Predicting Patterns In Spatial Ecology Using Neural Networks: Modelling Colonisation of New Zealand Fur Seals

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Abstract: Conventional mathematical models for ecological processes are often complex and restricted in their predictive capability through the non-linear and non-gaussian properties of the input data. In this paper we discuss the capability of an artificial neural network (ANN) model to predict the colonisation potential of New Zealand fur seals (*Arctocephalus forsteri*) around South Island, New Zealand. We used the distribution of food sources, sea configuration and coastline terrain to predict the potential condition of pups for coastline segments around South Island. We suggest that ANNs can be used effectively in combination with geographic information systems for ecological modelling.

1. INTRODUCTION

Conventional empirical modelling procedures often assume linear relationships among ecological variables, when often this is clearly not the case (Hornik *et al*. 1989; Lek *et al*. 1996; Guégan *et al*. 1998). However, artificial neural networks (ANN) have been proposed as a modelling platform on which non-linear models can be developed. One of the advantages of neural networks is their ability to discover patterns in data that are not readily observed by human researchers and conventional statistical methods. However, although neural network models have been used in many

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different research fields, few[1] have been applied to ecological applications. In this paper our main objective is to discuss the merits of a neural network linked to a geographic information system (GIS) for the analysis of spatial data in ecology. Specifically, we discuss an example of analysing spatial data in population ecology – predicting the colonisation potential of New Zealand fur seals (*Arctocephalus forsteri*) around South Island, New Zealand.

2. MODELLING THE EFFECTS OF THE MARINE ENVIRONMENT

Though the quality of the marine habitat is assumed to be highly dependent on spatial and temporal changes to the marine environment, the precise nature of this dependency is difficult to determine. However because of their position atop the marine food web, there should be some sort of measurable functional relationship between the biological parameters of higher predators and the available marine resources. The parameters associated with fur seals at breeding colonies may be useful in this respect, because the female seals are limited in the distance that they are able to forage for food from the breeding site. Thus the measurable condition of seals at the colony should be particularly sensitive to fluctuations in local prey availability.

In this study we examine the geographic variation in both the marine and terrestrial environment in the range of New Zealand fur seals (*Arctocephalus forsteri*) in a working model that can be used to compare the spatial configuration of marine resources (*e.g.*, Wanless *et al.* 1997) with the geographic variation in pup condition. Using neural networks and comparative parametric models, we constructed indices of coastline suitability for colonisation. The derived information is potentially important not only because it can provide insight into the poorly-understood processes of marine mammal colonisation, but also because it can enable management authorities to identify potential areas of conflict between humans (*i.e.*, usually commercial fisheries) and the expanding fur seal population.

The goal of this investigation is to model the effects of the local environment on the quality of New Zealand fur breeding sites. To construct such a model some reliable measure that indicates the quality of a breeding site is needed. Since New Zealand fur seals are in the process of re-colonising areas depleted by past human exploitation, with different colonies in different stages of this re-colonisation, the measurement of pup

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[1] For example, (Mastrorillo et al. 1997; Baran et al. 1996; Lek et al. 1996; Scardi 1996; Chon et al. 1996; Schreer et al. 1998).

production is not considered to be a particularly useful measure of breeding site quality here. It would seem that measuring the average condition and/or growth rate of the fur seal pups at a colony would serve as a better indicator. There are some difficulties, however, associated with conducting measurements of pup growth rates, so measuring the pup condition was considered to be more practical for this study.

3. NEW ZEALAND FUR SEAL COLONIES

The expected factors that affect seal colonisation are
- The proximity and availability of food sources
- Oceanic currents, along with the distance and configuration of the continental shelf
- The configuration of the local terrestrial coastline environment (which might provide suitable forms of shelter).

3.1 Model parameters

As a consequence, there were four types of data used for this investigation: (1) fur seal pup condition; (2) food sources; (3) sea configuration; and (4) coastline terrain. The goal was to examine the manner in which food sources and the physical attributes of the sea and coastline affect the condition of the fur seal pups.

Fur seal pup condition. 20 breeding colonies of New Zealand fur seals around the South Island were investigated during the period 1996-98. More than 6,000 seal pups from the twenty colonies were caught and measured with respect to length (to the nearest 0.1 m) and weight (to the nearest 0.1 kg) (Laws 1993). A condition index (CI) for seal was obtained by calculating the logistic regression of pup mass against the length and then calculating the ratio of the observed mass to the predicted value. Pup condition per colony was summarised by calculating the range of the pup condition index and dividing the range of all observed pups into distinct classes (the group divisions were identified where there was a clear separation between distinct clusters of performance values). The classes are shown in Table 1.

Table 1. Colony performance class ranges for 1996-98.

Year	Pup condition range	Class	No. Colonies
1996	0.9628 – 1.0346	0	5
	1.0727 – 1.0983	1	2
	1.1342 – 1.1471	2	3
	1.1945 – 1.2621	3	5
1997	0.9776 – 1.0532	0	8
	1.0837 – 1.1241	1	7
	1.1401 – 1.1713	2	4
1998	0.8425 – 0.8846	0	6
	0.9034 – 0.9211	1	8
	0.9295 – 1.0126	2	5

Food sources. Inshore trawl survey data (1979-97) for eight principle fur seal prey species were obtained from the New Zealand National Institute of Water and Atmospheric Research (NIWA) so that local availability of these species for each site could be estimated. The species were arrow squid (*Nototodarus sloanii*), New Zealand octopus (*Octopus maorum*), barracouta (*Thyrsites atun*), hoki (*Macruronus novaezelandiae*), red cod (*Pseudophycis bachus*), and jack mackerel (*Trachurus novaezelandiae, T. murphyi, T. declivis*).

Sea configuration. Fur seals forage over a bottom depth of 100 – 300 m, so the information about the local configuration of the continental slope and water depth was covered obtaining digitised data on the position of the 250, 500, 750, 1000, and 1250m isobaths for New Zealand waters (NIWA).

Coastline terrain. The terrain at areas where fur seals come ashore to breed is assumed to have an impact on their living conditions, so a broad terrestrial habitat classification was obtained from *The New Zealand Atlas of Coastal Resources* (Tortell 1981).

3.2 Fur seal colony models

The fur seal colonies were modelled with respect to how input parameters concerning food sources, sea configuration, and coastline terrain affected the mean pup condition of the colony. The neural network architecture was that of a feedforward, multilayer perceptron, consisting of an input layer of nodes (one for each input parameter), a single "hidden" layer, and an output layer (one node for each output class). Neural network modelling was performed in three basic steps:

1. Train the neural network by using the measured pup colony output class information as the training data. (The neural network training

employed a node connection-value penalty function, which resulted in the pruning of some node connections and hidden-layer nodes.)
2. Discretise the hidden-layer node activation values by means of a clusterisation method. (Note that the output values had already been discretised by identifying the pup condition output class clusters.)
3. Generate rules from the transfer of the discrete values to the hidden layer and to the output layer.

The clusterisation procedure performed in step 2 above is based on the Π^2 statistic and is described in (Purvis *et al.* 1997). When employed in connection with the hidden-layer node activation values, it provides boundaries of the subintervals of these values. If there are N activation values, then there are $N+1$ subintervals: $-1 < m_1 < m_2 < ... < m_{N-1} < 1$. A node activation (assuming that *tanh* is the node activation function) falls into the subinterval $[m_{j-1}, m_j]$ if its weighted inputs satisfy the condition:

$$tanh^{-1}(m_{j-1}) \ < \ weighted\ inputs \ < \ tanh^{-1}(m_j)$$

From these relationships it is possible to obtain rules, in the form of constraint equations, from the input layer to the hidden-layer values.
For the second-level rules (corresponding to rules from the hidden-layer to the output-layer values), we employed the X2R approach (Liu & Tan 1995):
– Generate a rule to cover the most frequently occurring pattern. This is the shortest rule that can differentiate the pattern from patterns of other output classes. Then remove this pattern from further consideration.
– Repeat the previous step until all patterns are accounted for.
– The generated rules are then grouped in terms of their class labels.
– For each rule cluster remove redundant rules and delete more specific rules in favour of more general rules for the cluster.
With the two sets of rules obtained, it is sometimes useful to combine them into a single set of rules (from input values to output values).

4. MODELLING RESULTS

Separate neural network models were trained for each of the years 1996, 1997, and 1998. The training results for these models are shown in Table 2.

Table 2. Neural network architectures and training performance.

Year	Input Nodes	Hidden nodes	Output Nodes	Training Accuracy
1996	17	4	4	87%
1997	17	10	4	100%
1998	17	10	4	79%

After training, some of the hidden nodes were pruned. For example for the 1997 data, one of the hidden nodes was pruned, leaving three hidden units. The hidden-layer subintervals generated by the clusterisation procedure for this network are shown in Table 3.

Table 3. 1997 Hidden-layer subintervals generated by clusterisation.

Hidden Unit	Subintervals
A1	[-1 to 0.196] and [0.196 to 1]
A2	[-1 to -0.32] and [-0.32 to 1]
A3	[-1 to 0.025], [0.025 to 0.034] and [0.034 to 1]

Generated inference rules associated with the above (1997) hidden-layer subintervals to the output layer were as follows:

```
    IF A1 ≥ 0.196 and A2 ≥ -0.320
       THEN performance class 1
    ElSE IF A2 < -0.320 AND 0.025 < A3 ≤ 0.034
       THEN performance class 2
    ELSE (DEFAULT) performance class = 0
```

The Generated rules associated with input-layer to the hidden-layer (in the form of constraint equations) were

```
   A1 = 0.9175*SQU - 0.3639*OCT - 0.9706*BAR +
         4.6167*B250 - 4.8612*B1000
   A2 = -0.4372*OCT
   A3 = 1.2198*HOK
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(where SQU = arrow squid, OCT = octupus, BAR = barracouta, BXXX = position of the XXXm isobath, and HOK = hoki).

Combining the two sets of 1997 rules yields the following composite 1997 rules:

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IF (0.9175*SQU - 0.3639*OCT - 0.9706*BAR + 4.6167*B250 -
             4.8612*B1000) ≥ 0.196
AND (-0.4372*OCT) ≥ -0.320
   THEN performance class = 1
ELSE IF (-0.4372*OCT) < -0.320
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```
AND 0.025 < (1.2198*HOK) ≤ 0.034
  THEN performance class = 2
ELSE (DEFAULT) performance class = 0
```

The performance of these inference rules when presented with the 1997 data is shown in Table 4.

Table 4. 1997 inference rule performance.

Class	Correct Patterns	Incorrect Patterns	%Correct
0	8	0	100.0
1	5	2	71.4
2	4	0	100.0
Total	17	2	89.5

Similar types of rules were derived for the 1996 and 1998 data. However the specific dependencies on food source parameters were not consistent across the three years. The performance of these rule sets is shown in Tables 5 and 6.

Table 5. 1996 inference rule performance.

Class	Correct Patterns	Incorrect Patterns	%Correct
0	5	0	100.0
1	2	0	100.0
2	0	3	0.0
3	5	0	100.0
Total	12	3	80.0

Table 6. 1998 inference rule performance.

Class	Correct Patterns	Incorrect Patterns	%Correct
0	3	3	50.0
1	7	1	87.5
2	4	1	80.0
Total	14	5	73.7

5. DISCUSSION AND CONCLUSIONS

The neural network model described in this paper was also compared with a conventional parametric statistical model (polytomous logistic regression – PLR) that was applied to the same data. Here all the coastal areas around the New Zealand South Island (the majority of which do not have any seal colonies) were given as input, and the two models were used to predict the distribution of pup condition classes for each of these sites. One would expect that the models would identify a significant overlap

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between the sites that already have fur seal colonies and the sites that are predicted to have a high proportion of 'healthy' seal pups. Such was the case with the neural network model, but the PLR model did not show this expected overlap. Thus, on the basis of this comparison, the neural network model appeared to yield results more consistent with physical evidence than the PLR model did.

There are additional advantages associated with neural network models. Neural network modelling does not require prior specification of data distribution characteristics and can have advantages (when compared with conventional parametric modelling techniques) in situations where the underlying causal links are not fully understood. Moreover, the existence of inference rule extraction techniques make it possible to use data mining techniques to derive knowledge from spatial data sets.

Despite reasonably good inference rule performance, however, the rules derived in this study did not yield consistent relationships with respect to dependency on food sources over the three years. These results could be affected by the facts that there was a weak La Nina condition in 1996 and a strong El Nino condition in 1998 and that there was no available data that covered possible variations in prey availability over the three years. These effects could lead to modifications of female foraging behaviour in response to relative prey availability that have not been modelled. The real test of these considerations will come with further colonisation information of new fur seal colonies as the population continues to expand and spread.

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