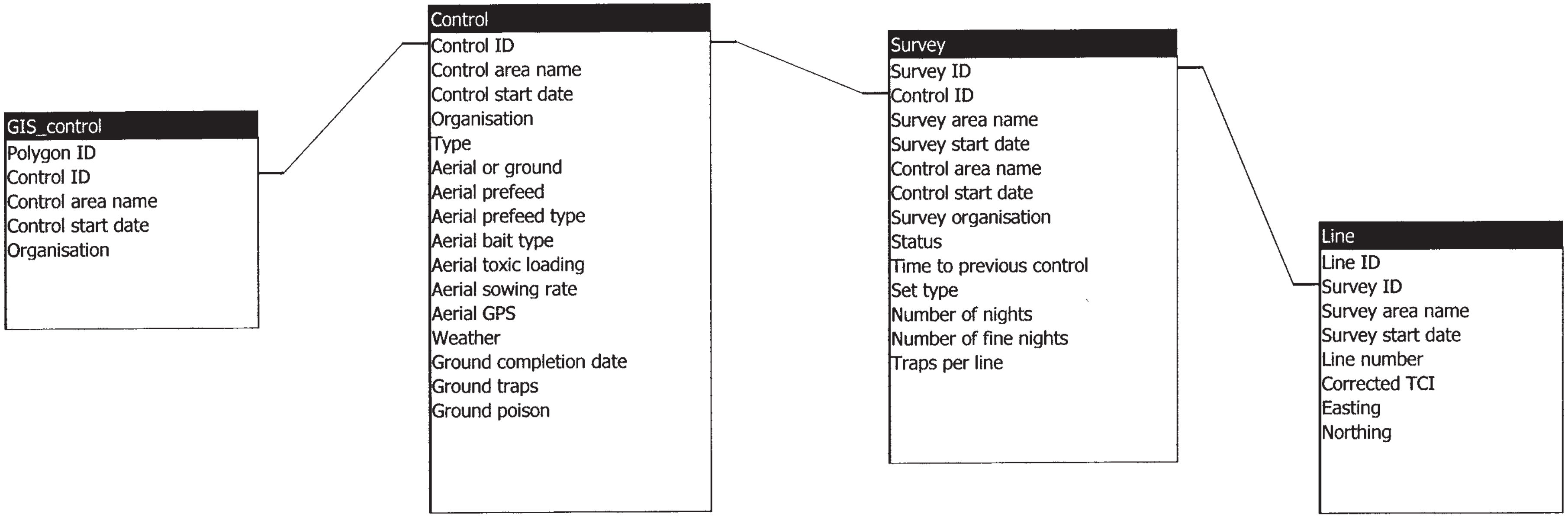

Figure 1. MS Access database structure showing the key linkages (relationships) between the individual data tables, and the variables within each data table.

Zealand Map Grid (NZMG) coordinate (easting and northing) for the line origin and often a line bearing. Trap lines digitised by Landcare Research were depicted as actual lines in a GIS, with links to the line and survey information. For analysis, the location of the line was depicted by a single point located halfway along the line.

The amounts of possum population monitoring data and control operation information obtained to date varied markedly between conservancies (see Table 3). However, this does not reflect the actual amounts of such data potentially available since several conservancies indicated that varying (sometimes considerable) amounts of data existed that they did not have the resources to locate and extract. Furthermore, this does not take into account the substantial amount of data potentially available from Animal Health Board-funded sources. Nevertheless, although the figures in Table 3 do not accurately reflect the overall amounts of population monitoring and control data available for each conservancy, they do provide one indication of where future efforts to obtain data could be directed. Coverage can also be assessed in relation to habitat types (Fig. 2), providing an alternative option for where future efforts to obtain data could be concentrated.

Several conservancies commented that our information request was timely in that it highlighted the shortcomings of their current recording, reporting, and storage systems for possum population monitoring data and control operation information. For example, in some conservancies, this information is retained at field centres with no overall system for collating, storing, and archiving these data. In some conservancies, the information we requested simply could not be easily located despite the fact that a considerable number of possum population surveys and control operations had taken place in recent years. This further illustrates that such information is not stored in a standard, consistent, or readily obtainable way. Even within individual conservancies there was sometimes variation in the way trap-catch and control operation data were recorded, reported, and stored. With respect to control operation information, this problem has been addressed with the recent development of an SOP for the operational reporting of animal pest control activities (Lawless 2002).

Clearly, there is a large amount of possum population monitoring data that could still be collected retrospectively. Table 3 and Fig. 2 can be used to identify the most critical 'gaps', both geographic and environmental, in the data. The greatest improvement in the GRASP models will come from including additional data from surveys done in environments or regions that are currently poorly sampled. For example, there are very few data from much of Northland, East Cape, Taranaki, Canterbury, Otago, and Fiordland. Figure 2 also highlights environmental combinations that have few data, such as agricultural lands in the Waikato and on the Canterbury Plains[4].

The collection and collation of additional pre-control trap-catch data, however, should proceed only after the adoption of a set of guidelines and standards

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[4] Despite a paucity of data from these areas, the uncontrolled-possum-population model predicts them to have moderately high TCIs (see Figs 6 and 7). Hence, more trap-catch data from surveys in these areas would improve the model by providing actual measurements in these environments and land covers.

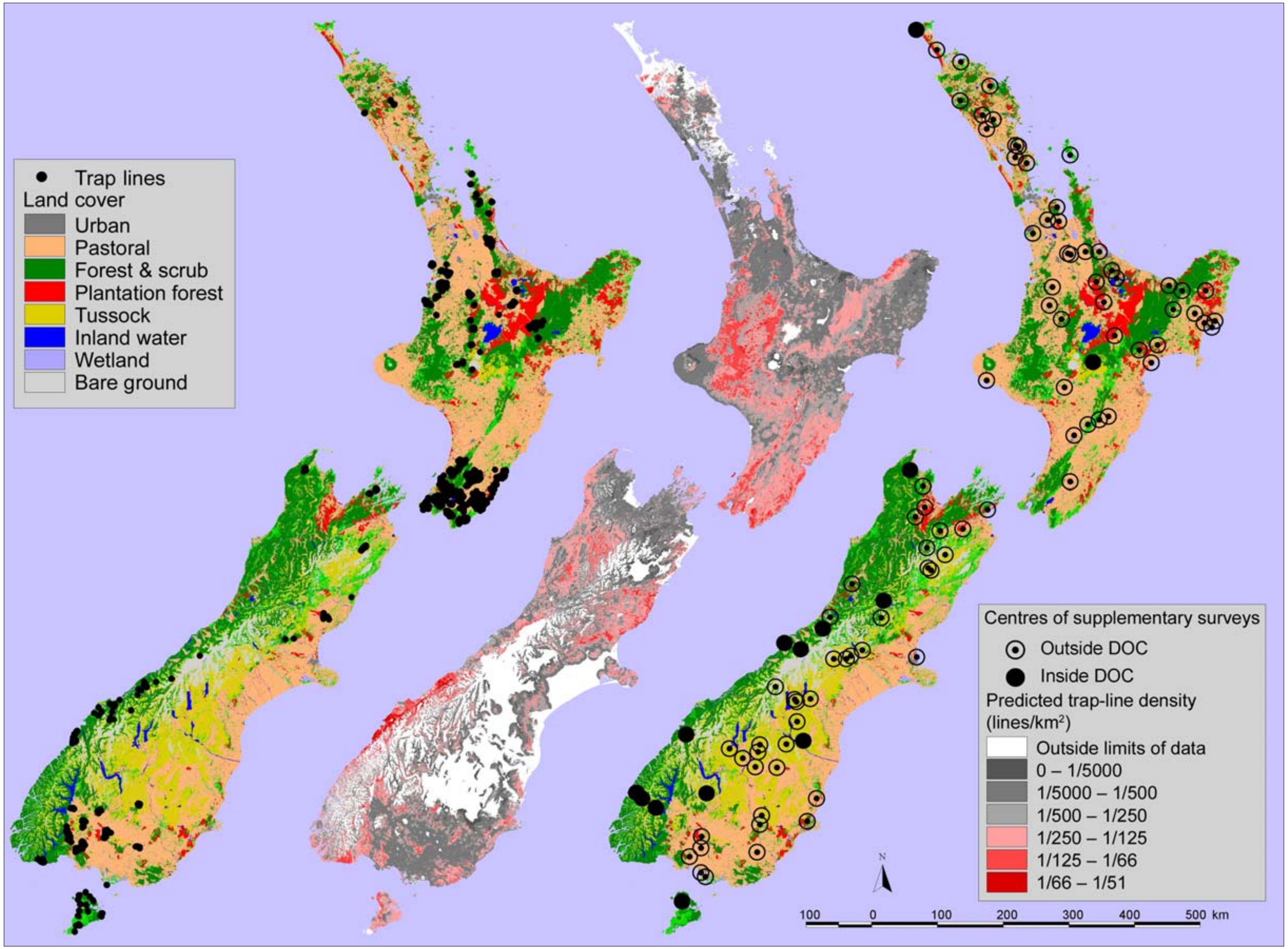

Figure 2. Locations of trap lines used to predict TCIs for uncontrolled populations, predicted density of trap lines according to environmental and land-cover variables, and nominal locations for supplementary surveys. Existing trap lines are shown overlain onto land-cover classes from the LCDB (left map). The predicted density of trap lines according to environmental and land-cover variables indicates the relative data-richness for areas and environments (centre map). The nominal locations of 100 supplementary surveys have been randomly chosen from environments and land covers that are poorly sampled in the existing data (right map; see Appendix 1 for a discussion of supplementary surveys).

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