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Applying Artificial Neural Network on Modelling Waterbird Diversity in Irrigation Ponds of Taoyuan, Taiwan

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1. Introduction

Irrigation ponds, or *pi-tang* in Chinese, are defined as an artificial construction made to impound water by constructing a dam or an embankment, or by excavating a pit or dugout. Some ponds at both microhabitat and the landscape scales may be a relevant influence for explaining bird communities due to a habitat effect or more-moderate and complex effects (Froneman et al., 2001). These ponds, regarding as wintering waterbird refuges, represent some of the multi-functional dimensions in the restoration results of agro-ecosystems. Previous studies detected that causes of species diversity are affected by habitat heterogeneity (Forman and Godron, 1986; Forman, 1995; Begon et al., 1996; Francl & Schnell, 2002; Fang et al., 2009). According to habitat selection as bio-choices, irrigation pond patterns associated with various microhabitats provide environmental clues that are used by birds to select stopover sites, such that ponds within the range of avian communities may potentially remain unoccupied or under-occupied if they lack those clues. Therefore, the appropriate microhabitats for a particular species in a guild might not be spatially constant if the habitat status changes the distance to the edge between pond cores to peripheral habitats, i.e., by water-table drawdown, farmland consolidation, or other anthropogenic influences. Pond-species relationships, thus, are connected like a neural network with a non-parametric nature, as clues suggest.

In fact, estimating the avian community is a difficult task as various species may inhabit same patch in a heterogeneous landscape, so taxonomic analysis of avian guilds would be advantageously coupling them here with the development of forecasting techniques based on habitat characteristics. Surprisingly, attempts to estimate entire avian guilds with scientific rigor on such grounds are scarce in the literature, except with a few taxonomic studies (McArthur et al., 1967). Conversely, a wealth of work deals with linear predictions on a regional scale (McArthur et al., 1967; Froneman et al. 2001). In this respect, they proposed theoretical linear-relationship models using a wide range of multivariate techniques, including several methods of multivariate linear discriminant analyses, canonical analyses, and logistic regressions.

Many critical reviews have indicated that these conventional models, usually based on multiple regressions, assume simple linear relationships between variables (Palmer, 1990; Reby et al., 1997). Some authors argued that regression model did not fit non-linear

relationships and interactions among variables. Virkkala (2004) stipulated that avian habitat selection is a dynamic and nonlinear process. Based on linear principles, they produce exclusive results since the main processes that determine the level of biodiversity or species abundance are often non-linear. To some extent, these methods are often rather inefficient after variable transformation when the data are non-linearly distributed. Therefore, species-habitat relationships often yield skewed and bimodal data. There are also other complexities associated with fluctuating avian populations and hierarchical decision-making on different scales before a final habitat selection. This highly complex relationship is inherently unpredictable between birds and their microhabitats. However, on the local scale many habitat models for birds have achieved considerable success in predicting habitat selection.

In addition, there is no specific a priori mathematical tool for predicting guild biodiversity, so the techniques used for prediction should also work for non-linear transformation. In ecology, multivariate-based models relating environmental variables to avian communities have been presented by several authors sometimes using non-linear transformations of independent or dependent variables to improve results. Even so, the results are still insufficient, with a low percentage of variance explained. Therefore, additive variables regarding bird and pondscape relationships require that networks be interwoven for detailed studies.

According to aforementioned analyses, this study assesses a non-linear relationship using neural network models instead of linear regression. We developed an approach adopted by Artificial Neural Networks (ANN) to model the relationship between pondscape and waterbird diversity. Study areas with thousands of irrigation ponds are unique geographic features from the original functions of irrigation converted to waterbird refuges. 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. ANN models can be non-linear and can model logical expressions such as "and", "or", "not", and "exclusive or" as the pages that follows.

The groundwork for neural networks was laid out in the 1940s in the field of neurophysiology. ANN, which originated about several decades ago (McCulloch & Pitts, 1943), was inspired by a desire to emulate human learning. ANN is highly effective for modeling nonlinear problems. Only recently it was shown that ANN models may efficiently model some non-linear systems in ecology. In recent avian studies, some authors have focused on an approach of ANN, which were developed as an original prediction method according to the principle of the operation of the human neural system (Ozesmi et al., 2006; Fang et al., 2009). The practical implication is that an ANN can accurately predict nest occurrence and breeding success of red-winged blackbird in response to ecological applications (Ozesmi et al., 2006).

Neural networks are determined by the neurons, or units, which are interconnected within the entire dynamic system. In this research, therefore, we attempted to apply this method to relate the structure and diversity of an assemblage of wintering birds to microhabitats. Our model considers pond shape and size, neighboring farmlands, and constructed areas in calculating parameters pertaining to the interactive influences on avian diversity, among them the Shannon-Wiener diversity index (Shannon and Weaver, 1949; Oertli et al., 2002).

2. ANN's methods

In our research, we used multiple logistic regression (MLR) models associated with ANN's models. The multiple logistic regression (MLR) models are identical to a neural network with no hidden units. For neural network hidden units, each hidden unit computed a

logistic regression (different for each hidden unit), and the output is therefore a weighted sum of logistic regression outputs. Initially, (ANN) were developed to provide simplified models of biological neural architecture. Each of these domains can be characterized as ones in which (a) multiple hypotheses need to be pursued in parallel, (b) enormous amounts of data need to be processed, and (c) the best current systems are far from equaling human performance.

The error back-propagation (BP) training algorithm has proven to be one of the most useful approaches in training the development of an ANN. This algorithm adjusts the connection weights according to the back-propagated error computed between the observed and the estimated results. This is a supervised learning procedure that attempts to minimize the error between the desired and the predicted outputs.

For this research, we chose a three-layered model with one input layer of three to four neurons (one for each input variable), one hidden layer of two to eight neurons (it is the number which gave the best prediction result), and one output layer of one neuron which was the output variable (see Fig. 1). Each input layer was connected to each neuron in the hidden layer via adjustable weighted links and likewise between the hidden layer and the output layer.
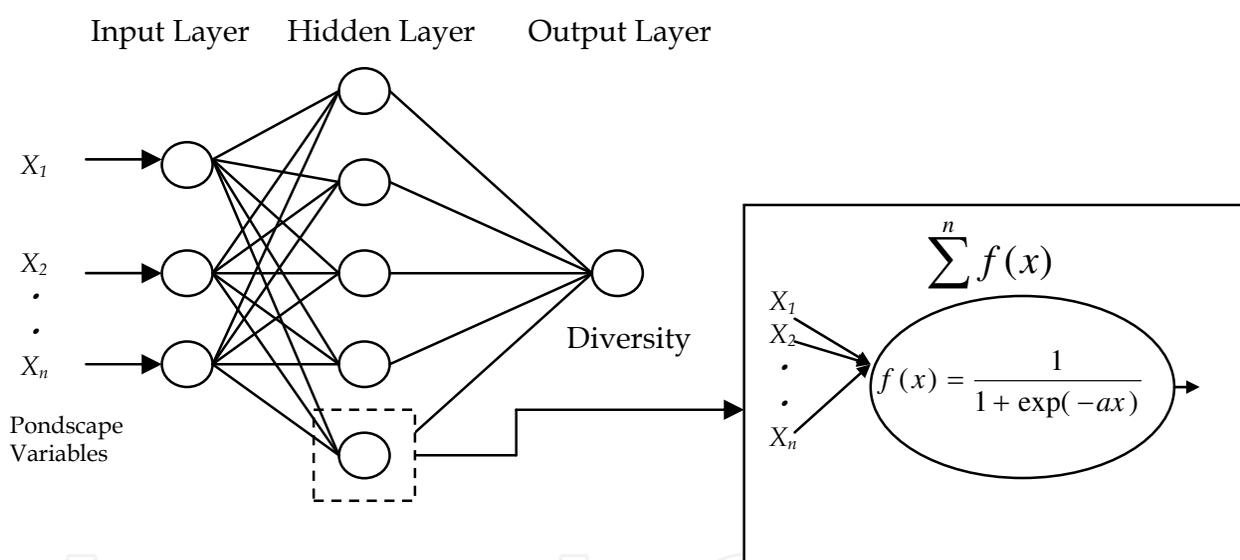

Fig. 1. Structure of neural networks used in this study based on the error back-propagation (BP) training algorithm. Input layer of neurons comprising as many neurons as pondscape variables at the entry of the system; hidden layer of neurons whose number is determined empirically; output layer of neurons with a single neuron (i.e., diversity) corresponding to the single dependent variable.

In the processes of BP training, the input data pattern is presented at the input neurons. These values are propagated through the network from the input to the hidden layer and then from the hidden layer to the output layer. At each stage the values, summed weighting inputs, are multiplied by the individual links on each connection. Then, the output layers are generated by the network based on the input data set. The errors, based on the differences between the "true" output and the "test" output, are fed back through the propagated loops. The individual weights associated with each of the connections to the hidden neurons are adjusted slightly to diminish the error.

Modelling was carried out in two phases to adjust with the training set and then test with the test set to determine the best ANN configuration. First, testing the model to calibrate the model variables. Second, to test the ANN models, we selected at random a training set (80% of the pond records, i.e., 35) and a validation set (20% of the pond records, i.e. 10). For each of the two sets, the model was determined with the training set and then validated with the test set. The quality of the model was judged through the correlation between observed and predicted values in the validation set. The ANN analysis was performed with the computer package, MATLAB 6.1 (MathWorks, Inc., Natick, MA, 2001).

3. Materials and supported methods

3.1 Materials sampled

In general, this study would detect differences between the linear model and non-linear model by logistic regression and ANN in the low-density rural population pondscape areas. There was a necessity to carefully select the predicted area of pondscape as well as environmental gradients between these models. Regarding the scientific rigor, all cases of sampling ponds, waterbirds, and other data related to this study are examined in material details as follows.

We selected ecologically significant Taoyuan Tableland associated irrigation ponds as our study area because one fifth of all the bird species find home on these ponds in Taiwan (Chen, 2000; Fang, 2004a). This tableland, at an area of 757 km² in size, comprises an area of 2,898 ha of irrigation ponds on the northwestern portion of Taiwan. Located approximately 30 km from the capital city of Taipei, this rural area was easily converted to urban lands due to the aggregated effects of urbanization and commercialization. Socioeconomic benefits are driving public opinion which is urging the government to approve land-use conversion from farmlands into urban uses. The Taoyuan Tableland lies between the northern border of the Linkou Tableland (23°05'N, 121°17'E) and the southern border of the Hukou Tableland (22°55'N, 121°05'E); it borders the town of Yinge in the east (22°56'N, 121°20'E) and the Taiwan Strait in the west (22°75'N, 120°99'E) (Department of Land Administration, Ministry of the Interior, 2002)(see Fig. 2.). It sits at elevations from sea level to 400 m and is composed of tableland up to 303 m and hills with sloping gradients from 303 to 400 m. It runs in a southeast-to-northwest trend, abutting mountains in the southeastern corner and the shore of the Taiwan Strait at the far end. With a high average humidity of 89%, the tableland is located in a subtropical monsoon region with humid winters and warm summers. January temperatures average 13 °C, and July temperatures average 28 °C. Annual average precipitation ranges from 1,500 to 2,000 mm.

The tableland gradually rose approximately 180,000 years ago. At that time, the Tanshui River had not yet captured the flow from the ancient Shihmen Creek, which directly poured out of the northwestern coast forming alluvial fans. Eventually, foothill faults caused by earthquakes during the same era, resulted in the northern region of Taiwan abruptly dropping by 200 m, and thus, the Taipei basin was born. Since the Taipei area had subsided, the ancient Shihmen Creek which meandered across the Taoyuan Tableland was captured by northward-flowing rivers some 30,000 years ago. The middle streams changed their courses because of the subsidence in the Taipei basin. The resulting Tahan Creek, became the upstream portion of the Tanshui River in the Taipei Basin. Due to blockage of water sources, downstream areas on the Taoyuan Tableland were deficient in water. This caused high flushing and drops in water yields. Historically, it was difficult to withdraw and

supply irrigated surface water from rivers due to the tableland's unique topography, thus, forming an obstacle for the development of agriculture (Huang, 1999; Chen, 2000).

This area has a population density of 2,331 persons/km² and its population is increasing at a rate of 2,000~3,000/month. Population pressures have contributed to reductions in historical areas of farmlands and irrigation ponds (Fang, 2001). Losses of farm-pond and farmland habitats have had series effects on a range of avian communities as well as other fauna and flora (Fang and Chang, 2004). On the Taoyuan Tableland, agricultural practices are intensifying, which is reducing the heterogeneity of the existing landform, and adding pollutants, also resulting from industrial practices.
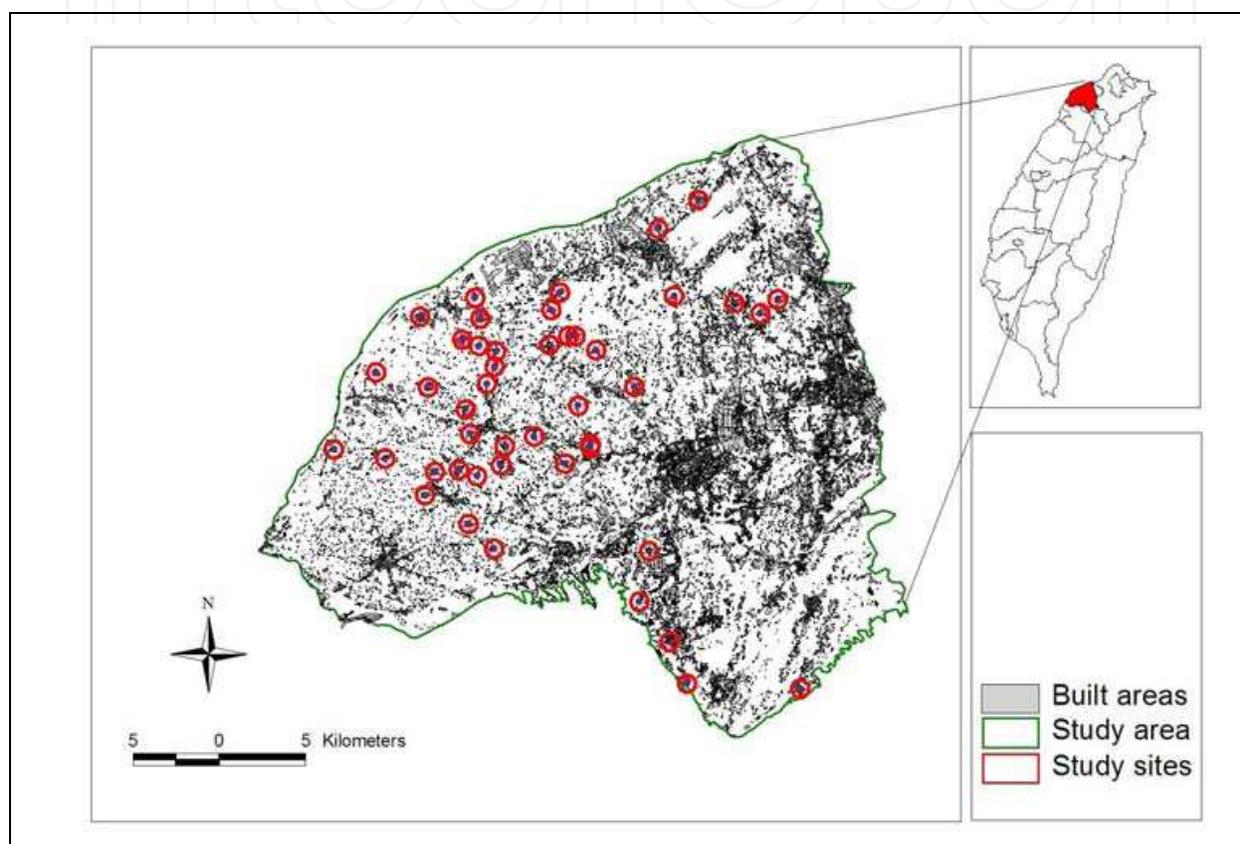

Fig. 2. Location away the city limits more than 2 km of forty-five study ponds in the range of the tableland.

3.2 Pond sampled

The pond complex in the Tableland is typical of the many farm-pond complexes found in the Taoyuan and Hsinchu Counties. The Tableland was first stratified into nine sub-regions, six in the north, five in the south, and thirty-four in the western regions. Data were collected at forty-five study sites in farm ponds in various size gradients (43 individuals > 1 ha; 2 individuals < 1 ha) according to large areas of ponds accounted for 628 individuals (>1 hectare) in Taoyuan Tableland (Fig. 2.). The number of farm-pond sites selected in each region was roughly proportional to the accessible area of each region riding by automobiles. We did not place sampling sites in eastern and southern urbanized high-density areas where the population was relatively intact. This was done because the bird composition of such an urban sites containing a large proportion of generalists would have driven a large

proportional bias with the other sites with more specialists, thus making it inappropriate for diversity analysis. Although we did not select sites based on any predetermined definition of the degree of urbanization along a rural-urban gradient (e.g. distance from urban core), the relatively large number of randomly selected survey sites ensured that there was a good representation of sites far away from major urbanized corridors approximately more than 2 km area, and far from natural forest areas in the eastern regions. The farm ponds studied ranged from the slight disturbed farmlands to the fairly natural farmlands. We placed the linear transect routes on areas that were accessible by trails and footpaths around ponds. Therefore, forty sites were situated within table range in western range, and five sites were situated in relatively continuous interlocked ponds in southern range. All pond sites were stratified selected randomly to minimize variability in vegetation structure and composition. Detailed measurements from tree species records on a subset showed them to be structurally very similar areas.
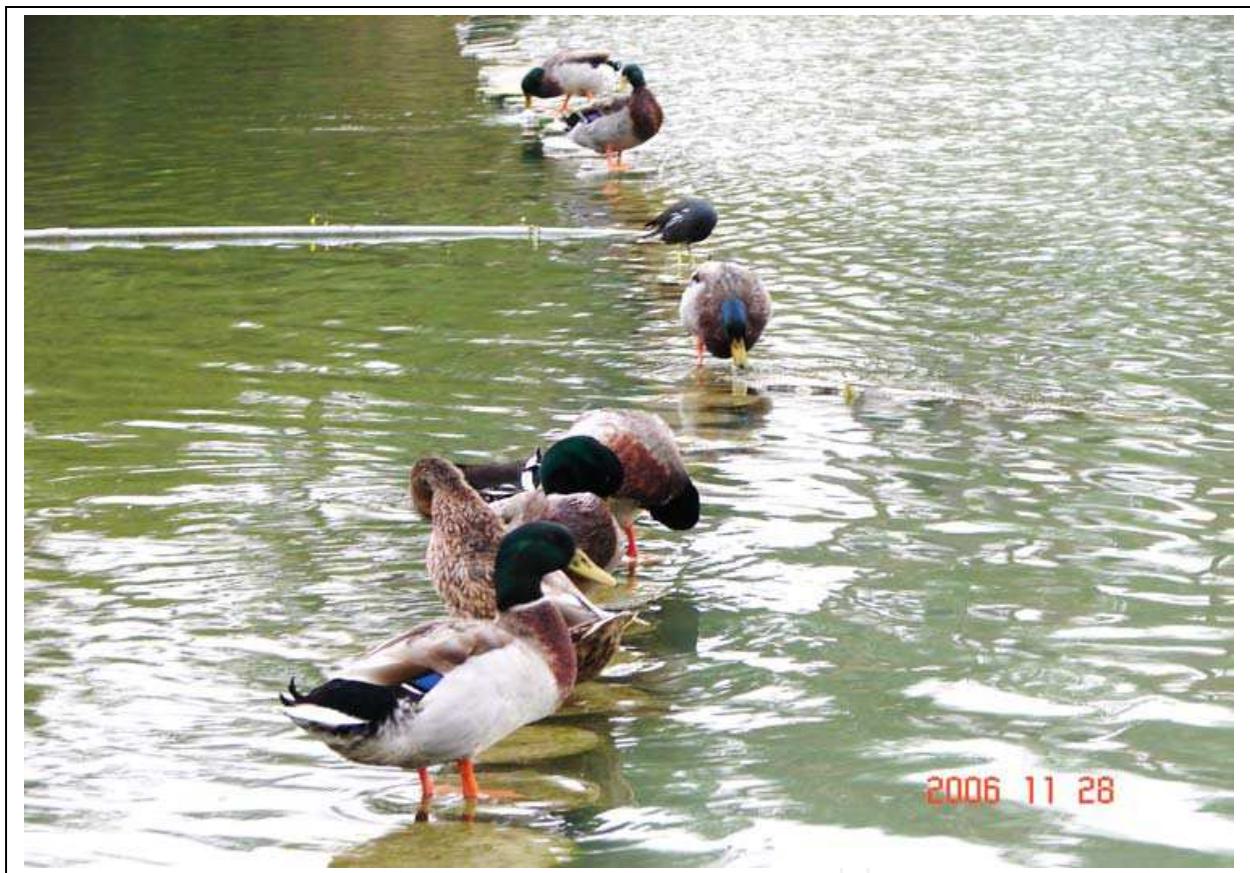

Fig. 3. Avian observers recorded all bird species seen within a 100-ha radius at 564.19-m basal radius of the bird census point at pond edge (photo by Wei-Ta Fang).

3.3 Waterbirds sampled

Avian observers recorded all bird species seen within a 100-ha radius at 564.19-m basal radius of the bird census point at pond edge associated with line transects along pond-edge trails during 30-minute periods (one case of irrigation ponds see Fig. 3.). Sites were visited four times in the winter seasons between November and February. To reduce the effects of bird-observer bias, three to four observers were grouped and rotated between ponds. The

observers counted birds that were in any habitats. All counts were conducted between 7:00 a.m. and 10:00 a.m. on days without rainy days when visibility was good (Bookhout, 1996).

Foliage-loving species was also recorded followed the point-count method. Avian presence/absence on foliage strata was recorded in each pond at each of the following height intervals: edge ground, wetland grasses (< 0.5 m in height), bushes (> 0.5- 2.5 m in height), trees (> 2.5 m in height). Points were sampled at 10-m internals along edge trails established down each side of each pond. Waterbirds were grouped into microhabitat guilds based on actual observations on the sites. Foliage-loving species were initially classified into four height categories: pond-edge ground, low foliage (< 0.5 m in height), middle foliage (> 0.5- 2.5 m in height), and high foliage (> 2.5 m in height). Species were subsequently classified into two groups: understory (ground and low foliage groups) and canopy (middle and high foliage groups).

We calculated the number of individuals detected of each species at each pond for each month. Then, we calculated mean values of these variables for each study microhabitat across all study ponds in a wintering season.

3.4 Pond metrics calculation

Most pondscape studies imply a comparison with rural or natural habitats and tend to group urban or suburban areas into a simple type (Boothby, 1997). But pondscape associated with farmlands is not alike. They vary greatly in internal and external factors. To find a habitat relationship, the major variables for species diversity in pondscape patches are categorized to meso-scale and micro-scale distribution, such as: (a) matrix heterogeneity (meso-scale), and (b) habitat diversity (micro-scale) in size, shape, isolation from sources, and boundary delineation of disturbances. Variables were selected concerning the main differences in vegetation, the intensity of anthropogenic influences, and their distance from urban limits and ocean edges. In this study, matrix heterogeneity was decided by insensitive farming by consolidation. Habitat diversity indices in area and shape were calculated by FRAGSTAT® according to Taoyuan's Geographic Aerial Map (1:5,000 of scale in digital database form) (Department of Land Administration, Ministry of the Interior, 2002).

These diversity indices were categorized as follows: (1) Largest Pond Index (LPI), (2) Mean Pond Size (MPS), (3) Number of Ponds (NP), (4) Mean Pond Fractal Dimension (MPFD), (5) Mean Shape Index (MSI), (6) Edge Density (ED), and (7) Total Edge (TE). The indices (1)- (3) were categorized as the indices of "area"; and the (4)- (7) were categorized as the indices of "shape" (McGarigal et al, 2002). Disrupted by anthropogenic influences, an isolation index was calculated: (8) the distance to city limit (in m), (9) the ratio of constructed area within a radius of 100 ha from the pond's geometric center (in $(m^2)/ha$), and (10) the ratio of all road and trail areas within a radius of 100 ha from the pond's geometric center (in $(m^2)/ha$). A source connectivity index was calculated: (11) the distance to coastline (in m), (12) the ratio of all surrounding pond areas within a radius of 100 ha from the pond's geometric center (in $(m^2)/ha$), and (13) the ratio of all river and canal system areas within a radius of 100 ha from the pond's geometric center (in $(m^2)/ha$). Afterwards, the disturbance and buffer zone was measured using the density of drawdown and foliage cover, and windbreak boundaries were delineated by field surveys and an examination of aerial photographs, 1:5,000 of scale (Agricultural and Forestry Aerial Survey Institute, 2003). The composition of the complex landscape matrix mentioned above could modify the degree of effects, probably by increasing or limiting the availability of foraging sources and resting sites for avian communities. All elevation (in m) of ponds and perimeters (in m) of pond edges were

measured by Global Position System (GPS)(GarminVista-Etrex, made in Taiwan) and rolling rulers (in m) associated with the calibration of aerial photographs, 1:5,000 of scale (Agricultural and Forest Aerial Survey Institute, 2003). Indices were required to calculate class and landscape levels as follows (McGarigal et al, 2002):

1.   Largest Pond Index, LPI.

$$LPI = \frac{\max\limits_{j=1}^{n}(a_{ij})}{A}(100) \tag{1}$$

a_{ij} = maximum pond ij area (in m²).
A = pond areas (in ha).
Level: CLASS, LANDSCAPE
Units: Percent
Range: 0 < LPI > 100
Description: LPI equals the pond area (m²) divided by total pond areas, multiplied by 100 (to convert to a percentage).

2.   Mean Pond Size, MPS.
MPS is the mean size of ponds (in ha.)

$$MPS = \frac{\sum\limits_{j=1}^{n} a_{ij}}{n_i}\left(\frac{1}{10000}\right) \tag{2}$$

a_{ij} =the area of pond ij (in m²).
n_i = the number of the pond ij, a single pond size (PS) in this case equal to 1.
Level: CLASS, LANDSCAPE
Units: Ha
Range: MPS > 0, without limit.
Description: MPS equals the pond area (m²) of all ponds of the corresponding patch type, divided by 10,000 (to convert to ha).

3.   Number of Ponds, NP.

$$NP = n_i \tag{3}$$

Level: CLASS, LANDSCAPE
Units: None
Range: NP > 1, without limit.
Description: NP equals the number of ponds of the corresponding patch type (class).

4.   Mean Pond Fractal Dimension, MPFD.

$$MPFD = \frac{\sum\limits_{j=1}^{n}\left(\frac{2\ln p_{ij}}{\ln a_{ij}}\right)}{n_i} \tag{4}$$

a_{ij} = the area of pond ij (in m²).
n_i = the number of the pond ij.

p_{ij} = the perimeter of pond ij (in m).
Level: CLASS, LANDSCAPE
Units: None
Range: $1 < MPFD < 2$
Description: MPFD reflects shape complexity across a range of pond size. It equals 2 times the logarithm of pond perimeter (m) divided by the logarithm of pond area (m²) (Li and Reynolds, 1994). MPFD approaches 1 for shapes with very simple perimeters such as circles or squares, and approaches 2 for shapes with highly convoluted and plane-filling perimeters.
5.   Mean Shape Index, MSI.

$$MSI = \frac{\sum\limits_{j=1}^{n} \dfrac{p_{ij}}{2\sqrt{\pi \times a_{ij}}}}{n_i} \qquad (5)$$

a_{ij} = the area of pond ij (in m²).
n_i = the number of the pond ij.

p_{ij} = the perimeter of pond ij (in m).

Level: CLASS, LANDSCAPE
Units: None
Range: MSI > 1, without limit.
Description: MSI equals the sum of the pond perimeter (m) divided by the square root of pond area (m²), and divided by the number of ponds. MSI represents the mean shape pattern. If MSI = 1, the pond is circular and increases without limit as pond shape becomes more curvilinear.
6.   Edge Density, ED.

$$ED = \frac{\sum\limits_{k=1}^{n} e_{ik}}{A}(10000) \qquad (6)$$

e_{ik} = the total parameters between pond$_i$ and landscape$_k$ (in m).
n = the number of the pond; a single pond in this case equal to 1.
A = pond area (in m²).
Level: CLASS, LANDSCAPE
Units: None
Range: MSI > 1, without limit.
Description: Edge density (in m/ha) equals the pond perimeter (in m) divided by the pond area. Edge density is a measurement of the complexity of the shape of pond.
7.   Total Edge, TE.

$$TE = \sum_{k=1}^{n} e_{ik} \qquad (7)$$

e_{ik} = the total perimeters between pond$_i$ and landscape$_k$ (in m).
n = the number of the pond; a single pond in this case equal to 1.

Level: CLASS, LANDSCAPE
Units: meters
Range: MSI > 0, without limit.
Description: Total Edge (TE) represents the total pond perimeters in meters.

3.5 Waterbird diversity analyses

There are two traditional bird analyses for entire avian communities and specific avian groups, richness, and diversity. Differences in the characteristics of avian groups and pondscape configuration may vary according to species-area relationships among regions. Therefore, to find differences in the response of species to habitat area and isolation, studies must include multiple analytical approaches to detect which analysis was better based on an entire community, or on a specific group.

Descriptive statistics for entire communities were used as the first stage of statistical avian data processing. The main aim was initial analysis of the distribution of avian communities sooner, such as an average individual value and; or a guild value was described for specific groups later. Afterwards, avian diversity was described in the result of diversity indices for all communities or a single group. To detect species evenness and abundance, we used Shannon-Wiener diversity index (H') (also named for Shannon index or Shannon-Weaver index), which is given a measure of the richness and relative density of a species to calculate diversity (Shannon and Weaver, 1949). This diversity measure conducted by Shannon and Weaver which originally came from information theory and measures the order observed within a particular system. Regarding to my studies, this order was characterized by the number of avian individuals observed for each species in the sampling ponds. The first step was to calculate P_i for each category (i.e., avian species), and then we multiplied this number by the log of the number. The index was computed from the negative sum of these numbers. In short, the Shannon-Wiener index *(H')* is defined as (8):

$$H' = -\sum_{i=1}^{S} P_i \log 2\, P_i \qquad (8)$$

S: avian species richness
Pi: The percentage of the *i* species in avian community

This index reflected bird richness in species and evenness amongst the avian community. The benefits of H' was sensitive by the change in threatened birds by avian study than that of Simpson's diversity index (D)(Dean et al., 2002). If the value of H' is higher, it means that species is abundant, or species distribution is even. However, species diversity is sometimes difficult to see relationships with spatial heterogeneity by limited survey data. Grouping and classification are required as well as for spatial heterogeneity reduction from the analyzed variables. It is the main procedure in this methodology for invoking avian groups with similar attributes of spatial behavior. The main approach in cluster analysis application is based on the idea to represent the grouping structure by avian data classification, based on the similarity in guilds between the species.

4. Results and discussion

The procedure was applied to waterbird assemblage of the Taoyuan Tableland, Taiwan. One variable was selected to describe its structure: Shannon-Wiener's diversity index (H') of

the same waterbird guild. Four environmental variables were selected as explanatory variables: pond size (PS), pond shape (MPFD)(see equation (4)), proportion of farmland area in peripherals (%FARM), and proportion of constructed area in peripherals (%BUILD) than that of other variables due to their intensive correlations. Correlations between observed values and values estimated by ANN models of the four dependent variables were moderately significant. The ANN models were developed from 35 sample sites of farm ponds chosen at random and were validated on the 10 remaining sample sites of farm ponds. The role of each variable was evaluated by inputting fictitious configurations of independent variables and by checking the response of the model. The resulting habitat profiles depict the complex influence of each environmental variable on the biological parameters of the assemblage, and the non-linear relationships between dependent and independent variables. The main results and the ANN potential to predict biodiversity and structural characteristics of species assemblages are discussed as follows.

4.1 Logistic modelling

Based on logistic regression and criteria selection, we present three strategic landscape scenarios as follows. The multiple linear regression (MLR) models decided as equation (4) and developed advanced Logit models by equation (9):

$$Logit\ (Y) = 1.90 - 3.02PS + 0.01TE \tag{9}$$

$$\frac{\ln[1000(TE_{km})]^2}{\ln(10000PS)} = 1.5 \tag{10}$$

$$TE_{km} = PS^{\frac{3}{4}} \tag{11}$$

$$Logit(Y) = \ln\frac{p}{1-p} = 1.90 - 3.02PS + 0.1PS^{\frac{3}{4}} \tag{12}$$

$$Logit(Y) = \ln\frac{p}{1-p} = 1.90 - 3.02(TE_{km})^{\frac{4}{3}} + 0.01TE_{km} \tag{13}$$

where TEkm = total edge (in km), PS = pond size (in ha)
The pond-loss likelihood (p), Logit (Y), PS, and TEkm were calculated as the Table 1. According to Table 1, the strategic landscape scenarios for farm pond adjacent land-uses were divided as: (a) Scenario A: conservative land use, (p =0.25); (b) Scenario B: moderate land use (p = 0.50); (c) Scenario C: intensive land use (p = 0.75) for waterbird refuges:
We used Scenario A for a conservative land use. If the likelihood of pond lossas a lower value is equal to 0.25, all ponds noted as threatened red spots (pond size > 0.996 ha, TEkm > 0.997 km) are required conservatively protected due to their loss likelihood. The base map of waterbird's diversity H' is suggested to designate waterbird refuges in 2 yellow patches (H'>1.5) against pond-loss likelihood overlaid by threatened red spots (Hpool: pond size > 0.996 ha, TEkm > 0.997 km). [Diversity H':0.4~0.6; 0.6~0.8; 0.8~1.0; 1.0~1.5; 1.5~1.741; Distance (km); 12].

Land-use Scenarios	Pond-Loss Likelihood (p)	PS (in ha)	TEkm (in km)	Logit (Y)= ln(p/1-p)
Extremely Conservative	0.05	1.6087	1.4284	-2.9444
Highly Conservative	0.10	1.3609	1.2600	-2.1972
Conservative	0.25	0.9962	0.9971	-1.0986
Moderate	0.50	0.6310	0.7080	0
Intensive	0.75	0.2666	0.3710	1.0986

Table 1. The Pond-loss likelihood rate and Logit functions.

We also used Scenario B for a moderate land use. If the likelihood of pond loss as a moderate value is equal to 0.50, all ponds noted as threatened red spots (pond size > 0.631 ha, TEkm > 0.708 km) are required moderately protected due to their loss likelihood. The base map of waterbird's diversity H' is suggested to designate waterbird refuges in 3 yellow patches (H'>1.5) against pond-loss likelihood overlaid by threatened red spots (Hpool: pond size > 0.631 ha, TEkm > 0.708 km). [Diversity H':0.4~0.6; 0.6~0.8; 0.8~1.0; 1.0~1.5; 1.5~1.741; Distance (km); 12].

Actually, Scenario C was used for an intensive land-use pattern, too (Fig. 4.). If the likelihood of pond loss as a high value is equal to 0.75, all ponds noted as threatened red
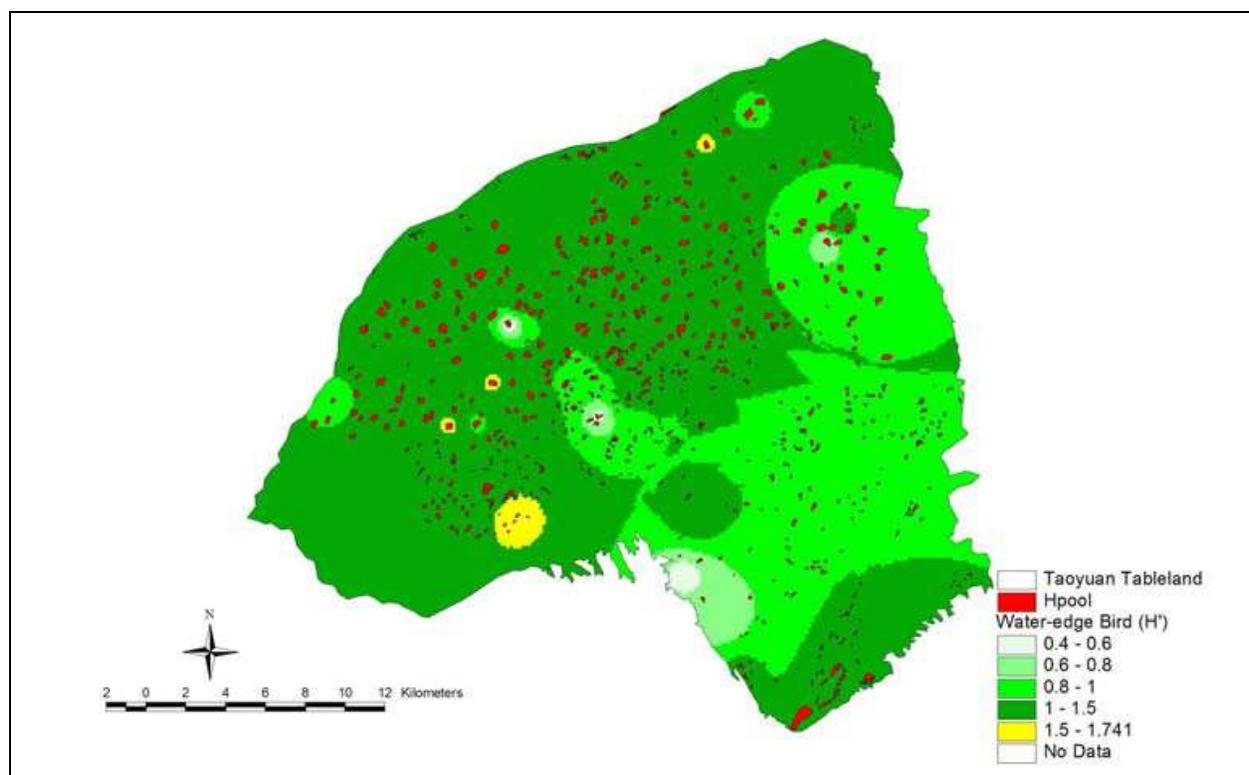

Fig. 4. Scenario C was used for an intensive land-use pattern (before ANN's application)

spots (pond size > 0.2666 ha, TEkm > 0.371 km) are required intensively protected due to their loss likelihood. The base map of waterbird's diversity H' is suggested to designate waterbird refuges in 4 yellow patches (H'>1.5) against pond-loss likelihood overlaid by threatened red spots (Hpool: pond size > 0.2666 ha, TEkm > 0.371 km). [Diversity H':0.4~0.6; 0.6~0.8; 0.8~1.0; 1.0~1.5; 1.5~1.741; Distance (km); 12].

4.2 ANN's application

On the basis of the results of this study, there were limitations for waterbird's diversity on the linear model simulation. First, the linear relationship is so simple that it could not indicate all non-linear relationship. Second, the pond sites numbers merely ranging from 1 to 45 simply could affect the precision of simulation results of bird distribution.

The diversity of waterbirds was predicted throughout the exercise using the backpropagation (BP) algorithm with a three mutli-layered neural network. The first layer, called the input layer, comprised 4 cells representing each of the environmental variables. The second layer, or hidden layer, is composed of a further set of neurons whose number depends on the best-calculated results without bias. Since BP algorithm was trained by the least mean square method. The least mean square training could reduce the error, or distance between the actual output and the desired output, by adjusting the weights. Training cases were presented sequentially and the weights are adjusted. We determined the number of second-layer neurons through a serious of iterations varied from two, four, and eight neurons. In each case, we calculated the correlation coefficients between true values of H' and the predicted value of ANN's H'. In our study, a network with one hidden layer of four neurons was selected. It was emphasized in a stable fit and avoided overtraining (see Figs. 5. & 6.).

In this study, the backpropagation (BP) neural network architecture is shown and consists of four layers of neurons connected by weights. We used MATLAB 6.1 (MathWorks, Inc., Natick, MA, 2001) to calculate a refining simulation model for extra values of H'.

The information was captured by the network when input data passed through the hidden layer of neurons to the output layer. The weights connecting from neuron one to neuron four were denoted as wji. Each neuron was calculated its output based on the amount of stimulation it received from the given input vector xi, while xi was the input of neuron i. The net input of a neuron was calculated as the weights of its inputs, and the output of the neuron was based on some sigmoid function which indicated the magnitude of this net input. So the net output uj from a neuron can be indicate as equations (14) and (15) (Fang et al, 2009).

$$u_j = \sum_{i=1}^{p} w_{ji} x_i \tag{14}$$

$$y_j = \varphi(u_j - \theta_j) \tag{15}$$

Where

w_{ji} is the incremental change in the weight from xi to uj

θ_j is a threshold to be passed through by non-linear activation function $\varphi(\cdot)$

x_i is the pondscape ith variable

u_j is the jth neuron from an outgoing signal to the magnitude of all observations

$\varphi(\cdot)$ activation function

y_j is the output of jth neuron in any layer
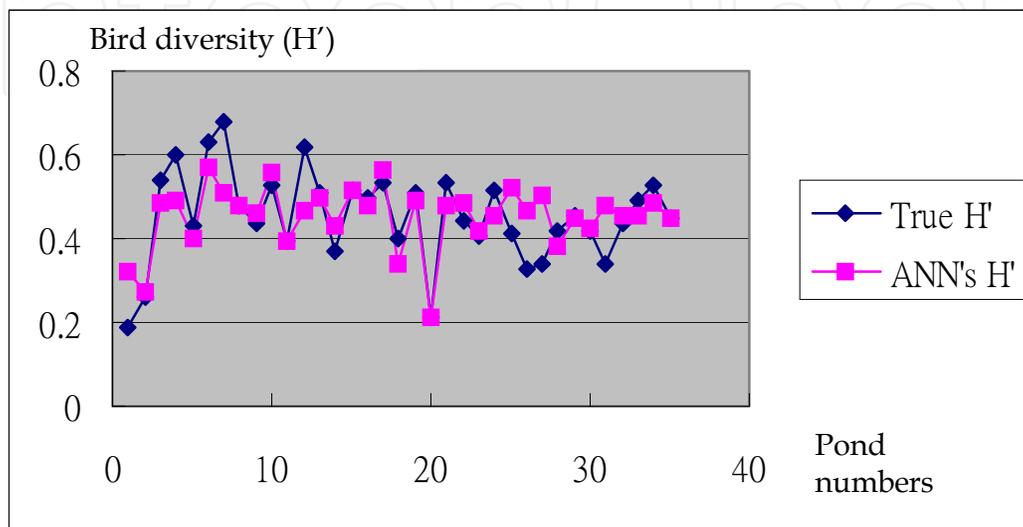

Fig. 5. The correlation trends between true H′ and ANN's predicted H′ in training sets for four neurons. (correlation coefficient (r) = 0.725537 ≒ 0.722752, n = 35).
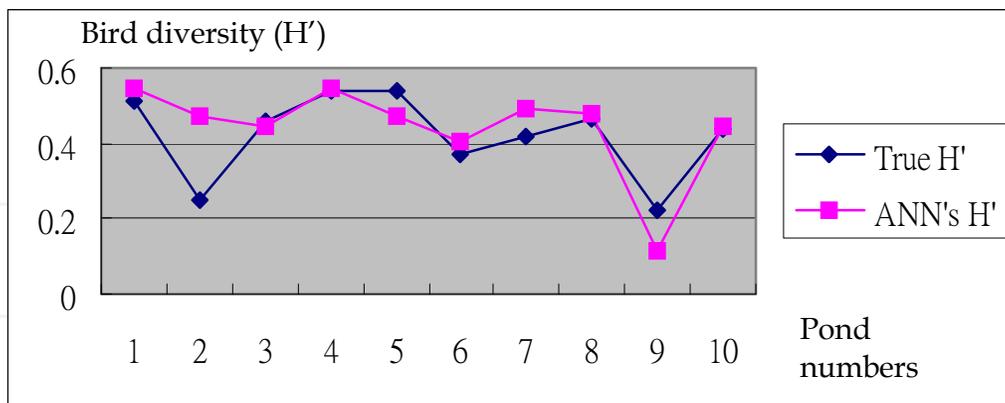

Fig. 6. The correlation trends between true H′ and ANN's predicted H′ in validated sets fitting for four neurons. (correlation coefficient (r) = 0.722752 ≒ 0.725537, n = 10).

The structure of the neural network used in this study. The input layer comprises 4 cells representing each of the 4-pondscape variables Xi (i =1, 4). The hidden layer comprises 4 neurons which calculate the dot products between its vector of weights wj =[wji, i =1,4] and x = [xi, i=1,4] from MATLAB 6.1.

This research chose continuous sigmoid as basic function:

$$\varphi(v) = \frac{1}{1+\exp(-cv)} \tag{16}$$

where v is the net effect, and c is a constant.

For a given input set, the network produced an output, and this response was compared to the known desired response of each neuron. The weights of the network were then changed to correct or reduce the error between the output of the neuron and desired response, and this process was keeping on. The weights were continually changed until the total error of all training set was reduced below the acceptable sums of errors. The BP algorithm for determining the optimal weights from training sets could be seen as similar to any function approximation technique like least square regression. But BP had an improved function to learn highly complex and non-linear data.

According to BP simulation, the strategic landscape scenarios for farm pond adjacent land-uses were refined as: (1) Scenario A: conservative land use, (p =0.25); (2) Scenario B: moderate land use (p = 0.50); (3) Scenario C: intensive land use (p = 0.75) for waterbird refuges as the pages that follow by Fig. 7. The Scenario B (moderate land use) has simulated to increase one waterbird's refuge (r = 0.72); and the Scenario C (intensive land use) has simulated to increase two waterbird's refuges (r = 0.72) (see Fig. 7.).
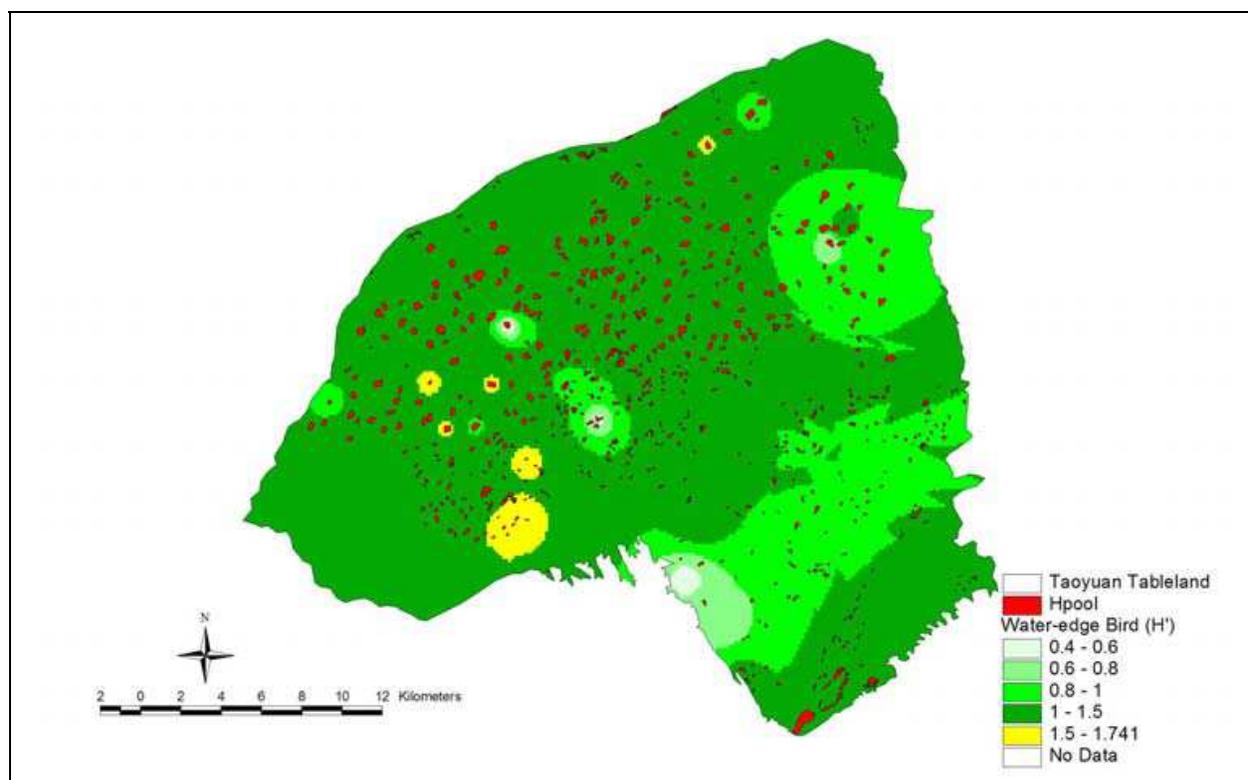

Fig. 7. Scenario C was used for an intensive land-use pattern (after ANN's application).

Scenario A was refined by the ANN's model for a conservative land use. If the likelihood of pond loss as a lower value is equal to 0.25, all ponds noted as threatened red spots (pond size > 0.996 ha, TEkm > 0.997 km) are required conservatively protected due to their loss likelihood. The base map of waterbird's diversity H' is suggested to designate waterbird refuges in 2 yellow patches (H'>1.5) against pond-loss likelihood overlaid by threatened red spots (Hpool: pond size > 0.996 ha, TEkm > 0.997 km)[Diversity H': 0.4~0.6; 0.6~0.8; 0.8~1.0; 1.0~1.5; 1.5~1.741; Distance (km); 12] (r = 0.72).

Scenario B was refined by the ANN's model for a moderate land use. If the likelihood of pond loss as a moderate value is equal to 0.50, all ponds noted as threatened red spots (pond size > 0.631 ha, TEkm > 0.708 km) are required moderately protected due to their loss likelihood. The base map of waterbird's diversity H' is suggested to designate waterbird refuges in 4 yellow patches (H'>1.5) against pond-loss likelihood overlaid by threatened red spots (Hpool: pond size > 0.631 ha, TEkm > 0.708 km)[Diversity H': 0.4~0.6; 0.6~0.8; 0.8~1.0; 1.0~1.5; 1.5~1.741; Distance (km); 12] (r = 0.72).

Scenario C was refined by the ANN's model for an intensive land-use pattern (see Fig. 7.). If the likelihood of pond loss as a high value is equal to 0.75, all ponds noted as threatened red spots (pond size > 0.2666 ha, TEkm > 0.371 km) are required intensively protected due to their loss likelihood. The base map of waterbird's diversity H' is suggested to designate waterbird refuges in 6 yellow patches (H'>1.5) against pond-loss likelihood overlaid by threatened red spots (Hpool: pond size > 0.2666 ha, TEkm > 0.371 km)[Diversity H':0.4~0.6; 0.6~0.8; 0.8~1.0; 1.0~1.5; 1.5~1.741; Distance (km); 12] (r = 0.72).

4.3 Discussion

The pondscape configuration was in fact a very relevant factor for avian diversity. However, pond shape (MPFD) was not recognized for its significant influences on waterbird's diversity. The final prediction results for a detailed H' contourmap were satisfactory, testifying then a good prediction of avian diversity which was better with ANN model (r = 0.72) than with linear regression model (r < 0.28), confirming the non-linearity of the relationship between the variables. From an ecological point of view, MPFD, the pond shape and %FARM, the ratio of farmland area, were the most significant variables in non-linear model rather than the linear model.

Some of the most significant findings came from the ANN's model. ANN was detected one of the tools that could resolve prediction problems, and this ANNs property is now well understood. On such finding was that pond shape (i.e., MPFD) to the pondscape might pose a tremendous influence to waterbird's diversity in Taoyuan Tableland. The value from ANN's method provided a good indication of the cumulative influences for the four environmental factors: such as %BUILD, %FARM, PS, and MPFD. The cumulative influences were those that resulted from the anthropogenic influences, and became statistically significant on waterbird's diversity. The above-mentioned environmental factors were selected from correlation analysis associated with linear regression model, and each factor to be detected its impact trend by ANN's model testing. Finally, the impact trends were calculated as the sequences of MPFD, %FARM, PS, and %BUILD, respectively. However, the correlation coefficients (r) of MPFD, %FARM, PS, and %BUILD were not following this sequence. Another significant finding from the extended simulation data

may suggest that consolidated area has contributed to a negative influence on the cumulative impacts to decline diversity H'. Therefore, non-consolidated area has become important to design wintering bird refuge due to its domination of the tableland, the refuge structures of regular pond shape, big pond size, high-density green spaces, and low-density housing development seemed to be regarded.

Conservation of avian diversity is influenced greatly by the extent to which intensive anthropogenic practices are applied in the pondscape. The models suggest small and curvilinear ponds together with urban development associated with high-density rural population landscapes will adversely affect waterbird species to a greater magnitude than agricultural practices in low-density rural population landscapes. Extensive agricultural practices associated with ranching enterprises appear to maintain the native plant communities essential for maintaining waterbirds. Considering the tremendous increase in development and intensive agricultural practices applied at the rural-urban fringe, native vegetation will continue to be replaced with human-made construction and introduced woodland species. Therefore, biologists and conservationists should focus their educational programs on maintaining avian species in the rural-urban fringe.

Increased species and structural diversity within these pond units would result in higher ecological values of spatial diversity resulting from the occurrence of habitat and regional scales. At the same time this reduces the need for making microhabitat density measurements to emphasize the "edge-effect" and also, to some extent, compensates for the under-representation of small habitats in the measurement of ecological value. For example, drawdown can be beneficial to shorebirds; foliage building at waterfront can be beneficial to waterfowl. There is clearly some mechanism responsible for the convergence of taxon density and composition across the pond size gradient for the greater part of the species assemblages. According to MacArthur & Wilson (1967), the nature of this mechanism is interesting as the island biogeographic concept predicts that smaller microhabitats should contain fewer species due to the effects of reduced immigration rates. For area-sensitive species, their incidence is expected to increase as pond size increases. In addition, a larger pond is also more likely to contain at least one individual of a species, especially an uncommon or rare one.

5. Conclusion

In Taoyuan Tableland, all ponds are similarly isolated. Within the complex pondscape, ponds are similarly isolated from each other and steppingstone colonization can take place to enable species to establish throughout the complex (Forman, 1995). A population may become move to surrounding ponds, or nearly so, due to stochastic or deterministic mechanisms and steppingstone recolonization might then ensure the persistence of that population among wintering stopovers. This is effectively the colonization effect where functional groups are continuously moving by colonization from nearby neighboring ponds. Because there are many ponds within the tableland and they are close together in space, vulnerable populations are likely to be enhanced by immigrants from multiple neighboring populations during migration. Stable microhabitats are also likely to receive immigrants from several neighboring populations. Migration between farm ponds is thus likely to be high and thus the whole pond complex is likely to be responding as a multiple community. There is likely to be a concentric-ringed gradient in pond systems between waterside species and habitat "islands". We confirmed that, due to similar mechanisms operating in all ponds

and the high connectivity between them, farm ponds are very close to the environmental gradients. Given the wide range examining in my study, it is quite possible that the predicted group diversity exist at different positions along this gradient. Therefore, the colonization effect can be helpful to predict waterbird's diversity (H') in surrounding study ponds throughout the values of input pondscape variables by ANN algorithm to determine a detailed regional contour map surrounding by urbanized areas.

6. Acknowledgements

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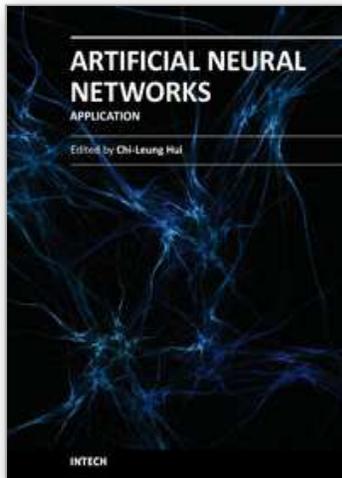
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