ELSEVIER

Ecological Modelling 120 (1999) 349–358

ECOLOGICAL MODELLING

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Use of artificial neural networks for predicting rice crop damage by greater flamingos in the Camargue, France

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Abstract

Since the 1980s, incursions of greater flamingo (*Phoenicopterus ruber roseus*) in rice fields have been reported almost every year in the Camargue, south-eastern France, and more recently in Spain. We assessed the performances of artificial neural networks (ANN) in predicting presence or absence of flamingo damages from 11 variables describing landscape features of rice paddies. The global matrix of 1978 records (276 with damage and 1702 without) for the 1993–1996 period was used to determine the suitable parameters: number of hidden layer nodes and number of iterations. In order to avoid particular inputs either in the training set or in the testing set, ten different randomly sampled training sets were available. A classic multilayer feed-forward neural network with back-propagation algorithm was used throughout these experiments. Data from 1993 to 1996 were used to predict data for 1997 (73 fields with damage and 1905 without) and 1998 (88 with damage and 1890 without). Three training set compositions were displayed: (I) the whole data set (1978 observations), (II) an equal number (276) of damaged and undamaged fields (552 observations), (III) a set with 1/3 of observations being damaged fields (276) and 2/3 undamaged (552). ANN faced some difficulty in predicting both presence and absence of damage. The number of each type record in the training set was particularly sensitive. ANN predicted the more frequent outcome, (i.e. absence of damage). Most often, better results were obtained when equilibrating the number of presences and absences. In this case, we obtained performances ranging from 64% up to 87% according to the presence and absence of data in the training set. When fitting ANN with the whole set of presences to predict damage 1 year later, these results stabilised at $\approx$79% for 1997 and between 66 and 72% for 1998 when more than half of the damaged fields were never visited by flamingos during the period 1993–1997. Our performances are quite similar to the results obtained by previous authors and predictability from 1 year to the following one also supports that ANN can be an alternative or a supplement to actual scaring methods in identifying potential damaged fields and propose agricultural management plans or concentrate scaring actions on these high-risk areas.

Keywords: Flamingos; Rice; Damage; Artificial neural networks; Prediction; Landscape features; Camargue; France

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0304-3800/99/$ - see front matter
PII: S0304-3800(99)00114-3

1. Introduction

Rice-crop damage by shorebirds, ducks and/or passerines has been studied mainly in North and South America, Africa and Australia, where rice is cultivated over very large areas. Damage by these 'pests' has been estimated at millions of dollars annually (Berryman, 1966; Wilson *et al*., 1989; Decker *et al*., 1990) and huge efforts have been made to find solutions (*e.g*. Meanley, 1971; Elliot, 1979; Ward, 1979; Holler *et al*., 1982; Avery and Decker, 1994; Avery *et al*., 1995; Katondo, 1996).

In Europe, rice cultivation is restricted to parts of the Mediterranean region and this phenomenon has received less attention. However, in spring 1978, greater flamingos (*Phoenicoterus ruber roseus*) began to feed in rice fields of the Camargue, the delta of the River Rhone in south-eastern France. Scaring campaigns have been carried out every year since 1981, and crop losses from flamingos have been reduced. This habit spread in 1993 to the Ebro delta, north-eastern Spain, and Spanish farmers now face the same problem as the French (Jimenez and Soler, 1996; Johnson and Mesléard, 1997).

Scaring programs, begun in 1981, involve use of gas exploders, rotating firing devices and Very pistols (André and Johnson, 1981; Hoffmann and Johnson, 1991). Even if these techniques are efficient in scaring or keeping away flamingos from some rice fields, they are costly and time consuming. Monitoring of flamingo movements and behaviours must occur over a wide foraging range (over 60 km from the breeding site at the Etang du Fangassier; Johnson, 1989). We based our study on the hypothesis that some plots were more attractive than others, e.g. that landscape features may influence the flamingo's choice of plots in which to forage (André and Johnson, 1981; Sourribes, 1993; Rogers, 1995; Jimenez and Soler, 1996; Durieux, 1997).

A model identifying the most vulnerable plots could be helpful to farmers and wildlife managers by helping to evaluate the risk of crop damage in problem areas. Due to the non-linearity of most of the variables in ecology and the use of qualitative traits in the data set, we computed ANN to propose predictive models for the damage caused by flamingos in rice fields and to characterize the explicative landscape variables.

2. Study area

The Camargue delta of the River Rhône, lies on the Mediterranean Sea coast. Rice was introduced into the area in the early 1940s and today paddies cover some 24 000 ha (16% of the total surface area of the Camargue and 46% of the agricultural land, Chauvelon, 1996). Our study was carried out in the Fumemorte Basin, one of six independent drainage basins of the delta. This sector is in the eastern part of the delta proper and comprises ≈ 70 km^2. Rice fields represent some 31% of the total surface of the basin and 61% of the agricultural land. There are also extensive areas of natural land (32%) and abandoned farm lands (23.2%). The agricultural land is subdivided into small cultural units, 75% being less than 3 ha (Chauvelon, 1996). The southern part of the basin is 2 km from the unique breeding site of the greater flamingo in France (16.5 km for the northern part). The Etang du Fangassier is the only breeding site of the greater flamingo in France and one of the most important in the Mediterranean area (Rendon Martos and Johnson, 1996).

Flamingos frequent rice fields between sunset and sunrise from the end of April to the beginning of June. This period corresponds to the critical germination period of rice in the Mediterranean region (Fasola and Ruiz, 1996; Barbier and Mouret, 1992). Damage to crops is caused in four ways (Hoffmann and Johnson, 1991): (i) trampling which prevents germination; (ii) disturbance of the grain, causing it to float to the surface where it is blown to the downwind shore; (iii) seedlings destroyed by trampling and (iv) ingurgitation of rice seeds. Whether flamingos visit the fields in search of invertebrates or to feed on the rice grain, or both, is not known. It has been shown, however, that flamingos prefer some paddies to others and visit the same fields on consecutive nights and from 1 year to the next (Rogers, 1995; Jimenez and Soler, 1996).

3. Methods

3.1. Monitoring damage

We analysed occurrence of rice-crop damage by flamingos for the period 1993–1998. From 1993 to 1995, data were taken from internal reports of the Parc Naturel Régional de Camargue, and by interviewing landowners. Only ascertained flamingo damaged paddies were considered. For the period 1996–1998, three methods of monitoring rice crop damage were used (Durieux, 1997):

1. a bi-weekly aerial survey (at 400 ft) of the Fumemorte basin in the morning. Each field with turbid water or with tracks was visited the same day to confirm that flamingos were responsible for these tracks (presence of feathers, footprints).
2. daily observations at dusk and at night in strategic places on farmlands considered vulnerable. Information gathered by this method was scarce due to the darkness and size of the area surveyed.
3. interviews with farmers who plotted on a map the distribution of fields frequented by flamingos and the number of birds involved. This inquiry was carried out at the end of June, but farmers telephoned the 'French Rice Centre' or the 'Tour du Valat Biological Station' immediately when they noticed groups of flamingos in their fields.

The presence or absence of damage was coded (1) and (0) respectively.

3.2. Environmental variables

We considered 11 environmental variables for each of 1978 rice fields of the Fumemorte Basin. These were: surface area; distance from natural marshes; distance from the breeding site; distance from the closest wooded hedge or copse; distance from power lines; distance from habitations; distance from principal roads; distance from secondary roads; height of hedges surrounding the paddy; number of wooded sides; adjacent (1) or not (0) to damaged field.

Surface area was measured in ha and distances were considered from the geometric centre of the field (in m or km). The height of hedges was assigned to one of five classes according to the main vegetation occurring in the Camargue (Durieux, 1997): < 50 cm (herbaceous plants or absence of vegetation); 50 cm–150 cm (mostly Reed, *Phragmites australis*); 150 cm–3 m (hedges composed of Reed, Tamarisk, *Tamarix gallica*, Hawthorn, *Crataegus monogina*, Phillyrea, *Phillyrea angustifolia*, Elderberry, *Sambucus nigra*), 3 m–15 m (Narrow-leaved Ash, *Fraxinus excelsior*, Laurel, *Laurus nobilis*; Oleaster, *Eleagnus angustifolia*); > 15 m (Common Alder, *Alnus glutinosa*, Downy Oak, *Quercus pubescens*, Italian Cypress, *Cupressus sempervirens*, Elm, *Ulmus campestris*, White Poplar, *Populus alba*, False Acacia, *Robinia pseudacacia*).

3.3. ANN modelling

3.3.1. Fitting and testing

The global matrix of 1978 records (276 with damage and 1702 without) for the 1993–1996 period was used to train the ANN and to determine the suitable parameters: number of hidden layer nodes (HN) and number of iterations. In order to test the classification quality of the model, the data matrix was randomly decomposed into two sets. The first set was used to train the neural networks (training sets). The remaining individuals (testing sets) were used to evaluate the quality of their assignment in a hold-out procedure (Kohavi, 1995). Due to the larger number of absences of damage, three set compositions were sampled: sets A, B and C (Table 1). In order to avoid particular inputs either in the training set or in the testing set, ten different training sets C were randomly sampled (C1–C10).

We used a classic multilayer feed-forward neural network with back-propagation algorithm (Rumelhart *et al.*, 1986) throughout these experiments. We trained networks with one hidden layer of one to 15 neurons. The output variables were: 0 = absence of damage, 1 = damage.

Training the network consisted of using a training data-set to adjust the connection weights in order to obtain the maximum number of individuals correctly classified. The connection weights, initially taken at random in the range [− 0.3, 0.3],

Table 1
Three randomly sampled training and testing sets used for fitting ANN models

Set	Training sets			Testing sets		
	Damage	No damage	**Total**	Damage	No damage	**Total**
A	207	1277	**1484**	69	425	**494**
B	207	414	**621**	69	1288	**1357**
C	207	207	**414**	69	1495	**1564**

were iteratively adjusted by a method of gradient descent based on the difference between the observed and expected outgoing signals. The number of iterations (necessary to guarantee the convergence of estimated values toward their expectations) was first limited to 500, then to 400 in order to avoid an overfit (see Gallant, 1993). Training was performed first on sets A, B and C with six, eight, ten, 12 and 15 hidden neurons, second on three sets C with one, two, three, four, five, six, seven, eight, ten, 12 and 15 hidden neurons, third on ten sets C with six hidden neurons.

3.3.2. Predicting

Data from 1993 to 1996 were used to train a model and predict data from 1997 (73 with damage and 1905 without) and 1998 (88 with damage and 1890 without). Three training set compositions were displayed: (I) the whole data set (1978 observations), (II) an equal number (276) of damaged and undamaged fields (552 observations), (III) a set with 1/3 of the observations being damaged fields (276) and 2/3 undamaged (552). ANNs were trained with ten sets of each composition.

Note that all the paddies used by flamingos in 1997 were previously visited by birds while 48 paddies (out of 88) were first visited by the flamingos in 1998. The contribution of each environmental variable was determined from trainings of ten type II data sets using the Goh procedure (Garson, 1991; Goh, 1995).

4. Results

4.1. Fitting and testing models

The larger number of 'absences' in the set A induced the learning of absences far better than presences (Fig. 1). Training with the set B was good for both absence and presence, but presence was poorly predicted ($\approx$ 50% of correct classification). The best results were obtained when equilibrating the 'presences' and 'absences' (set C). After 180 iterations, performances fluctuated, according to the number of neurons of the hidden layer (HN = 6–15), between 80 and 99% for training, and between 61 and 84% for testing. For the next steps of analysis, we considered 400 iterations when the correct classification percentage was between 84 and 99% for training, and between 61 and 77% for testing, in order to avoid anoverfit. When training the ANN with three sets C, there was little variation in the testing scores according to the number of hidden layer nodes (Fig. 2). However, predictions seemed to be more balanced with an intermediate number of hidden layer nodes (HN = 6): 69 to 75% for absences and 68 to 77% for presences. Training ANN with an equal set of presences and absences gave the best correct classification percentages after 400 iterations when using a model with 6 hidden layer nodes. This configuration was used for the following analysis. The correct prediction, repeated 5 times, for ten randomly sampled testing sets, associated with equilibrate training sets, varied from 64% (set 4) to 87% (set 2) for presences (Fig. 3), and from 65% (set 1) to 79% (set 3) for absences. However the scores were balanced and quite homogeneous for all the sets.

4.2. Prediction

A model (I) with an intermediate number of hidden layer nodes (HN = 6) and trained with the whole 1993–1996 data set predicted more ab-

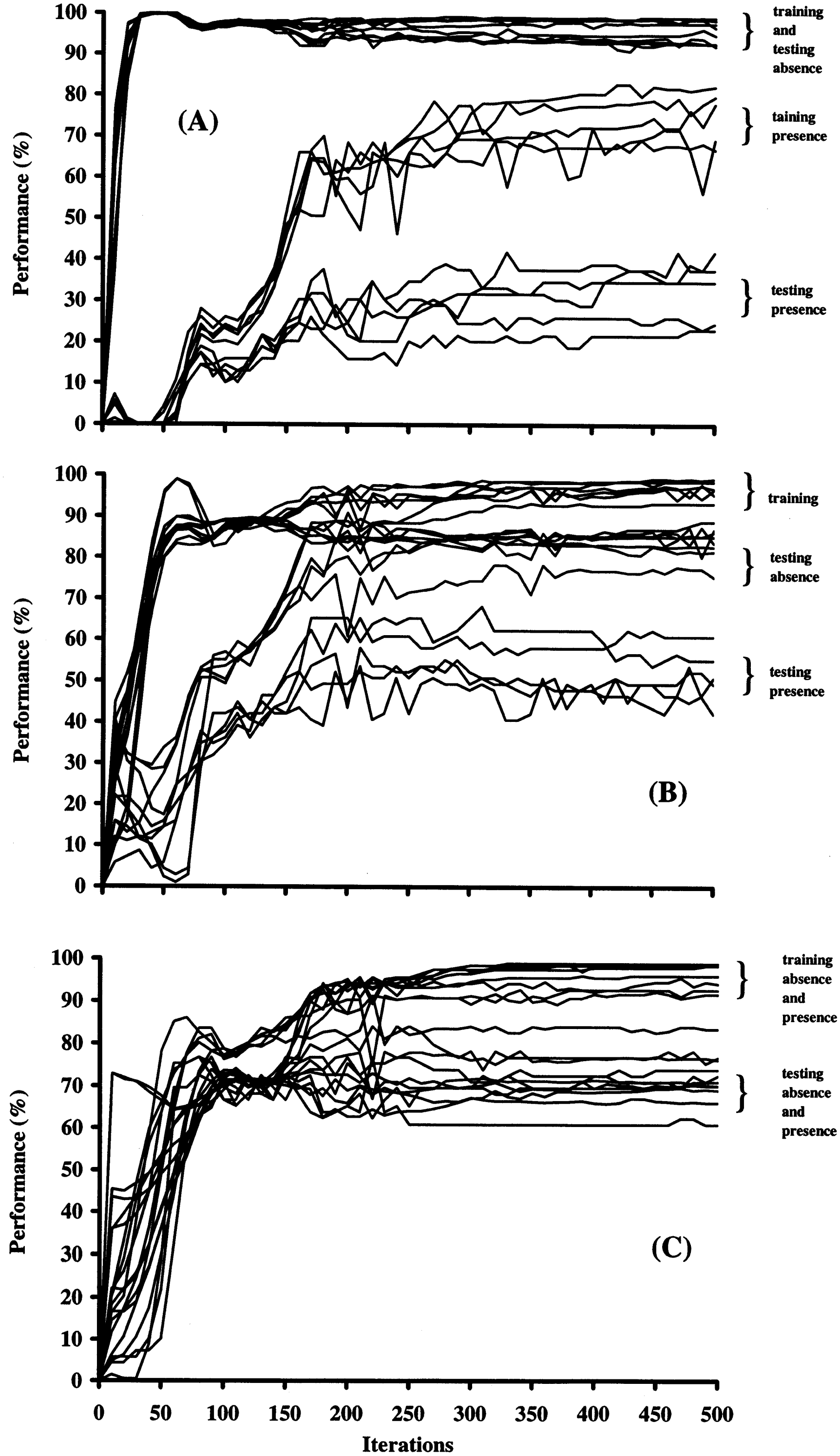

Fig. 1. Number of iterations and performance (percentage of correct classification) obtained for three set compositions (A, B, C; see text) by ANN model in training and testing. Five configurations of hidden layer nodes are represented (HN = 6, 8, 10, 12, 15).

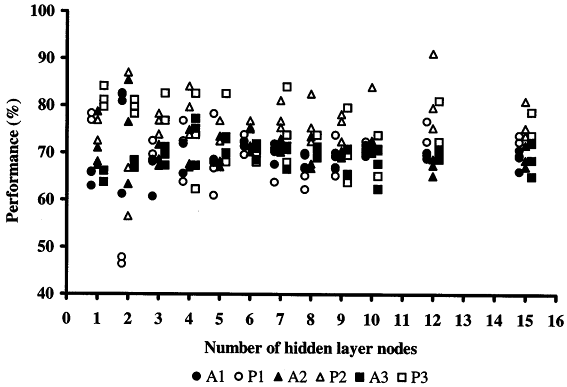

Fig. 2. Performances of three networks with an equilibrate number of presences and absences (207) according to the number of hidden layer nodes. For each network, training was proceeded three times and tested three times with the rest of the observations. A = absences, P = presences.

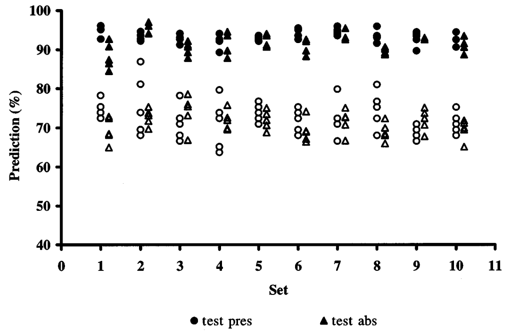

Fig. 3. Predictive power of ANN models (HN = 6) determined from five trainings of ten sets with an equilibrate number of presences (pres) and absences (abs).

sences (92.4%) than presences of flamingos in rice fields (53.4%) in 1997. A model (II) with similar number of HNs (6) but with an equal number of presences and absences predicted more the presences (93.2%) than the absences (65.7%). A similar model (III) with 1/3 of observations being presences and 2/3 being absences gave a balanced prediction for 1997. Predictive scores of model III were quite stable for ten trainings $\approx 79\%$ for both presences and absences (Table 2).

Predictions differed slightly for 1998 (Table 3). A model using a type III training set and same training scores as 1997, predicted more absences than presences ($\approx 76\%$ vs 60%). There were no such differences between accuracy of classification using a type II training set. Despite higher training scores, the predictive scores were lower than in 1997, mainly for absences. These results can be easily related to the somewhat different location of damage in 1998 compared with the previous years.

Table 2
Predictions for 1997 of ten type III (1/3 observations being presences and 2/3 being absences) ANN models with an intermediate number of hidden layer nodes (HN = 6)

Training	Testing	Training	Testing		
(1993–1996)	(1997)	Presences (%)	Absences (%)	Presences (%)	Absences (%)
III.1	1905 $A+73$ P	80.8	94.7	83.5	79.6
III.2	id.	79.3	89.3	80.8	77.6
III.3	id.	85.9	91.8	78.1	77.6
III.4	id.	79	93.1	72.6	80.5
III.5	id.	83	94.2	79.4	79.7
III.6	id.	75.3	95.5	71.2	80.4
III.7	id.	80	94.5	80.8	79.5
III.8	id.	81.2	92.4	78.1	77.9
III.9	id.	80	91.3	78.1	77.7
III.10	id	81.5	94	84.9	81.3

Table 3
Predictions for 1998 of ten type II (equal number of absences and presences) and ten type III (1/3 observations being presences and 2/3 being absences) ANN models with an intermediate number of hidden layer nodes (HN = 6)[a]

	Model II				Model III			
	Training		Testing		Training		Testing	
Set	Presence (%)	Absence (%)	Presence (%)	Absence (%)	Presence (%)	Absence (%)	Presence (%)	Absence (%)
1	92.03	93.84	69.32	66.19	85.15	95.29	60.23	76.88
2	93.84	88.04	76.14	65.34	82.61	92.75	57.96	75.19
3	91.67	93.84	73.86	65.19	79.71	92.39	51.14	77.73
4	89.13	93.12	68.18	68.36	86.96	93.3	63.64	74.79
5	92.03	88.04	71.59	66.14	81.88	95.11	56.82	78.73
6	92.75	89.49	70.46	64.55	84.78	93.3	64.77	78.25
7	93.12	90.22	73.86	65.93	80.8	93.12	55.68	76.51
8	92.39	90.58	68.18	65.87	84.78	93.48	60.23	77.78
9	92.39	92.03	73.86	67.19	86.23	93.3	56.82	76.24
10	93.48	91.3	70.46	64.07	85.51	92.57	63.64	76.35
Mean	92.283	91.05	71.591	65.883	83.841	93.461	59.093	76.845
S.D.	1.301	2.169	2.731	1.240	2.435	0.983	4.252	1.285

[a] S.D. = standard deviation.

4.3. Contributions of environmental variables

From one model to another, all variables displayed high contributions (Table 4). However the contributions of the surface of rice fields (SUP), and also of the distance from the colony (DCO), was often weak, while the distance from natural marshes (DNM) and the distance from the closest wooded hedge (DWO) exhibited high contributions in most of the models. Note that contributions of input variables varied considerably among models. For example, model four attributed a huge contribution to the distance from natural marshes (DNM), the number of closed sides (NWS) exhibited also a heavy contribution, while these variables were weakly implicated in model seven.

5. Discussion

Artificial neural networks faced some difficulties in predicting both presence and absence of damage. The number of each type record in the training set was particularly sensitive. As previously observed by Spitz *et al*. (1996), Mastrorillo *et al*. (1997), Manel *et al*. (1999), ANNs delivered better prediction for the largest occurrence. Better results were obtained when equilibrating the number of presences and absences. This is a problem, because in ecology absences are often far more frequent than presences, and obviously, information is lost by decreasing the number of absences in training sets. The weak improvement of the performance of ANN with the increasing number of hidden layer neurons could be related to close relative input variables, but we can hardly conceive that it is the case with environmental variables such as distance to the natural marshes and number of wooded sides to the field.

When equilibrating correct predictions of presence and absence of damage, we obtained performances ranging from 64% up to 87% according to the sampled data in the training set. When fitting ANN with the whole set of presences to predict damage 1 year later, these results stabilized ≈ 79% for 1997 and between 66 and 72% for 1998 when more than half of the damaged fields were never visited by flamingos during the period 1993–1997. These performances are quite similar to the results obtained by Spitz *et al*. (1996) in predicting the impact of Wild Boar (*Sus scrofa*) on cultivated fields (approximately 80% for presence, but only 42% for absence).

Damage of rice fields by flamingos may be a trivial problem on an international or on a national scale, but, at a regional or local scale the situation is more critical. Flamingo damage for the Camargue has been estimated at approximately \$153 000 annually (Johnson and Mesléard, 1997). Even if crop losses attributable to flamingos has no perceptible impact on farming in terms of national crop production, like other bird problems in Europe (O'Connor and Shrubb, 1986; Edgell and Williams, 1991), the same fields can be visited on consecutive nights and over consecutive years (Rogers, 1995) and crop losses can be important for a single farmer.

Until now, several non-lethal or lethal techniques were advanced to prevent damages to rice paddies by birds (Meanley, 1971; Elliot, 1979; Ward, 1979; Wilson *et al.*, 1989; Decker *et al.*, 1990; Hoffmann and Johnson, 1991; Avery *et al.*, 1995). However, the effectiveness of these operations is shown to be conditioned by the number of birds and by the mobility and behaviour of the species concerned (O'Connor and Shrubb, 1986; Brugger *et al.*, 1992). Rather than searching for short-term methods of control which are not necessarily efficient, nor ethical (Morrisson, 1975; Van Vessem *et al.*, 1985; Caughley and Sinclair, 1994), long-term solutions to this particular problem should be sought. Predictability from 1 year to the next supports the idea that ANN can be an alternative or a supplement to actual scaring methods in identifying vulnerable fields. This would enable agricultural management plans to be established or scaring actions to be concentrated on these high-risk areas.

The next step of our study is to extend predictions to the whole of the Camargue and to accurately identify vulnerable fields in order to concentrate scaring methods or propose management actions on these high-risk areas. This study interestingly revealed the ability of ANN to predict damage by greater flamingos from a small set of environmental variables which it is easy to collect. However, before extending the model, some new analyses are needed to improve the predictions, and also to find a method of identifying the most relevant environmental variables for modelling the prediction (discriminant analysis,

Table 4
Relative importance of input variables for ten type II sets[a,b]

Set	SUP	DNM	DCO	DWO	DTL	DHA	DPR	DSR	HHS	NWS	CON
II.1	9.22	9.85	9.86	10.18	8.23	6.30	9.20	9.43	8.35	11.84	7.55
II.2	9.18	13.30	10.80	11.3	9.28	8.54	4.11	5.41	8.99	9.59	9.41
II.3	10.4	13.40	6.48	13.7	8.7	10.40	8.32	9.14	6.80	3.84	8.85
II.4	4.31	19.20	5.85	9.77	5.8	9.91	8.14	9.24	7.43	12.00	8.32
II.5	5.17	12.50	5.41	12.5	7.74	12.80	8.90	7.39	9.52	9.63	8.44
II.6	11.30	7.13	8.93	11.8	8.57	14.2	6.71	12.30	7.68	4.47	6.85
II.7	3.69	9.14	5.38	11.8	9.92	8.96	10.90	9.91	8.93	13.70	7.64
II.8	5.03	12.00	8.70	9.48	9.36	9.21	9.84	11.00	7.35	8.26	9.75
II.9	9.81	11.20	5.79	10.20	5.27	7.46	10.20	10.20	8.18	13.60	8.17
II.10	7.87	10.80	9.83	10.20	11.50	11.80	6.23	8.53	7.87	5.75	9.63
Mean	7.6	11.85	7.7	11.09	8.44	9.96	8.25	9.26	8.11	9.27	8.46
S.D.	2.79	3.23	2.12	1.36	1.85	2.42	2.06	1.9	0.85	3.63	0.96

[a] SUP: surface area, DNM: distance from natural marshes, DCO: distance from the breeding site, DWO: distance from the closest wooded hedge or copse, DTL: distance from power lines, DHA: distance from habitations, DPR: distance from principal roads, DSR: distance from secondary roads, HHS: height of hedges surrounding the paddy, NWS: number of wooded sides, CON: adjacent (1) or not (0) to damaged field.

[b] S.D. = standard deviation.

logistic regression . . .), as in ANNs usually all the variables contribute to the models. However, the use of qualitative traits, which is possibly responsible for the important variation of contributions between different trainings, can be a problem for other classification methods. While keeping a small set of input variables, the temporal structure of damage should be usefully investigated if flamingos exhibit more site-fidelity than proximate response to environmental factors.

Acknowledgements

The authors are grateful to Dr L. Hoffmann, President of the Tour du Valat Foundation, for his support to this study. We are indebted to J. Toutain and A. Sanche, Aéroclub de Montpellier, C. Pin, D. Vernet and V. Heurteaux, Station Biologique de la Tour du Valat, for their help in the field and aerial surveys. The authors thank R. Viannet, Parc Naturel Régional de Camargue, M. Roux-Cuvellier, Centre Français du Riz, Dr. S. Mañosa i Rifé, University of Barcelona, Spain, for their availability and all the numerous and interesting discussions they had. This study was funded by the Sansouïre Foundation, the MAVA Foundation, and the Centre Français du Riz.

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