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MAPPING AVIAN HABITAT SUITABILITY USING LINEAR AND NON-LINEAR TECHNIQUES IN THE CASE OF WETLAND LANDSCAPES

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Abstract

Habitat quality is crucial for wildlife management that impacts the conservation of sensitive landscapes such as wetlands. With advancements in GIS, habitat modelling now effectively predicts species occurrences and habitat suitability. This study aims to model and map habitat suitability for case bird species of Kentish plover in Tuzla Lagoon using multiple techniques. Kentish plover nesting data were collected from 293 nests, and reproductive success measures such as lay date, egg volume, and nest fate were analysed. Spatial habitat modelling techniques, including regression, co-kriging, artificial neural networks, and decision trees, were used with IKONOS imagery and ground data. The overall prediction accuracies were poor for lay date across all techniques, with the decision tree being the most accurate, while egg volume was best predicted by co-kriging, egg success by linear regression, and nest fate by both binomial logistic regression and ANN with 75% accuracy.

Keywords: *Habitat Suitability, Habitat Modelling, Wetland Landscapes, Avian Habitat, Remote Sensing, GIS*

SULAK ALAN PEYZAJLARI ÖRNEĞİNDE DOĞRUSAL VE DOĞRUSAL OLMAYAN TEKNİKLER KULLANARAK KUŞ HABİTAT UYGUNLUĞUNUN HARİTALANMASI

Öze

Habitat kalitesi, sulak alanlar gibi hassas peyzajların korunmasını adına geliştirilecek yaban hayatı yönetim süreçleri için kritik öneme sahiptir. CBS'deki gelişmelerle birlikte, habitat modellemesi artık fauna varlığı ve habitat uygunluğunu etkili bir şekilde tahmin edebilecek seviyelere ulaşmıştır. Bu kapsamda bu çalışma ile Tuzla Lagünü'nde yaşayan Akça cılıbıt kuş türünün habitat uygunluğunu birden fazla teknik kullanarak modellemeyi ve haritalamayı amaçlanmıştır. Çalışma kapsamında 293 yuvadan toplanmış ve yumurtlama zamanı, yumurta hacmi ve yuva kaderi gibi üreme başarısı ölçütlerini içeren veri seti analiz edilmiştir. Çoklu doğrusal regresyon, co-kriging, yapay sinir ağları ve karar ağaçları dahil olmak üzere mekansal habitat modelleme teknikleri kullanılmıştır. Yöntem doğruluklarının karşılaştırılması sonucunda yumurtlama zamanı için tüm yöntemler düşük doğrulukta sonuçlar üretmiş olmakla beraber karar ağacı, yumurta hacmi için co-kriging, yumurta başarısı içinse doğrusal regresyon en yüksek doğruluğa ulaşmıştır. Yuva kaderi için ise hem ikili lojistik regresyon hem de yapay sinir ağları yöntemleri %75 doğrulukla en iyi tahmine ulaşmıştır.

Anahtar Kelimeler: *Habitat Uygunluğu, Habitat Modelleme, Sulak Alan Peyzajları, Kuş Habitatı, Uzaktan Algılama, CBS*

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1. INTRODUCTION

Habitat quality is one of the key concepts in wildlife management and linked with protection of critical habitats and conservation of sensitive and endangered species. Determining habitat quality indicators of species maintain effective conservation management decisions.

Habitat modelling gained a significant capability with the development of GIS techniques. Predictive habitat models generally explore the relationship between species' occurrences and set of predictor variables to estimate probability of species occurrence at given unrecorded locations or to estimate suitability of an area for species (Segurado & Araujo 2004). This has led to the development of numerous statistical techniques for predictive habitat models (for detailed review Guisan & Zimmerman 2000). These methods differ into two main groups according to quality of occurrence data required. First group of methods such as generalised linear models, generalised additive models, classification and regression tree analyses, artificial neural networks etc. require high quality presence/absence data of species to rank the habitat suitability (Manel et al., 1999; Manel et al., 2001; Guisan & Zimmerman 2000; Brotons et al., 2004). Second group of methods including Ecological Niche Factor Analysis, Bioclim, and Domain require presence data only and were developed to enable to use data where is unavailable (Hirzel et al., 2002; Brotons et al., 2004; Argáez et al., 2005).

Conventional predictive habitat modelling studies with just using presence or absence data can estimate probability of species occurrence and habitat suitability through spatial locations. In this respect, these studies have limitation in providing detailed output such as fitness, micro-habitat preferences, and reproductive success of species depends on their habitat selection. Such detailed knowledge is necessary for more effective conservation of animals like birds that are under threat of gradual rising effects of human activities including, agriculture, industry, transportation, grazing, climate change, pollution etc.

Numerous environmental factors like reproductive success of species and biological factors in addition to presence/absence data can also be involved in determining habitat selection (Partridge, 1978; Burger, 1985; Good, 2002). Habitat suitability, closely related to individual fitness since it influences the probability of successfully raising offspring, is a very important factor for birds, like all other animals, especially for their breeding habitats (Martin, 1988). As a result of this, predictive habitat models can be used in addition to determine distribution of species also for predicting biological features of species in relevant locations.

Reproductive success usually reports the percentage of eggs or nests in a population sample that is successful in producing young. "Egg success" is the percentage of eggs that produce young that leave the nest and "nest success" is the percentage of nests with eggs that produce young that leave the nest (Murray, 2000). These measures are often used to compare species reproductive success among nests, patches, habitats or populations (Lack, 1968; Ricklefs, 1969; Skutch, 1985). Also lay date, egg volume and nest fate can be considered to represent reproductive success since the strong relationships between them have been reported by several studies (Nisbet & Cohen 1975; Nisbet, 1978; Nisbet et al., 1978; Ricklefs, 1969).

Environmental predictors can exert direct or indirect effects on species (Austin, 2002). The interaction between species and physical environment may result various spatial patterns of reproductive success which can be observed at different scales. Some of these environmental factors that influence spatial reproductive success patterns of birds, are: i) Proximity to feeding places is one of the most important processes under limitation or competition for food that influence reproduction (Martin, 1987; Collias & Collias, 1984); ii) nest predation often is the primary source of nesting mortality for a wide range of bird species (Ricklefs, 1969); iii) nesting substratum influence the variations in breeding success (Li & Martin 1991), the places inaccessible to predators, such as cliffs, tall trees, and thick vegetation have high breeding success (Burger & Gochfeld 1987); iv) adult behaviour, altered by disturbance, is most detrimental to reproduction during the egg-phase (Cairns, 1980), especially disturbance resulted from human activities (Gillett et al., 1975); v) Grazing impacts on vegetation , possibly through changes in availability of suitable nest sites (Kantrud & Kologiski, 1982; Bock

& Webb, 1984; Riley et al., 1992) and also affect nest success by nest trampling (Shrubb, 1990); vi) reproductive success is also affected by time of nesting, the earliest nesters of birds lay the largest clutches and the largest eggs, and in the absence of predation they are consistently the most successful (Nisbet, 1978).

This study aimed to model the spatial patterns of habitat suitability using spatial habitat modelling techniques including multi-linear and logistic regression, geostatistical interpolation (co-kriging), artificial neural networks, and decision tree together with the support of remote sensing and Geographical Information Systems (GIS). The estimates of models were derived from the data set of Kentish plover (*Charadrius alexandrinus*) population in Tuzla Lake, Cukurova Delta, located Eastern Mediterranean coast of Turkey. The accuracy of the models was derived from correlation coefficient figures. The strengths and weaknesses of these techniques were discussed to determine the most accurate approach for mapping habitat suitability.

2. MATERIAL AND METHOD

2.1. Study Area and Data Set

The study area is located on Turkey's Eastern Mediterranean coast, along the Çukurova Plain's coastal edge. The region is home to numerous agricultural lands and coastal wetland ecosystems (Figure 1). The Tuz Lagoon, the westernmost lagoon on the coast, is situated at the edge of the Tuzla district is primarily an agricultural area with peanut, tomato, wheat, watermelon, and honey production as its main industries. The lagoon is brackish and encircled by large salt marshes, sand dunes, shallow temporary pools, and mudflats around the lake's edges. (Berberoglu, 1994).

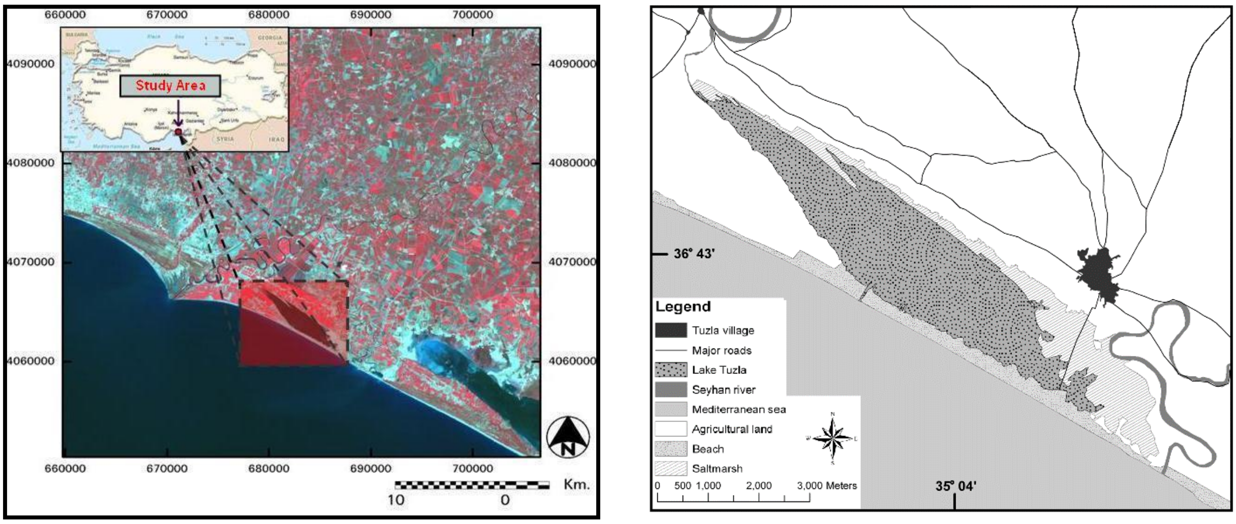

Figure 1. Location of the study area

This area serves as significant breeding grounds or resting points for migrating birds during the winter season. The study location is situated along a main migration path connecting Bosphorus (and Eastern and Southern Europe) with the Middle East (and Eastern Africa). It is designated as an Important Bird Area (IBA) by BirdLife International and is acknowledged by the Turkish Society for the Protection of Nature (DHKD) (refer to Magnin & Yarar, 1997). Thus, the total number of birds observed around the lake is 178 species (Székely, 1999). Kentish Plover is one of the migrant breeders of these that can be observed in the site with approximately 1000 pairs (Lendvai et al., 2004). Kentish Plovers reared their chicks on the north shore and alkaline grassland of *Salicornia europaea* and *Antrochnemum fruticosum* in a 50–800 m strip on the north side of Tuzla Lagoon (Figure 1). The research area also provides pivotal breeding sites for marine turtles: Loggerheads *Caretta caretta* and Green Turtles *Chelonia mydas*.

However, this complex ecosystem is not robust and is prone to a number of detrimental changes. The impacts of the rapid development occurring in this coastal zone include salinization of freshwater resources and soil, pesticides, exploitation for tourism and recreation, lagoon management that is not appropriate, erosion of the shore, drainage from wastewater and irrigation, wetlands, and sand dunes; these factors also contribute to the degradation and loss of beaches caused by accelerated coastal erosion. However, agricultural activities have the most detrimental impacts on the wetland ecosystem in Tuzla. The settlement of Tuzla also causes pollution and predation from domestic animals. Grazing has a considerable negative effect especially on ground nesting birds' habitats by reducing vegetation density or nest trampling. Additionally intensive fishing poses a large pressure on this ecosystem by removing a significant part of fish biomass from the lake (Székely, 1999).

The current LU/LC pattern was mapped using IKONOS imagery acquired on 14 June, 2002. The IKONOS imagery has a spatial resolution of 4 m and four wavebands sensitive in the visible and near-infrared portions of the electromagnetic spectrum. In addition, land cover data were recorded on the date of IKONOS imagery acquisition by using GPS with an accuracy of 4 m. Other data utilised in the analysis included ground data set collected by Szekely (1999).

2.2. Method

2.2.1. Ground data

Kentish plover data were collected by Tamas Szekely and his research team during the breeding season from April to July in 1999. This data set based on 293 observed nests and includes information on nest ID, observation date, egg number, egg size, egg floating stages, number of chicks and fate.

Reproductive success measures such as lay date, egg volume, egg success and nest fate were used as training and testing data sets to model these variables. Lay date data were calculated as an average of all eggs in the nest. Eggs lay date was estimated by differencing the nest observation date and incubation day which is indicated by egg's floating stage (for a review see Noszály & Székely, 1993). Each lay date was arranged according to first field work date (1 April).

Egg volume (V) data were estimated using equation 1 as an average of eggs' volume in the nest (Szentirmai and Székely 2004).

$$V=0,486w^2l \qquad \text{(Eq 1.)}$$

Where;

V = egg volume

w = egg's width

l = egg's length

Egg success was calculated by dividing the number of chicks that hatched by eggs incubated in the nest (Murray, 2000) and nest fate was categorized as succeed (hatched) and failed (predated, deserted and tramped).

Accuracy figures of the model results were derived using 20 % of the ground data.

2.2.2. Remote sensing and GIS

Explanatory variables were derived from the mosaic image of two IKONOS images that were recorded 14 June 2002 over the study area. Approximately 15 evenly distributed ground control points (GCPs) were selected from each image. The IKONOS images were geometrically corrected and geocoded to the Universal Transverse Mercator (UTM) coordinate system using the nearest neighbour algorithm. The transformation had a root mean square (RMS) error of between 0.4 and 0.6, indicating that image rectification was accurate to within 1 pixel. The image was classified into six land cover classes using a maximum likelihood algorithm.

Tuzla Village, Tuzla Lake and agricultural lands were digitized from the image. Impacts of proximity were included to the model by producing the distance layers to these features within a GIS environment. Additionally, *Salicornia europaea*'s patches which are dominant vegetation cover in the field were extracted from classified image and used to create distance layer to *Salicornia europaea* patches.

Normalized Difference Vegetation Index (NDVI) that represent amount of healthy vegetation in the field was derived as an additional explanatory variable for the models by using near infra red (band 4) and red band (band3) wavebands of IKONOS image. Four wavebands of IKONOS image (blue, green, red and near infra red) were also included into the model as complementary variables.

2.2.3. Modelling

Explanatory variables were used within four different modelling techniques including regression, co-kriging, artificial neural network and decision tree. Explanatory variable selection involved feature selection for the most relevant input variables for modelling. This was accomplished using the Stepwise Linear Regression (SLR) method to find Maximum Adequate Model (MAM) provided by the R Project for Statistical Computing (Development Core Team, 2006). The SLR method selects the best subset of predictor variables to be employed in modelling using a stepwise procedure, which repeatedly alters the model at the previous step by adding or removing predictor variables (Helsel & Hirsch, 1992). The Akaike Information Criteria (AIC) statistic is expressed as:

$$AIC = -2\ln(L) + 2p \qquad \text{(Eq 2.)}$$

where *L* is the likelihood of the model parameters, *p* is the number of free parameters (number of explanatory variables plus one) (Johnson & Omland, 2004). The AIC statistic provides a convenient criterion for determining whether a model is more accurate by modulates the log-likelihood of the fitted model with the number of predictors, and include only the variables that maximize the proportion of the null deviance explained by the model (Zaniewski et al., 2002)

2.2.3.1. Linear regression

Multivariate linear regression was performed to model reproductivity variables including lay date, egg volume and egg success, additionally nest fate was modelled using binomial logistic regression.

2.2.3.2. Co-kriging

As a second technique co-kriging was performed. Co-kriging utilizes not only the primary variable but also utilizes cross-correlated secondary variables. Co-kriging is thus a linear interpolator of both primary and secondary data values (Li et al., 2006). It is a mathematical interpolation tool that can be utilized when measurements have been made at scattered sampling points. Co-kriging is an extension of kriging in which random variables are simultaneously predicted by utilizing their inter-relationships and their spatial co-dependence (Myers, 1982; Wu & Murray, 2005). It is based on a theory of regionalized variables whose values vary from place to place (Kleijnen & Wim van Beers, 2005). Co-kriging gives weights to data that minimize the estimation variance (co-kriging variance) (Isaaks & Srivastana, 1988). When more than one property has been measured, then co-kriging will be preferred for spatial prediction through cross-variogram functions (Lark, 2003). Co-kriging was performed to every response variable using ArcGIS software with their tree most significant explanatory variables retained from MAM.

2.2.3.3. Artificial neural network (ANN)

An important advantage of using an artificial neural network model is its non-parametric nature. It is not necessary to transform data to match a certain distribution. Neural network models can be non-linear and can model logical expressions such as ‘and’, ‘or’, ‘not’, and ‘exclusive or’. For non-linear relationships and interactions among variables neural networks may result more accurate predictions than linear statistical models (Özesmi & Özesmi, 1999). Because of non-parametric structure of ANN (Özesmi & Özesmi 1999), it is commonly used for predictive habitat models (Mastrorillo et al., 1997; Manel et al., 1999; Özesmi & Özesmi 1999; Thuiller 2003).

The multi-layer perceptron described by Rumelhart et al. (1986) is the most commonly encountered ANN model in ecological modelling (because of its generalization capability) so this model is used in this study. This type of ANN model consists of three or more layers each of which is interconnected to the previous and subsequent layers, but there are no interconnections within a layer. Each layer consists of processing elements called units or nodes. The first layer is called the input layer and serves as a distribution structure for the data being presented to the network. It holds input values and distributes these values to all units in the next layer. The final processing layer is called the output layer and in the present case it comprises our response variables. Layers between input and output layers are termed hidden layers. The number of hidden layers and units within the network are defined by the user (Berberoğlu et al, 2009)

The three steps of an ANN procedure are testing, allocation, and training. The neural network is trained by providing it with known response variable values along with pixel values. Building a model of the data generation process is the goal of network training, which enables the network to generalize and forecast outputs from inputs it has never seen before in the testing stage. Various learning algorithms are available for network training. In ecological modeling, back-propagation via the generalized delta rule is the most often utilized algorithm. (Rumelhart et al., 1986). The difference between the expected and actual feed-forward network output is measured, and network weights are changed to minimize the error. A forward and a backward phase via the ANN structure make up the back-propagation algorithm. When training data is entered into the network, the weights connecting network units are randomly set, signaling the start of the forward phase of training. After comparing the network's actual output to the target, an error measure is computed. This error is fed backward through the network towards the input layer during the backward phase, changing the weights of the connections in the preceding layer in proportion to the error. This procedure is carried out repeatedly until a predetermined number of iterations is reached or the overall error in the system drops to a predetermined level.

2.2.3.4. Decision tree

Decision tree is a powerful statistical technique ideally suited for the analysis of complex ecological data (De’Ath and Fabricius 2000; Kerns and Ohmann 2004). Rather than estimating a mean value for a range of environmental variables (as with most parametric techniques), decision trees identify specific thresholds of environmental conditions above or below which a response variable can be found (Moore et al., 1991). The response variable is usually either categorical (classification trees) or numeric (regression trees), and the explanatory variables can be categorical and/or numeric (Miller & Franklin, 2002).

The tree is created by splitting the data based on a single explanatory variable using a simple rule. Each split divides the data into two distinct groups that are as similar as possible. The splitting process is then repeated for each group separately. The goal is to create homogeneous groups for the response variable while keeping the tree relatively small. The tree's size is determined by the number of final groups. The splitting continues until the tree becomes too large, at which point it is pruned to the desired size. Each group is characterized by either the distribution (for categorical responses) or mean value (for numeric responses) of the response variable, the size of the group, and the values of the explanatory variables that define it. (De’Ath & Fabricius, 2000).

This study modelled the lay date, egg volume and egg success using regression tree (RT) however, nest fate was modelled with classification tree (CT) due to its categorical structure.

2.2.4. Accuracy assessment

Using data from holdout tests, the final model's accuracy was validated. As a result of their foundation in set-aside test data that wasn't utilized to fit the model, test error estimates were regarded as reliable. Twenty percent of the data nests for each response variable were chosen at random to evaluate accuracy. The correlation coefficient (r), which is a measure of prediction precision, was used to assess the performance of the model by comparing the actual and predicted values for the test samples that were set aside. However, using the same test data set, the error matrix was used to evaluate the model results for nest fate.

3. RESULTS

Response variables were derived from original data set includes 293 nests. 288 nests have lay date data, 231 nests have mean egg volume data, 105 nests have fate data, and 108 nests have egg success data that were adequate for modelling process (Figure 2).

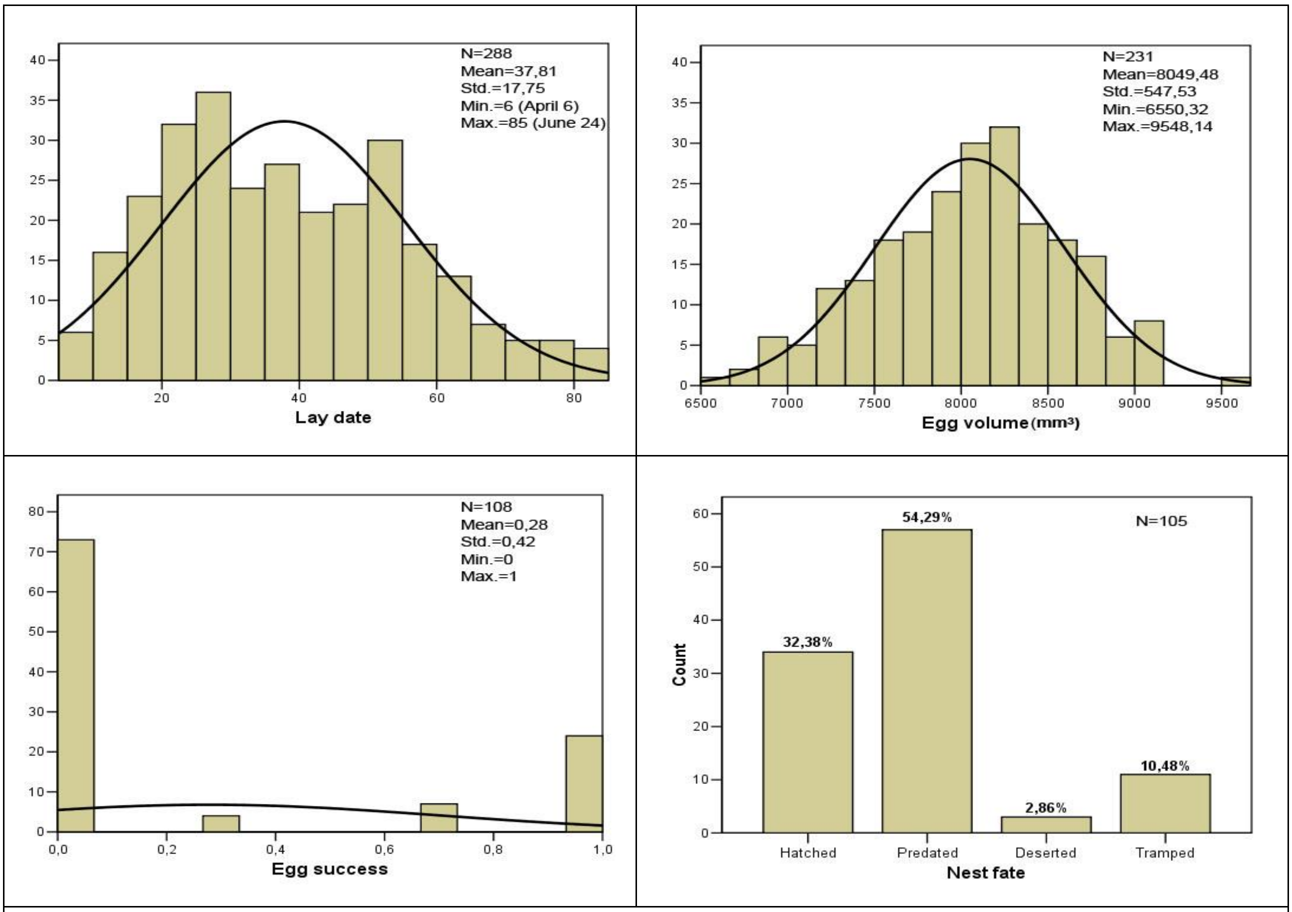

Figure 2. Histograms and descriptive statistics of response variables

Additional explanatory variables were extracted from the mosaic of IKONOS image wavebands and NDVI for nest locations. The descriptive statistics of explanatory variables for each nest and whole study area are listed in Table 1.

Table 1. Descriptive statistics of explanatory variables.

Variables	NESTS				WHOLE STUDY AREA			
	Mean	**Std. dev.**	**Min.**	**Max.**	**Mean**	**Std. dev.**	**Min.**	**Max.**
Distance to village	2578.61	1419.28	601.33	5163.10	1562.23	938.82	0	5097.47
Distance to lake	73.99	67.87	3.56	409.80	254.10	222.67	0	970.68
Distance to agricultural lands	231.77	238.18	4.00	937.37	251.44	231.44	0	998.31
Distance to salicornia patches	41.16	30.10	0.00	118.12	35.74	41.37	0	384.52
NDVI	0.02	0.10	- 0.27	0.44	0.09	0.21	-0.39	1.00
IKONOS blue band	504.47	49.95	390.89	668.72	522.88	62.61	353.05	849.97
IKONOS green band	572.34	82.47	396.32	797.61	609.13	99.04	342.48	1071.90
IKONOS red band	486.19	93.32	273.66	773.26	527.73	110.65	214.77	982.44
IKONOS near infra red band	489.47	117.32	188.57	810.29	563.07	113.75	156.12	1205.80

To take the advantage of quadratic effect, the environmental variables together with squared values were included as explanatory variable to backward stepwise procedure in linear regression models of lay date, mean egg volume, and egg success response and also in multinomial logistic regression model of fate. The MAMs of these response variables were determined by seeking minimum AIC value with backward elimination.

The results of linear and binomial logistic regressions MAMs were given in Table 2. The explanatory variables of distance to agricultural fields, distance to lake, IKONOS red wave band, quadratic terms of distance to lake, IKONOS red band and distance to village were considered variables by performing minimum AIC for MAM of lay date ($R^2=0.123; F_{6,127}=5.072; p=0.00006$). The MAM of egg volume ($R^2=0.064; F_{4,176}=3.01; p=0.02$) was explained with four variables of NDVI, IKONOS red band and their quadratic terms which remained after the stepwise procedure. Egg success reached minimum AIC with its MAM ($R^2=0.202; F_{4,81}=5.13; p=0.001$) that was explained with seven retained explanatory variables of distance to agricultural fields, distance to lake, quadratic terms of distance to agricultural fields and distance to village. Distance to village is the most significant variable for nest fate following to stepwise logistic regression.

Table 2. MAM for linear and binomial logistic regressions

Response variable	Explanatory variable	B	t value	P(>|t|)
Lay date	Dist. to agricultural fields	-0,0694	-2,87	0,005
	Dist. to lake	-0,4452	-2,54	0,012
	IKONOS red band	-0,8804	-2,34	0,02
	Square of dist. to lake	0,0043	1,86	0,064
	Square of IKONOS red band	0,0032	2,21	0,028
	Square of dist. to village	-0,0003	-3,50	0,001
	Full model: R^2 =0,123, $F_{6, 127}$=5,072, p=0.00006			
Egg volume	NDVI	20,99	1,88	0,061
	IKONOS red band	-39,59	-2,75	0,007
	Square of NDVI	-0,15	-2,25	0,026

	Square of IKONOS red band	0,14	2,56	0,011
	Full model: R^2 =0,064, $F_{4,\,176}$=3,01, p=0.02			
Egg success	Dist. to agricultural fields	-0.00841	-2.713	0.008
	Dist. to lake	-0.00517	-2.185	0.032
	Square of dist. to agricultural fields	0.00002	1.694	0.094
	Square of dist. to village	-0.00001	-2.974	0.004
	Full model: R^2 =0.202, $F_{4,\,81}$=5.13, p=0.001			
Response variable	**Explanatory variable**	**B**	**z value**	**P(>|z|)**
Nest Fate	Dist. to village	0.00593	3.35	0.001
	Square of NDVI	-8.988	-2.27	0.023
	Square of dist. to village	0.000001	-3.45	0.001
	IKONOS red band	-0.0713	-1.83	0.068
	Square of IKONOS blue band	-0.00002	-1.82	0.069
	Square of IKONOS red band	0.00008	1.92	0.056

Because of the parametric nature of co-kriging, it was not performed to the response variable of fate which had a categorical structure. However, co-kriging was applied with remaining response variables of the most three significant explanatory variables from MAMs of regression analyze as co-dependent variables. Co-kriging models -like all other kriging models- provide prediction error measurements that can be used for model selection in a basic way (Boone & Krohn, 2002; Anderson et al., 2003). The models that have mean standardized error (MSE) close to zero and root-mean-square standardized error (RMSE) close to one have more accurate predictions (Jiguet et al., 2005). According to these measurements for all response variables were very similar to each other. However, lay date was predicted (*MSE:-0.00026; RMSE:1.005*) more accurate than others and egg volume had second most accurate prediction (*MSE:-0.00028; RMSE:0.99*) according to egg success prediction (*MSE:-0.0023; RMSE:0.98*) using co-kriging models (Table 3).

Table 3**.** Co-kriging modelling output error statistics

Parameters	**Lay date**	**Egg volume**	**Egg success**
Mean	-0.012	0.14	0.0005
Root-Mean-Square	17.22	561.1	0.4002
Average Standard Error	17.19	576.5	0.4122
Mean Standardized Error (MSE)	-0.00026	-0.0003	0.0023
Root-Mean-Square Standardized Error (RMSE)	1.005	0.989	0.9850

The prediction success of ANN primarily depends on its five parameters: (i) size of training set, (ii) network architecture, (iii) learning rate, (iv) learning momentum and (v) number of training cycles. The settings chosen for the parameters in this analysis were as follows:

(i) Size of training set: for every response variable the size of training set is given in

(ii) Network architecture: The number of input units was 18 which were defined below as explanatory variables. The neural network architecture which results in the most accurate output can be determined only experimentally and this can be a lengthy process for large classification tasks. This is frequently regarded as an ANN method's drawback. Nonetheless, heuristics for determining the approximate size of a network can be derived using certain geometrical argument (Lippmann, 1987; Paola & Schowengerdt 1997). Single hidden layer works well most of the time. Although the number of hidden layers has an impact, the number of units within the hidden layers is the significant factor. A network should ideally have two or three times as many input layer units in its first hidden layer. So, the network architecture consisted of single hidden layer with 42 nodes.

(iii) Learning rate: The percentage of the calculated weight change that will be used for weight adjustment depends on the learning rate. This operates as a low-pass filter, allowing the network to ignore tiny features in the error surface. Its range is 0.1 to 0.9. Less changes in the network's weights at each cycle correspond with a lower learning rate. What makes the error surface unique determines the ideal learning rate. Due to the highest level of classification accuracy, the networks were trained using a learning rate of 0.2. On the other hand, compared to a higher learning rate, this rate needs more training cycles.

(iv) Learning momentum: To fit the current direction of movement in the weight space with the weight changes that have occurred in the past, momentum is added to the learning rate. Adjusting the weights and ranges between 0 and 9 points is an extra adjustment to the learning rate. With a learning momentum value of 0.3, the networks were trained using a back-propagation learning algorithm.

(v) Number of training cycles: The networks underwent training until the root mean square (rms) error was lowered to a level that was deemed appropriate. Because it is simple to over-train, which lowers the network's capacity for generalization, this is one of the most crucial design considerations for ANNs. 6000 cycles were used to train the network.

In network training process, to each hidden and output neuron the linear transformation that fits best the available data. The quality of the overall fit of all those linear transformations may be assessed by various measures (Holeńa et al., 2003). The most commonly used measures to assess the quality of the overall fit of network is the mean squared error (MSE), i.e. the mean squared distance between the output values that the network computes for a given sequence of inputs, and the output values that for those inputs have been experimentally measured. Once a measure of the overall data fit is fixed, neural network training reduces the task of finding the linear transformations optimal with respect to that measure. In the case of MSE, this means finding those linear transformations that lead to the minimal sum of squared distances between the computed and measured outputs (Hagan et al., 1996; Rumelhart et al., 1986). In respect of these, egg volume neural network process has the best prediction in terms of its MSE value. The lay date has close prediction error results after egg success (Table 4).

Table 4. ANN Modelling output statistics

Parameters	**Lay date**	**Egg volume**	**Egg success**	**Fate**
MSE	0.043	0.032	0.143	0.108
Gradient	10.75	0.246	2.410	0.264

Regression tree models was established using response variables of lay date, egg volume, egg success and evaluated using all explanatory variables as input. The modes were implemented using Cubist software with 10-fold cross validation. The error statistics drived from cross validation were given in Table 5. Using a small number of reference data samples for both training and accuracy assessment, cross-validation is intended to produce reasonably realistic accuracy estimates (Michie et al. 1994). N subsets of the training data set make up an N-fold cross-validation. The accuracy of the classification created using all reference samples is represented by the average value of the accuracy estimates obtained by utilizing each subset to assess the classification created using the remaining training samples (Huang et al., 2001).

Table 5. Regression tree modelling output statistics

Variable	Average error	Relative error	Correlation coefficient
Lay date	14.4	0.96	0.25
Egg volume	412.6	0.79	0.40
Egg success	3.4	0.89	0.31

The relative error magnitude is the ratio of the average error magnitude to the error magnitude that would result from the mean value; for accurate models, this should be less than 1. The correlation coefficients are the agreement between the cases' actual values of the target attribute and those values predicted by the model (Rulequest Research, 2008). All regression tree models were acceptable according to their relative error values. The egg volume is the best modelled variable with regression tree regarding to its correlation coefficient and also its relative error.

For nest fate, classification tree algorithm along with the 5% confidence level of pruning and 10-fold cross validation was used. Fate was predicted with an average 4.3 rules and an average error rate of 32,1% (Table 6).

Table 6**.** Classification tree modelling output statistics of nest fate

Folds		1	2	3	4	5	6	7	8	9	10	Mean	SE
Rules	numbers	1	3	3	8	3	3	9	3	7	3	4.3	0.8
	error (%)	37.5	25.0	37.5	25.0	25.0	37.5	22.2	33.3	44.4	33.3	32.1	2.3

The prediction results of linear regression, binomial logistic regression and decision tree techniques were mapped using various techniques (Figure 2, 3, 4, and 5). The prediction results were extracted from these images for all response variables along nest location coordinates of test data sets.

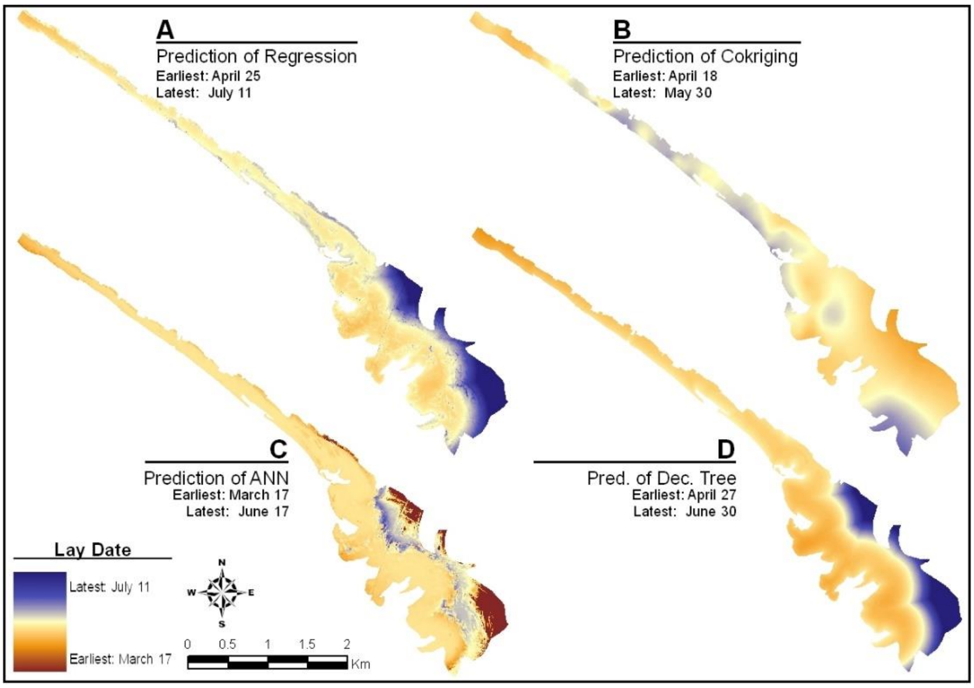

Figure 2. Prediction results lay date

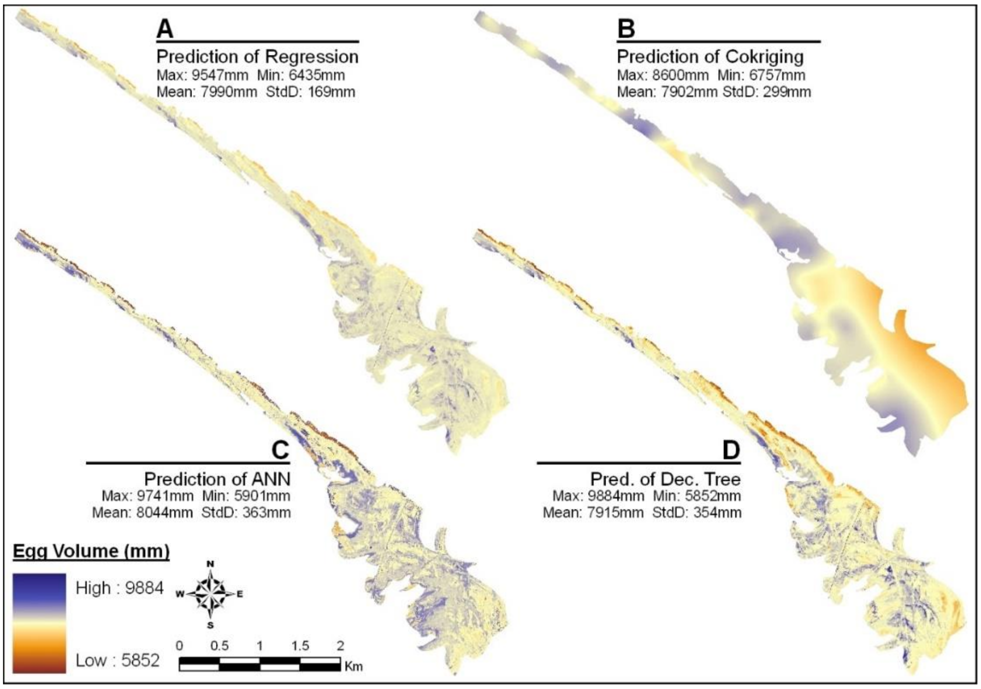

Figure 3. Prediction results of gg volume

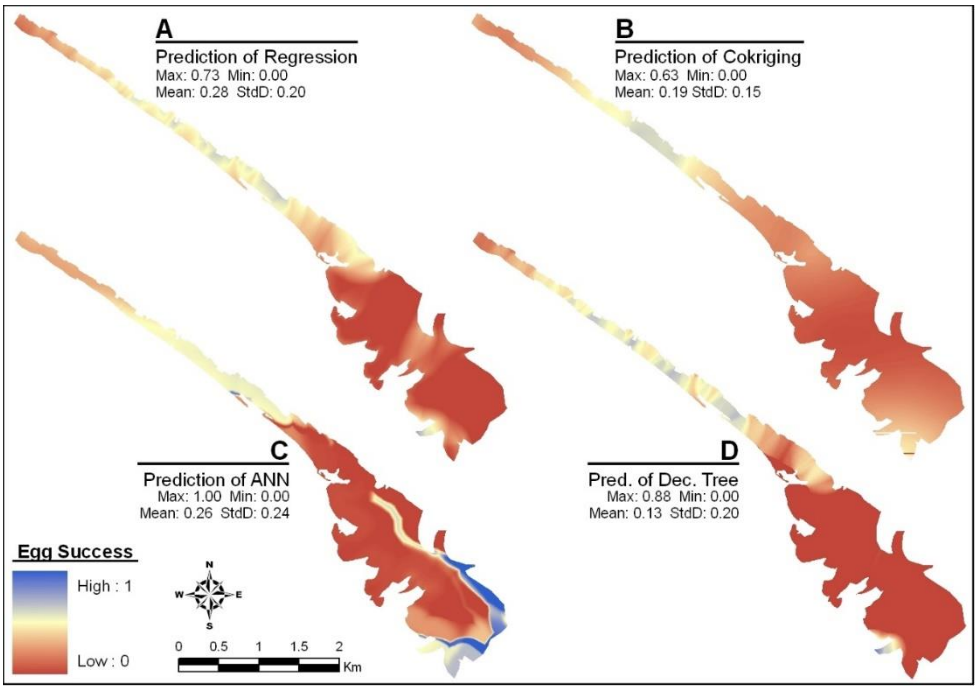

Figure 4. Prediction results egg success

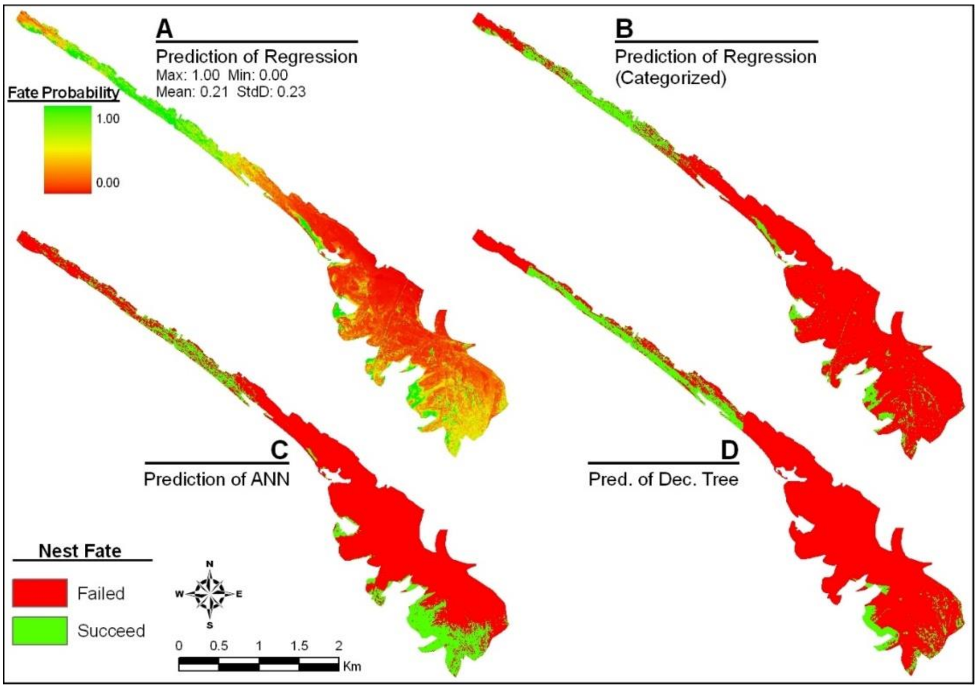

Figure 5. Prediction results nest fate

The outputs of all four modelling techniques were compared by correlating the test data set values (Table 7).

Table 7. Accuracy results of modelling techniques

Variables	Unit	Regression	Co-kriging	ANN	Decision tree
Lay date	Corr.Coef.	0.13	0.14	0.05	0.19

Egg volume	Corr.Coef.	-0.26	0.29	0.05	-0.25
Egg success	Corr.Coef.	0.43	0.34	0.28	0.34
Nest fate	Percent	75	-	75	60

The overall prediction accuracies were poor for the lay date in terms of the coefficient correlation of all four techniques. However, decision tree resulted the most accurate result and decision tree had similar accuracy with linear regression and co-kriging. Egg volume predictions were very limited. Because egg volume has negative correlation coefficient for regression and decision tree predictions. However, co-kriging predicted success for egg volume. Most accurately Linear regression performance for egg success and accuracy magnitude moderately better than other techniques according to their correlation coefficient scores. Fate was predicted reasonably for all tree techniques. Binomial logistic regression and ANN predicted fate with an accuracy of 75% which is more accurate than the decision tree technique.

4. CONCLUSION

This paper aimed to compare various modelling techniques which are frequently used for habitat modelling. However, this study differs from recent habitat modelling studies in various ways such as, utilization of breeding success measurements as response variables rather than presence or presence/absence data only. Thus, distribution patterns of Kentish plover breeding success and the relationship between breeding success features and environmental factors were analysed.

Using regression models, especially with a stepwise elimination process provides a unique advantage different from other techniques to determine environmental variables have impact on desired response variable and their magnitudes.

MAMs of regression results supported that;

- Kentish plover lay date affected by human disturbance, proximity to feeding source and vegetation occurrence. These impacts are directly related to reproductive success according to Nisbet and Cohen (1975), and the largest clutches were laid by early nesters (Nisbet, 1978).

- Egg volume of Kentish plover was affected by vegetation occurrence. This was proved by variables of NDVI and IKONOS red bands which are good indicators for healthy vegetation. This result supports the finding of Burger & Gochfeld (1987) and Li & Martin (1991) for other species. They suggested that nesting substratum is an environmental factor that influences the variations in breeding success.

- The impacts on lay date and egg volume were also effectual for egg success. Especially the most significant two variables distance to agricultural fields and village for egg success support that human activities are the main constraint on the breeding habitat of Kentish plover. This result is backed up by the studies of Stephens et al. (2005), Vander Haegen (2005), and Showler et al. (2010) which support the idea of decreasing the nest location proximity to settlement and agricultural fields decline the bird reproductive success.

- Distance to village was the most significant variable for nest fate among the other response variables. This establishes the fact that predation made by domestic dogs coming from Tuzla village. This conclusion supports the result of Ricklefs (1969), Marzluff & Neatherlin (2006),and Mönkkönen (2007) who suggested that nest predation often is the primary source of nest mortality for a wide range of bird spices.

Each modelling technique within this study has differed in terms of accuracy and error measurements depend on their nature. To ensure comparability of four modelling techniques, 20% of response variable data was set aside for accuracy figures. However, four response variables could be investigated according to error or accuracy outputs of modelling techniques to find out the compatibility between response variable and modelling techniques.

Lay date has the most significant model (*p=0.00006*) for regression among the other response variables. Models' coefficient of determination scores revealed that egg success regression has the best goodness of fit ($R^2=0,2$). The nest fate regression model is exluded as its regression method is binomial logistic regression.

The co-kriging models with mean standardized error (MSE) close to zero and root-mean-square standardized error (RMSE) standardized error close to one results more accurate predictions (Jiguet et al., 2005). Co-kriging models for all three response variable resulted very close MSE and RMSE scores. However lay date was predicted most accurately with co-kriging than those response variables (Table 3). This was the result of parametric nature of co-kriging because it has the the same order as normality scores of response variables. Thus, co-kriging produces more accurate predictions if response variables have better normality values.

Egg volume was estimated with the smallest mean square error with ANN modelling. The results from other response variables with ANN have close mean square error values to each other in the order of lay date, nest fate and egg success. In contrary, majority of the literature have shown that ANN represented non-linearity such as species environment (Guégan et al, 1998; Walley & Fontama, 1998). Particulary ANN has the advantage in modelling species presence and absence (Mastrorillo et al,1997).

Decision tree produces relative error and correlation coefficient to measure the performance of the models. Egg volume which has the largest normality results than other response variables, was modelled with the best scores of relative error and coefficient by regression tree (except fate because of its categorical data structure). However other response variables modeled with decision tree have closer relative error and correlation coefficient values. Decision tree induction is a nonparametric approach for building classification models. In other words, it does not require any prior assumptions regarding the type of probability distributions satisfied by the class and other attributes.

There is no reason to believe that major differences in performance should occur between response variables. Probably of greater importance is the choice of criteria used to assess performance (Fielding and Bell 1997), the nature of the data on which prediction is based (e.g. linearity, species prevalence, data quality, sampling error) and the assumptions that must be satisfied by any given operation. However, comparing modelling techniques using various response provides better performances of modelling techniques understanding of with variables which are a measure or an indicator of breeding success for avian.

The comparison of modelling techniques over response variables showed the potential of techniques estimating success for breeding success measures. All four modelling techniques achieved low accuracies for all response variables especially for egg volume and lay date. Reasons for the low accuracies can be attributed to data set which was not collected specifically for this study or the difference between resolution of imaginary used (IKONOS 4m) and defective accuracy of GPS technology (36 m) on the time data collected.

In spite of low accuracy scores, results introduced the ascendant techniques for every breeding success measures. Response variable of lay date had best estimate with decision tree and egg volume were estimated most accurately by co-kriging according to their correlation coefficient scores. The technique comparison results of lay date is not agree however egg volume is agree with the suggestion of Boone and Krohn (2002) co-kriging gives better results with better normality values. Linear regression technique had the best accuracy scores than other techniques while estimating response variables of egg success instead of its poor normality score. Nest fate moderately good estimate results for all techniques (except co-kriging). Especially binomial logistic regression and ANN have better estimates than decision tree with same score of 75%. This is an expected result according to these two suggestions; i) binomial logistic regression performs better than various ecological modelling techniques (Manel et al., 1999; Pearce & Ferrier 2000; Manel et al., 2001); ii) ANN to be to be advantageous in modelling species presence and absence (Mastrorillo et al., 1997)

This study emphasized that regression models with stepwise process is a powerful technique to determine which variable have an impact and what their magnitude for habitat modelling studies especially modelling with breeding success measures. According to these results the variable of IKONOS Red band which reflect the vegetation remained in all MAMs except the one for egg success. This points the vegetation occurrence mostly as the primary factor that effects the Kentish plover habitat in Tuzla. The human disturbance which is the only factor that effects egg success and the factor of proximity to feeding side are the secondary factors that influence the Kentish plover in Tuzla.

Lay date and egg volume which had better normality results were the only response variables which had best scores according to models' own error measures. This shows being a statistically normal response variable especially which are more detailed than presence or presence absence data like breeding success measures, still has advantages while being predicted by modelling techniques which are either parametric or non-parametric.

All four response variables have their own best accuracy results with four different modelling techniques. This result mentioned that these four modelling techniques have a potential for such kind of habitat modelling studies depend on breeding success. However, nest fate has the best accuracies with ANN (Cai et al., 2014; Yılmaz et al., 2020) and regression (Dinsmore et al., 2002; Webb, 2012). With this result in a general view regression model have slight more advantage than other techniques in this studies frame. This can be related to regression models well developed history and its various types according to variables data structure such as linear regression or logistic regression which were used in this study.

In addition to the best accuracy results with four different modelling techniques, all accuracy results were not good enough for all response variables over these modelling techniques. In this study, these two general results can be related to the following factors:

- Response data set which was derived from an overall data set that have a general purpose and is not specific for this study.
- User's error while recording data especially location of nests also depends on the Global Positioning System (GPS) technology limitation at that time.
- Limitations depend on that time's technology for satellite images which were used as base maps and explanatory variables in this study.
- The ongoing poor performances of modelling approaches on estimating much more complex structures of ecological relations.

Under these conditions to determine habitat characteristics of species in a detailed way such as depending on breeding success measures in this study there must be more studies which (i) have specific data set, (ii) try to develop new techniques to understand the phenomenon of ecology, (iii) use recent potentials of current technologies like Remote sensing and GIS.

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REFERENCES

Arn, R. P., Lew, D., & Peterson, A. T. (2003). Evaluating predictive models of species' distributions: Criteria for selecting optimal models. Ecological Modelling, 162(3), 211-232.

Argáez, J. A., Christen, J. A., Nakamura, M., & Soberón, J. (2005). Prediction of potential areas of species distributions based on presence-only data. Environmental and Ecological Statistics, 12(1), 27-44.

Austin, M. P. (2002). Spatial prediction of species distribution: An interface between ecological theory and statistical modelling. Ecological Modelling, 157(2-3), 101-118.

Berberoglu, S. (1994). A research on the impact of afforestation on the coastal dune ecosystem in Eastern Mediterranean region of Turkey (Master's thesis). Institute of Science, University of Cukurova, Adana, Turkey.

Berberoğlu, S., Şatır, O., & Atkinson, P. M. (2009). Mapping percentage tree cover from Envisat MERIS data using linear and nonlinear techniques. International Journal of Remote Sensing, 30(18), 4747-4766.

Bock, C. E., & Webb, B. (1984). Birds as grazing indicator species in southeastern Arizona. Journal of Wildlife Management, 48(4), 1045-1049.

Brotons, L., Thuiller, W., Araújo, M. B., & Hirzel, A. H. (2004). Presence–absence versus presence-only modelling methods for predicting bird habitat suitability. Ecography, 27(4), 437-448.

Burger, J. (1985). Habitat selection in marsh-nesting birds. In M. Cody (Ed.), Habitat Selection in Birds (pp. 253-281). New York: Academic Press.

Burger, J., & Gochfeld, M. (1987). Nest-site selection by the Herald Petrel and White-tailed Tropicbird on Round Island. Wilson Bulletin, 103(1), 126-130.

Cai, T., Huettmann, F., & Guo, Y. (2014). Using stochastic gradient boosting to infer stopover habitat selection and distribution of Hooded Cranes Grus monacha during spring migration in Lindian, Northeast China. PLoS One, 9(2), e89913.

Cairns, D. (1980). Nesting density, habitat structure and human disturbance as factors in Black Guillemot reproduction. Wilson Bulletin, 92(3), 352-361.

Collias, N. E., & Collias, E. C. (1984). Nest building and bird behavior. Princeton, NJ: Princeton University Press.

De'Ath, G., & Fabricius, K. E. (2000). Classification and regression trees: A powerful yet simple technique for ecological data analysis. Ecology, 81(11), 3178-3192.

Development Core Team. (2006). R: A language and environment for statistical computing. Royal Foundation for Statistical Computing. Retrieved from http://www.R-project.org (accessed February 10, 2006).

Dinsmore, S. J., White, G. C., & Knopf, F. L. (2002). Advanced techniques for modeling avian nest survival. Ecology, 83(12), 3476-3488.

Fielding, A. H., & Bell, J. F. (1997). A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation, 24(1), 38-49.

Gillett, W. H., Hayward, J. L., & Stout, J. F. (1975). Effects of human activities on egg and chick mortality in a Glaucous-winged Gull colony. Condor, 77(4), 492-495.

Good, T. P. (2002). Breeding success in the western Gull × Glaucous-winged Gull complex: The influence of habitat and nest-site characteristics. Condor, 104(2), 353-365.

Guégan, J. F., Lek, S., & Oberdoff, T. (1998). Energy availability and habitat heterogeneity to predict global riverine fish diversity. Nature, 391(6664), 382-384.

Guisan, A., & Zimmerman, N. E. (2000). Predictive habitat distribution models in ecology. Ecological Modelling, 135(2-3), 147-186.

Hagan, M. T., Demuth, H., & Beale, M. (1996). Neural network design. PWS Publishing.

Helsel, D. R., & Hirsch, R. M. (1992). Statistical methods in water resources. Elsevier Science Publishers.

Hirzel, A. H., & Guisan, A. (2002). Which is the optimal sampling strategy for habitat suitability modelling? Ecological Modelling, 157(2-3), 331-341.

Holeńa, M., & Baerns, M. (2003). Experimental design for combinatorial and high throughput materials development. In J. N. Cawse (Ed.), Wiley, New York (p. 163).

Huang, C., Yang, L., Homer, C., Coan, M., Rykhus, R., Zhang, Z., Wylie, B., Hegge, K., Zhu, Z., Lister, A., Hoppus, M., Tymcio, R., DeBlander, L., Cooke, W., McRoberts, R., Wendt, D., & Weyermann, D. (2001). Synergistic use of FIA plot data and Landsat 7 ETM+ images for large area forest mapping. Thirty-Fifth Annual Midwest Forest Mensurationists Meeting and the Third Annual Forest Inventory and Analysis Symposium, October 17-19, 2001, Traverse City, MI.

Isaaks, E. H., & Srivastava, R. M. (1988). An introduction to applied geostatistics. Oxford University Press.

Jiguet, F., Julliard, R., Couvet, D., & Petiau, A. (2005). Modeling spatial trends in estimated species richness using breeding bird survey data: A valuable tool in biodiversity assessment. Biodiversity and Conservation, 14(14), 3305-3324.

Johnson, J. B., & Omland, K. S. (2004). Model selection in ecology and evolution. Trends in Ecology & Evolution, 19(2), 101-108.

Kantrud, H. A., & Kologiski, R. L. (1982). Effects of soils and grazing on breeding birds of uncultivated upland grasslands on the northern Great Plains. US Fish and Wildlife Service, Wildlife Resource Report 15.

Kerns, B. K., & Ohmann, J. L. (2004). Evaluation and prediction of shrub cover in coastal Oregon forests (USA). Ecological Indicators, 4(2), 83-98.

Kleijnen, J. P. C., & van Beers, W. C. M. (2005). Robustness of kriging when interpolating in random simulation with heterogeneous variances: Some experiments. European Journal of Operational Research, 165(3), 826-834.

Lack, D. (1968). Ecological adaptations for breeding in birds. Methuen.

Lark, R. M. (2003). Two robust estimators of the cross variogram for multivariate geostatistical analysis of soil properties. European Journal of Soil Science, 54(1), 187-202.

Lendvai, Á. Z., Kis, J., Székely, T., & Cuthill, I. C. (2004). An investigation of mate choice based on manipulation of multiple ornaments in the Kentish plover. Animal Behaviour, 67(4), 703-709.

Li, P., & Martin, T. E. (1991). Nest-site selection and nesting success of cavity-nesting birds in high-elevation forest drainages. Auk, 108(2), 405-418.

Li, Z., Zhang, Y., Schilling, K., & Skopec, M. (2006). Co-kriging estimation of daily suspended sediment loads. Journal of Hydrology, 327(3-4), 389-398.

Lippmann, R. P. (1987). An introduction to computing with neural nets. Institute of Electrical and Electronic Engineers ASSP Magazine, 2(4), 4-22.

Magnin, G., & Yarar, M. (1997). Important bird areas in Turkey. DHKD.

Manel, D., Dias, J. M., Buckton, S. T., & Ormerod, S. J. (1999). Alternative methods for predicting species distribution: An illustration with Himalayan river birds. Journal of Applied Ecology, 36(5), 734-747.

Manel, S., Williams, H. C., & Ormerod, S. J. (2001). Evaluating presence-absence models in ecology: The need to account for prevalence. Journal of Applied Ecology, 38(5), 921-931.

Martin, T. E. (1987). Food as a limit on breeding birds: A life-history perspective. Annual Review of Ecology and Systematics, 18(1), 453-487.

Martin, T. L. (1988). Processes organizing open-nesting bird assemblages: Competition or nest predation? Evolutionary Ecology, 2(1), 37-50.

Marzluff, J. M., & Neatherlin, E. (2006). Corvid response to human settlements and campgrounds: causes, consequences, and challenges for conservation. Biological conservation, 130(2), 301-314.

Mastrorillo, S., Lek, S., Dauba, F., & Belaud, A. (1997). The use of artificial neural networks to predict the presence of small-bodied fish in a river. Freshwater Biology, 38(2), 237-246.

Michie, D., Spiegelhalter, D. J., & Taylor, C. C. (Eds.). (1994). Machine learning, neural and statistical classification. Ellis Horwood.

Miller, J., & Franklin, J. (2002). Modeling the distribution of four vegetation alliances using generalized linear models and classification trees with spatial dependence. Ecological Modelling, 157(2-3), 227-247.

Moore, I., Grayson, R., & Ladson, A. (1991). Digital terrain modelling: A review of hydrological, geomorphological, and biological applications. Hydrological Processes, 5(1), 3-30.

Mönkkönen, M., Husby, M., Tornberg, R., Helle, P., & Thomson, R. L. (2007). Predation as a landscape effect: the trading off by prey species between predation risks and protection benefits. Journal of animal ecology, 76(3), 619-629.

Myers, D. E. (1982). Matrix formulation of co-kriging. Mathematical Geology, 14(3), 249-267.

Murray, B. G. (2000). Measuring annual reproductive success in birds. Condor, 102(2), 470-473.

Nisbet, I. C. T., & Cohen, M. E. (1975). Asynchronous hatching in Common and Roseate terns: Sterna hirundo and S. dougallii. Ibis, 117(1), 374-379.

Nisbet, I. C. T. (1978). Dependence of fledging success on egg-size, egg composition and parental performance in Common and Roseate terns, Sterna hirundo and S. dougallii. Ibis, 120(2), 207-215.

Nisbet, I. C. T., Wilson, K. J., & Broad, W. A. (1978). Common terns raise young after death of their mates. Condor, 80(1), 106-109.

Noszály, G., & Székely, T. (1993). Clutch and egg-size variation in the Kentish Plover (Charadrius alexandrinus) during the breeding season. Aquila, 100, 161-179.

Özesmi, S. L., & Özesmi, U. (1999). An artificial neural network approach to spatial habitat modelling with interspecific interaction. Ecological Modelling, 116(1), 15-31.

Paola, J. D., & Schowengerdt, R. A. (1997). The effect of neural network structure on a multispectral land use/land cover classification. Photogrammetric Engineering and Remote Sensing, 63(5), 535-544.

Partridge, L. (1978). Habitat selection. In J. R. Krebs & N. B. Davies (Eds.), Behavioural ecology: An evolutionary approach (pp. 351-376). Blackwell Scientific Publications.

Pearce, J., & Ferrier, S. (2000). Evaluating the predictive performance of habitat models developed using logistic regression. Ecological Modelling, 133(3), 225-245.

Ricklefs, R. E. (1969). An analysis of nesting mortality in birds. Smithsonian Contributions to Zoology, 9, 1-48.

Riley, T. Z., Davis, C. A., Ortiz, M., & Wisdom, M. J. (1992). Vegetative characteristics of successful and unsuccessful nests of Lesser Prairie-Chicken. Journal of Wildlife Management, 56(2), 383-387.

Rulequest Research. (2008). An overview of Cubist. Rulequest Research. Retrieved from http://www.rulequest.com/cubist-unix.html

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning internal representations by error propagation. In D. E. Rumelhart & J. L. McClelland (Eds.), Parallel distributed processing: Explorations in the microstructure of cognition. Volume 1: Foundations (pp. 318-362). MIT Press.

Segurado, P., & Araújo, M. B. (2004). An evaluation of methods for modelling species distributions. Journal of Biogeography, 31(10), 1555-1568.

Showler, D. A., Stewart, G. B., Sutherland, W. J., & Pullin, A. S. (2010). What is the impact of public access on the breeding success of ground-nesting and cliff-nesting birds. Systematic Review, 16.

Shrubb, M. (1990). Effects of agricultural change on nesting lapwings Vanellus vanellus in England and Wales. Bird Study, 37(2), 115-127.

Skutch, A. R. (1985). Clutch size, nesting success, and predation on nests of Neotropical birds, reviewed. In R. A. Buckley, M. S. Foster, E. S. Morton, R. S. Ridgely, & R. G. Buckley (Eds.), Neotropical ornithology (pp. 575-594). Ornithological Monographs No. 36.

Stephens, S. E., Koons, D. N., Rotella, J. J., & Willey, D. W. (2004). Effects of habitat fragmentation on avian nesting success: a review of the evidence at multiple spatial scales. Biological conservation, 115(1), 101-110.

Székely, T. (1999). Report on ecology and behaviour of birds at Tuzla Lake in 1999. Centre for Behavioural Biology, School of Biological Sciences, University of Bristol.

Szentirmai, I., & Székely, T. (2004). Diurnal variation in nest material use by the Kentish Plover Charadrius alexandrinus. Ibis, 146(3), 535-537.

Thuiller, W. (2003). BIOMOD – Optimising predictions of species distributions and projecting potential future shifts under global change. Global Change Biology, 9(8), 1353-1362.

Vander Haegen, W. M. (2007). Fragmention by agriculture influences reproductive success of birds in a shrubsteppe landscape. Ecological Applications, 17(3), 934-947.

Yılmaz, K. T., Alphan, H., Kosztolányi, A., Ünlükaplan, Y., & Derse, M. A. (2020). Coastal wetland monitoring and mapping along the Turkish Mediterranean: determining the impact of habitat inundation on breeding bird species. Journal of Coastal Research, 36(5), 961-972.

Walley, W. J., & Fontama, V. N. (1998). Neural network predictors of average score per taxon and number of families at unpolluted sites in Great Britain. Water Resources, 32(3), 613-622.

Webb, S. L., Olson, C. V., Dzialak, M. R., Harju, S. M., Winstead, J. B., & Lockman, D. (2012). Landscape features and weather influence nest survival of a ground-nesting bird of conservation concern, the greater sage-grouse, in human-altered environments. Ecological Processes, 1, 1-15.

Wu, C., & Murray, A. T. (2005). A co-kriging method for estimating population density in urban areas. Computers, Environment and Urban Systems, 29(5), 558-579.

Zaniewski, A. E., Lehmann, A., & Overton, J. M. (2002). Predicting species spatial distributions using presence-only data: A case study of native New Zealand ferns. Ecological Modelling, 157(2-3), 261-280.