Artificial Neural Network Modeling of Bird Behavior and Reactions to Environmental Parameters in Wajiro Tidal Flat Reclamations

Abella, Lorene
Department of Applied Quantum Physics and Nuclear Engineering : Graduate Student

Akasaka, Ryo
Institute of Environmental Systems : Contract Researcher

Shikasho, Narumi
Department of Applied Quantum Physics and Nuclear Engineering : Graduate Student

Matsumoto, Tatsuya
Institute of Environmental Systems : Research Associate

他

出版情報：九州大学工学紀要. 63 (4), pp.211-226, 2003-12. 九州大学大学院工学研究院
バージョン：
権利関係：

Memoirs of the Faculty of Engineering, Kyushu University, Vol. 63, No. 4, December 2003

Artificial Neural Network Modeling of Bird Behavior and Reactions to Environmental Parameters in Wajiro Tidal Flat Reclamations

by

Lorene L. ABELLA*, Ryo AKASAKA**, Narumi SHIKASHO***,
Tatsuya MATSUMOTO†, Koji MORITA†† and Kenji FUKUDA†††

(Received September 24, 2003)

Abstract

Reclamation projects give an impression that a severe environmental damage is certain. However, the extent of damage cannot be measured by a rule of thumb. In this paper, an analysis of the environmental conditions focusing on the population of certain bird species was performed. It is only natural to surmise that bird population is decreasing due to man-made structures, much more destroying a natural habitat, though, at this stage of the study the degree as to how much the population has changed remains unknown. A model of the biological brain, known as artificial neural networks (ANN), which is the main essence of this research, might open doors to a more rigorous investigation of the environmental changes that are occurring due to tidal flat reclamations. This network is able to train itself from input parameter values and thus can predict values of desired output variables. A specific type of ANN algorithm used for calculation is the backpropagation algorithm, which is also known as the generalized delta rule. Input parameters like air temperature, daylight hours, and tidal flat organisms that birds feed were chosen. Sensitivity analysis was performed to identify the birds' behavioral patterns and their reaction to the state variables.

Keywords: Artificial Neural Networks (ANN), Backpropagation Algorithm, Tidal flat reclamation, Sensitivity analysis

1. Introduction

Reclamation of tidal flats in Japan has become uncommon governmental projects aimed

*Graduate Student, Department of Applied Quantum Physics and Nuclear Engineering
**Contract Researcher, Institute of Environmental Systems
***Graduate Student, Department of Applied Quantum Physics and Nuclear Engineering
†Research Associate, Institute of Environmental Systems
††Associate Professor, Institute of Environmental Systems
†††Professor, Institute of Environmental Systems

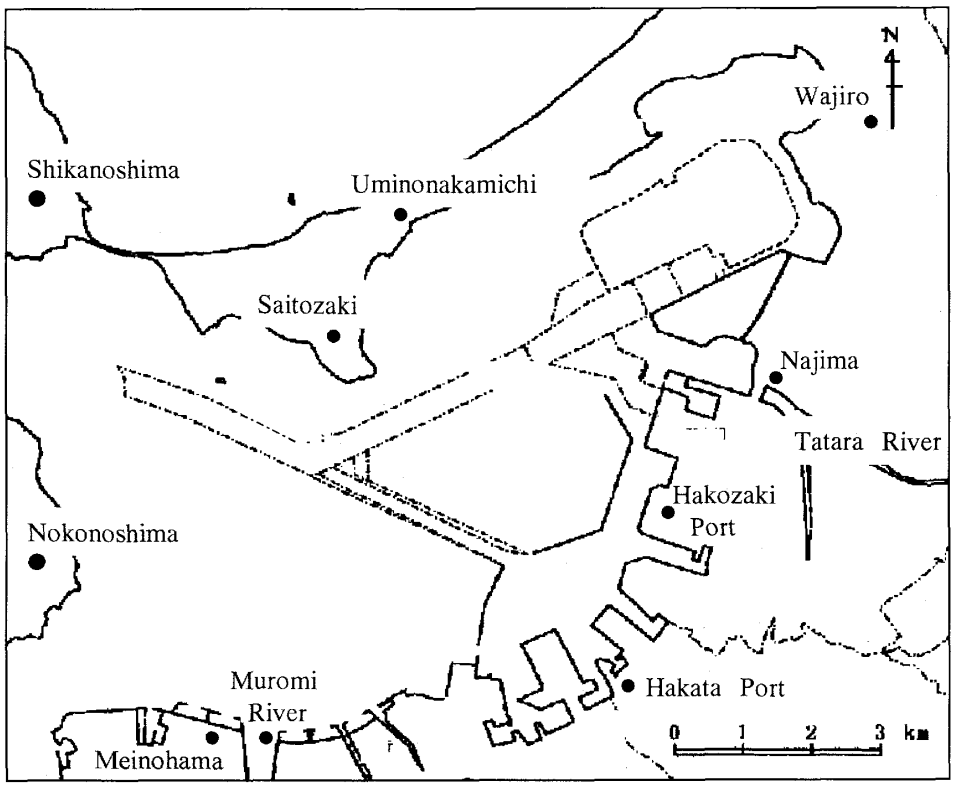

Fig. 1 Island City Map[1].

to increase land size. The relative increase of these projects caught the public's attention and resistance due to fear that the extent of environmental damage might be severe. In Fukuoka Prefecture, the Island City reclamation project is on its way to completion. The Wajiro tidal flat is the one used for its construction, thereby, the Fukuoka City Harbor Bureau has collected data for the last nine years to keep track of environmental changes in the area such as atmospheric temperatures, pH and turbidity of seawater, rainfall, and population of various fowls and marine life, etc. A map of Island City project is shown in **Fig. 1**.

Consider any species or environmental condition of any ecological system and imagine the interrelationships that exist among various species. Take for example, air temperature. As a general rule of thumb, it is natural to assume that when air temperature decreases as winter approaches, particular bird species would start migrating to warmer countries and stay there until its country of origin would start to warm up again. However, take into account what effect this migration process might have on other species and on other environmental conditions as mentioned above. A mere visualization and mental analysis of environmental system changes such as the change brought about by inter-specific relationships and competition and the direct influence of environmental conditions on them seem impossible. At a quite early stage of this study it is rather impossible to be able to understand how and at what rate these changes occur, but, the reactions or behavioral patterns of the control variables, i.e., the bird species selected, with respect to the state variables have been so far effectively modeled using the Backpropagation *Artificial Neural Networks* (ANN) algorithm.

2. Artificial Neural Networks (ANN)

Artificial neural networks have been modeled from the neural networks of the biological brain. As a biological *neuron* receives and transmits signals from and to other neurons so

does the artificial neuron. Shown in **Fig. 2.1** is a diagram of a biological neuron.

The zones that receive signals, or *synapses*, are the cell body and the dendrites, the branch-like extensions from the cell body. The axon, a fiber-like structure extending from the cell body, carries impulses, signals, or information from the neuron to the other neurons. Consider the figure shown in **Fig. 2.2**. Let the x's represent all other neurons and the w's as the weights. The weighted sum, which is the state of the neuron per epoch, is the sum of the product of the weights between the neuron and the afferent neurons and the incoming signals from all these neurons; and transforming this value, which in this case uses the sigmoid

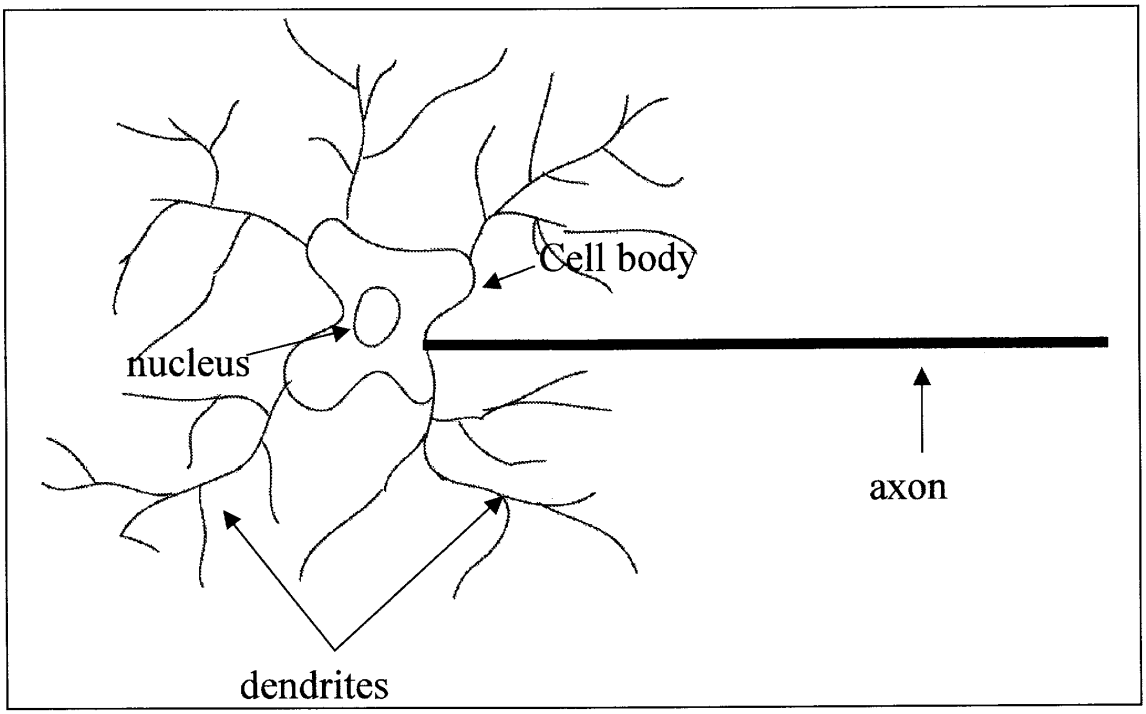

Fig. 2.1 The Biological Neuron.

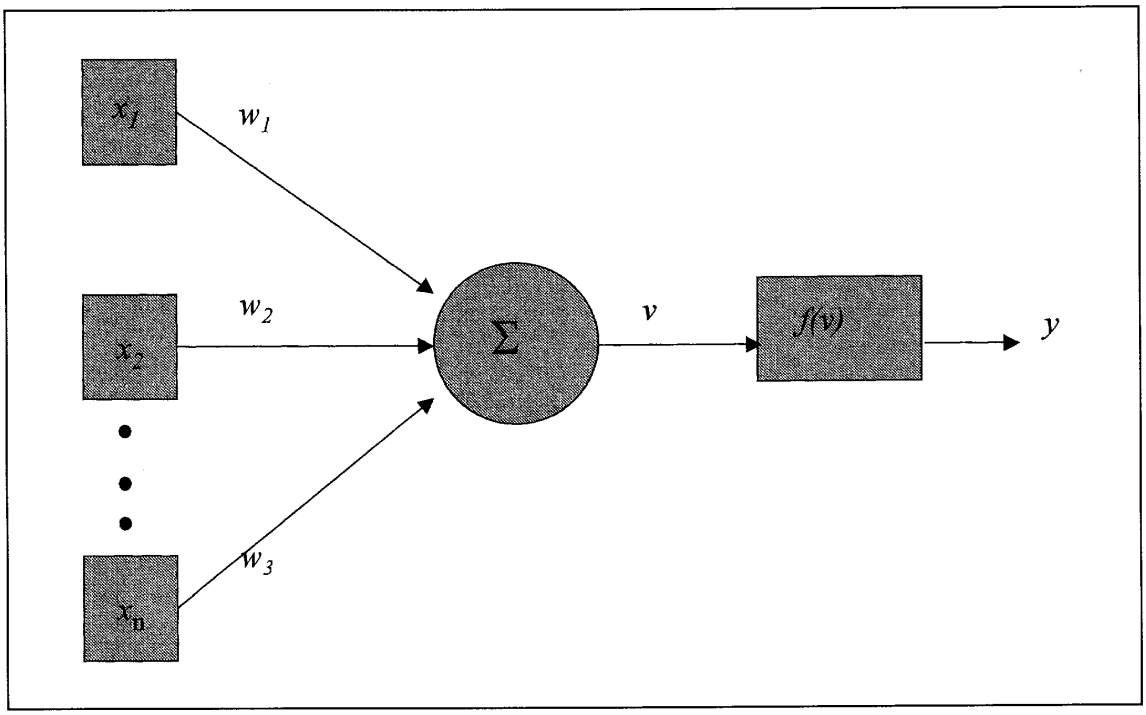

Fig. 2.2 The Artificial Neuron.

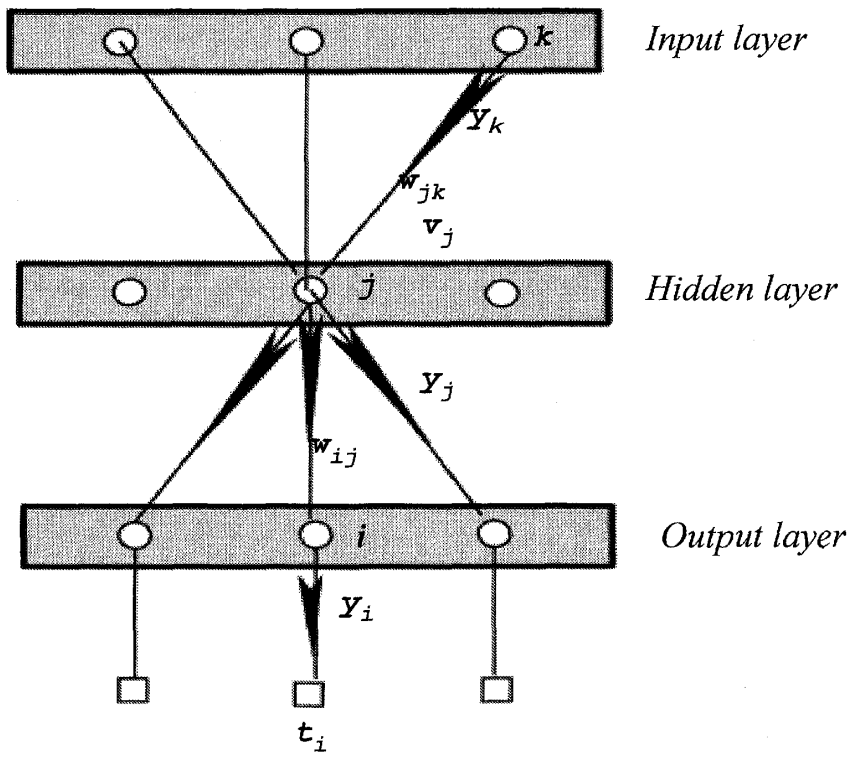

Fig. 2.3 A Three-layer Network.

function, gives the output signal of the neuron per epoch. This signal is then fed to other neurons as input. Transfer functions vary; examples are the unit-step function and the sigmoid function to name a few. The sigmoid function, however, is more widely used in neural networks and has values between 0 and 1.

A three-layer network (*refer to* **Fig. 2.3**) was used and the number of neurons for each layer varies with the number of parameters selected. Input signals are fed to the neurons in the input layer, consequently, the sum of the signals it receives would be transmitted to the hidden layer as input signals, and the same process occurs with the hidden neurons to the output neurons in the hidden and output layers, respectively. The interconnection between two neurons is associated by a certain value called the *weight* that is updated during training to transform the input values in order to come as close to the desired output values as possible. An output signal (*which is also the state of a neuron at a given time*) from a neuron is determined by the following transfer equation known as the sigmoid function:

$$y_i = f(v_i) = \frac{1}{1+e^{-v_i}} \tag{1}$$

v_i is the sum of the signals it received (which is also the state of the neuron before transformation) and y_i is the output of the neuron, which is fed as an input signal to other neurons in the succeeding layer. The same transfer function is used to calculate the output signals of all other neurons of each layer in the network.

2.1 Backpropagation Algorithm

The weights are updated using the *back propagation algorithm* (BPA), which enables efficient calculation of the error gradient using the chain rule of differentiation. The word backpropagation is derived from the process by which the error after being initially calculated in the forward direction is propagated backwards from the output neurons of each layer

to the neurons in the preceding layer.[2] The weights at the start of training are of arbitrary values. The network then updates them iteratively, and each iteration is known as an epoch.[3]

2.1.a Neurons between Hidden and Output Layers

Considering again **Fig. 2.3** the connections of the neurons in both the hidden and output layers labeled as L_h and L_o, respectively, are illustrated. If j denotes a neuron in the hidden layer and i as a neuron in the output layer, then the input signal v_i has the form,

$$v_i = \sum_{j \in L_h} w_{ij} y_j \tag{2}$$

If a teaching signal, t_i, is introduced the error can be calculated as,

$$E = \frac{1}{2} \sum_{i \in L_o} (t_i - y_i)^2 \tag{3}$$

The constant value 1/2 is used for convenience and does not affect nor influence error minimization.[4]

By the update rule, the weight between neurons j and i is expressed as,

$$w_{ij}^{(n+1)} = w_{ij}^{(n)} - \eta \left(\frac{\partial E}{\partial w_{ij}} \right)^{(n)} \tag{4}$$

where η is called the learning rate whose value is any small number greater than zero and is decided freely. However, very low values might retard the changing of the weights while larger values, tend to cause the weights to change by too large an amount that does not improve the network performance.[5] The superscripts (n) and $(n+1)$ indicate the nth and $n+1^{th}$ learning cycles that pertain to the old and new weight and error values, respectively. Manipulating eqns. (2) to (4) and taking the partial derivatives, and from the chain rule one can obtain the partial differential of the error signal with respect to the weight which is expressed as,

$$\left(\frac{\partial E}{\partial w_{ij}} \right) = -\delta_i y_j, \ j \in L_h, \ i \in L_o \tag{5}$$

with

$$\delta_i = (t_i - y_i)(1 - y_i) y_i \tag{6}$$

2.1.b Neurons between Input and Hidden Layers

If k indicates a neuron in the input layer, L_i, as expressed earlier, it follows that the weight between neurons i and j will have the form,

$$w_{jk}^{(n+1)} = w_{jk}^{(n)} - \eta \left(\frac{\partial E}{\partial w_{jk}} \right)^{(n)} \tag{7}$$

and the partial differential of the error signal with respect to the weight is similar to eqn. (6) and is given by,

$$\left(\frac{\partial E}{\partial w_{jk}} \right) = -\delta_j y_k, \ k \in L_i, \ j \in L_h \tag{8}$$

with

$$\begin{aligned} \delta_j &= (1 - y_j) y_j \sum_{i \in L_o} (t_i - y_i)(1 - y_i) y_i w_{ij} \\ &= (1 - y_j) y_j \sum_{i \in L_o} \delta_i w_{ij} \end{aligned} \tag{9}$$

3. Predictions and Validations

3.1 Methodology

Shown in **Table 3.1** are thirty-one data sets used to train the network for the tidal flat in Wajiro. The first eight parameters were fed as input signals, namely, average air temperature, rainfall quantities, length of daylight hours, and the population of phytoplankton, zooplankton, benthos, tide flat organisms, and inter-tidal organisms. The remaining four, which are the total bird population and the total number of snipes, curlews and related class, plovers and related class, and herons/egrets, served as output signals.

Calculations were performed in such a manner where each data set was used to test the network while the 30 others were used for training. This was repeated until all data sets have been utilized for testing. Each training process is completed once the average error of prediction equals or goes below the training or prediction accuracy. One data set out of thirty-one has been used for testing which evaluates the extent as to how much the network has learned and based on its results the optimum training accuracy can be determined. The network was trained from a 5 percent-accuracy to a 35 percent-accuracy range. **Figure 3.1a** shows a graph of the training accuracy versus the prediction error. It can be seen that as accuracy increases prediction error decreases. In **Fig. 3.1b**, the graph of the training accuracy versus that of the testing error is quite irregular but it is reasonable to choose 25 percent as the optimum training accuracy.

3.2 Results

Graphs that show prediction results at a 25 percent-accuracy are illustrated in **Fig. 3.2a–3.2d**. The mean errors are quite low and in the vicinity of 31, 38, 49, and 39 per cent for total bird population, snipes and curlews, plovers, and herons/egrets, respectively. Considering the magnitude of the errors as a whole it can be observed that training with neural networks is remarkable.

Test results for the input parameters are shown in **Fig. 3.3a–3.3d**. Focusing on the snipe population, it can be observed that the calculated values are fairly distributed above and below the regression line. Mean errors are at about 37, 59, 62, and 35 per cent for total bird population, snipes and curlews, plovers, and herons/egrets, respectively. It has been observed that learning of the network as well as testing results is highly improved when the number of data and input parameters are increased. For a network with just 7 input parameters, testing errors can go as high as 142 percent which is more than twice of that which is presented above.

Table 3.1 Data Collected at Wajiro Used as Input and Output to the Network[6].

No.	Date	Air Temp. °C	Rainfall mm	Daylight hours	Phytoplankton cells/mL	zooplankton no./m2	benthos no./m2	tidalflat org. no./m2	intertidal org no./m2	total bird population	snipes/ curlews	plovers	herons/ egrets
1	H05-08	25.2	454.5	120.0	2104	460137	16368	55545	153863	4752	320	18	735
2	H05-11	14.4	129.5	93.0	1618	434474	26307	35696	117008	34469	4702	494	246
3	H06-02	7.2	97.5	110.8	9530	1098100	20065	18791	77263	34235	3699	279	101
4	H06-05	20.5	69.5	208.4	15752	860629	23319	44974	98758	2219	1828	30	90
5	H06-08	29.8	32.0	279.3	13934	2406000	9364	60716	326967	4682	246	111	691
6	H06-11	15.2	34.0	167.8	666	186230	17412	87121	143420	28444	2342	333	292
7	H07-01	6.9	86.5	113.3	4348	356890	10825	69830	105901	36252	4034	608	156
8	H07-05	18.4	256.0	216.9	4276	695700	25679	130774	186009	3662	1961	69	284
9	H07-08	29.3	109.0	227.4	1286	663520	23546	66415	227916	5916	604	117	758
10	H07-11	12.3	38.5	153.7	8187	558620	15578	52485	164478	30484	1997	241	228
11	H08-01	6.5	41.5	121.2	2694	353930	35701	58858	209921	38187	2119	185	224
12	H08-05	19.4	50.5	225.7	76964	464100	40798	128089	109462	3591	1241	57	460
13	H08-08	28.2	179.5	207.9	9697	373180	27804	77904	153048	4650	630	57	4749
14	H08-11	14.2	70.0	88.4	224	655938	14528	101912	119276	26824	2016	219	634
15	H09-01	6.2	68.0	114.2	13031	443200	23296	44153	112891	35547	1480	259	150
16	H09-05	20.4	181.5	191.9	110044	622590	55660	163504	180912	3033	980	53	361
17	H09-08	28	322.5	205.0	1072	209045	22309	75269	230379	5283	198	29	1436
18	H09-11	14.9	180.0	131.0	3166	494160	96463	56226	111687	26676	1358	142	372
19	H10-01	6.6	208.0	61.7	219	328980	48967	61807	93493	28360	1975	517	262
20	H10-05	21.2	268.5	161.4	23434	1069720	74162	126049	99319	4927	2129	59	366
21	H10-08	29.2	175.0	198.5	23278	2035560	40301	86983	261626	7232	574	45	1621
22	H10-11	14.3	43.5	148.9	489	449200	69173	90517	237036	22762	1729	413	456
23	H11-01	7.3	42.0	120.2	40255	162240	83022	65520	105314	30418	1728	248	198
24	H11-05	19.7	128.5	243.2	20105	598450	65208	47875	249995	4349	2050	37	447
25	H11-08	27.6	194.5	128.7	31579	1162720	45962	96993	239323	4615	233	23	953
26	H11-11	13.8	100.5	128.4	958	629750	18379	52464	103833	25408	1262	112	512
27	H12-01	7.7	71.0	100.0	1911	613950	24134	57291	69028	30073	1385	200	271
28	H12-05	18.2	101.0	210.1	11567	560800	64874	113130	167630	3825	2055	66	397
29	H12-08	27.8	100.0	214.2	43865	3117100	28114	71178	181409	5178	539	82	1046
30	H12-11	14.3	143.0	129.1	24022	805893	30218	55018	174506	20305	1635	411	267
31	H13-01	5.9	134.5	84.1	1005	670500	30861	50071	124381	30524	1427	213	191

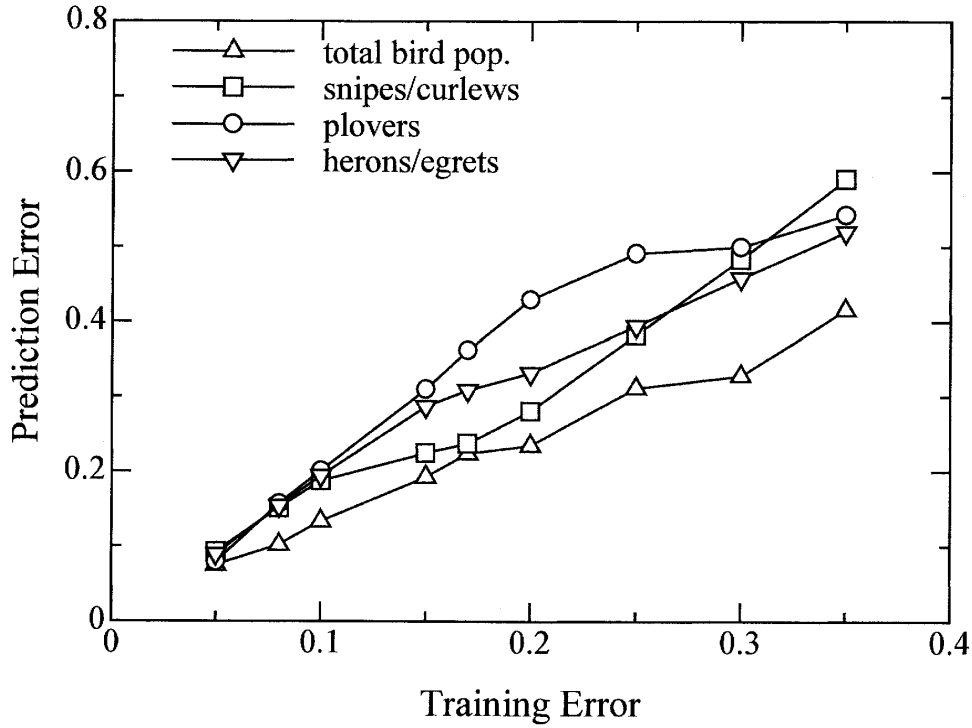

Fig. 3.1a Optimum Training Error Determination (Training Error vs. Prediction Error).

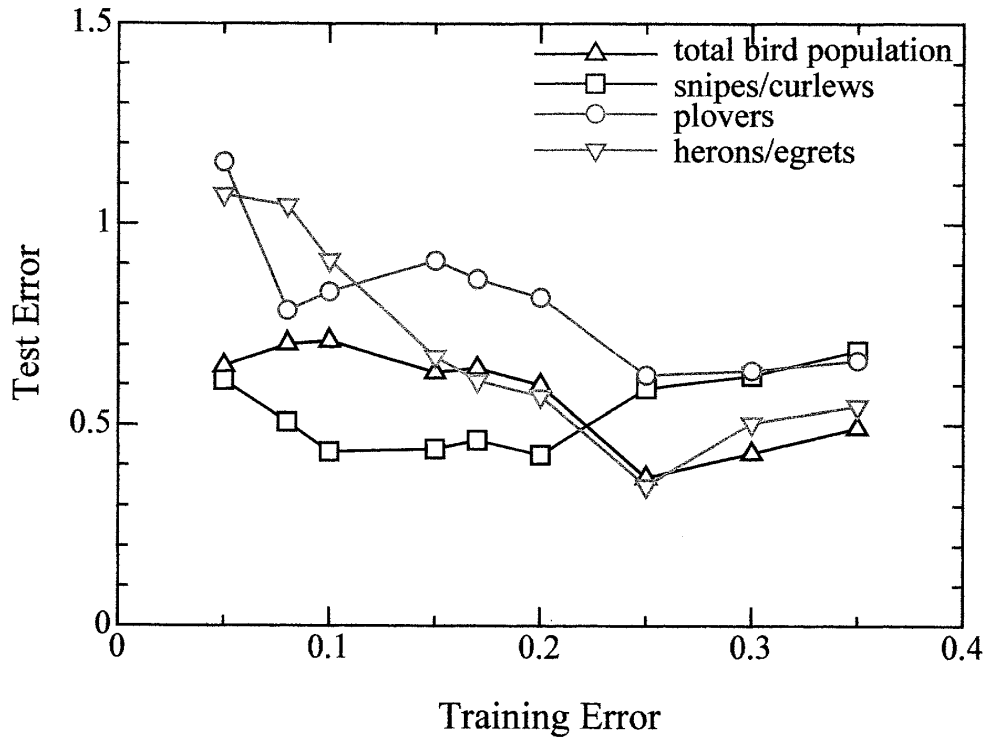

Fig. 3.1b Optimum Training Error Determination (Training Error vs. Testing Error).

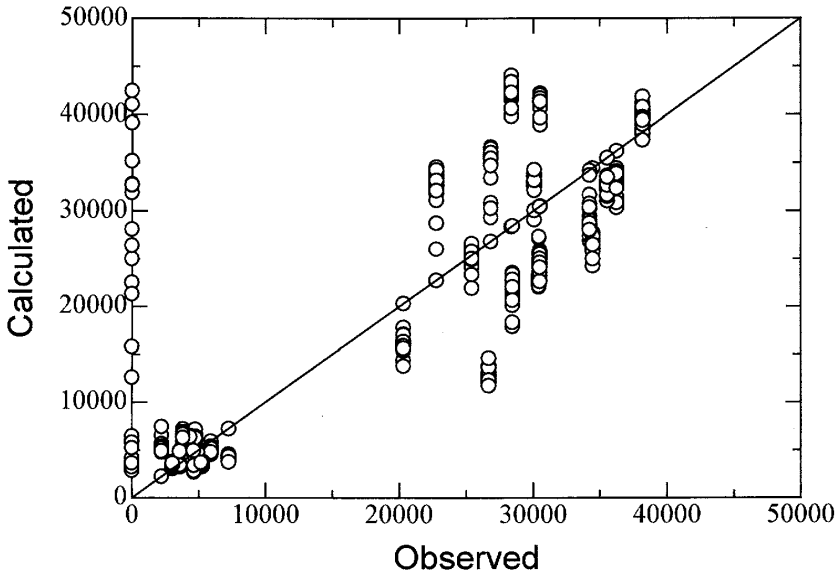

Fig. 3.2a Training Results (Total Bird population).

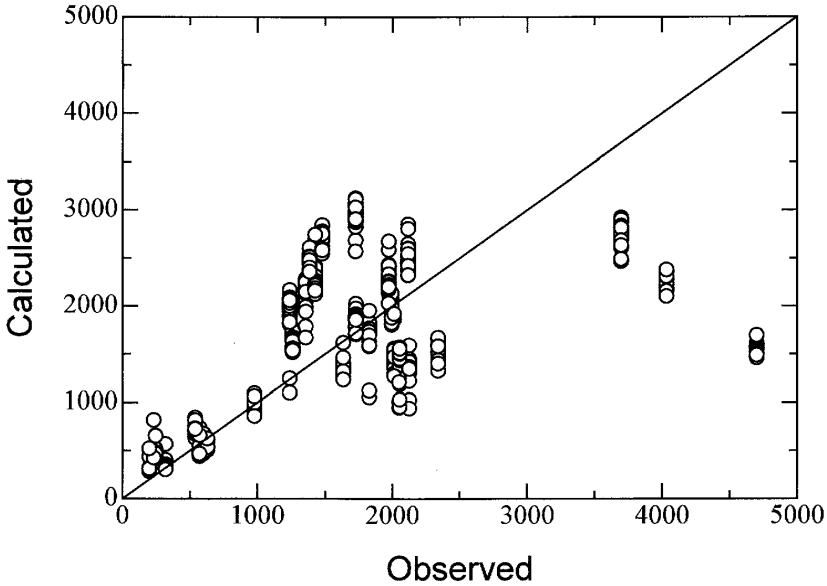

Fig. 3.2b Training Results (Snipes/Curlews).

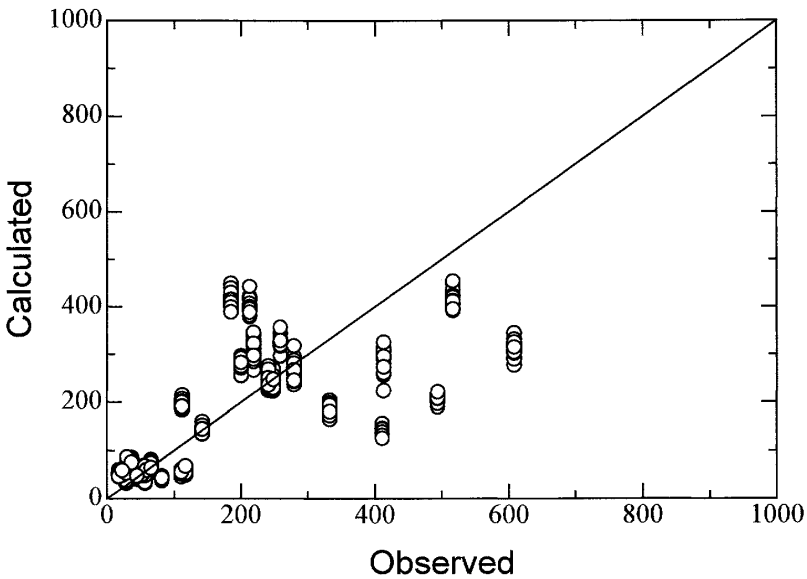

Fig. 3.2c Training Results (Plovers).

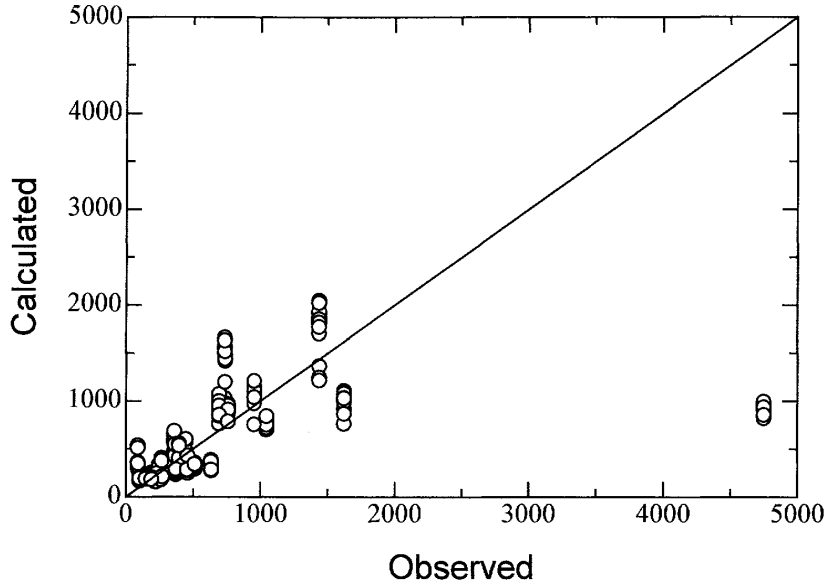

Fig. 3.2d Training Results (Herons/Egrets).

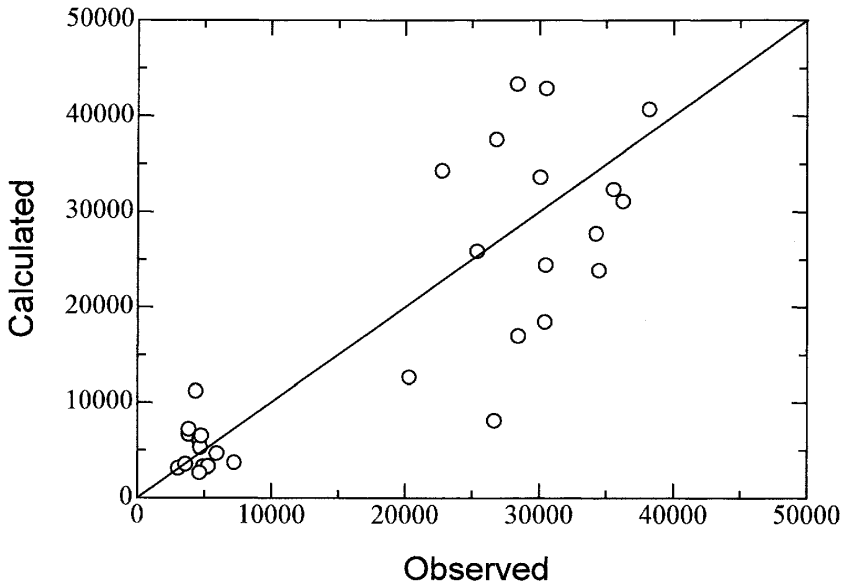

Fig. 3.3a Testing Results (Total Bird Population).

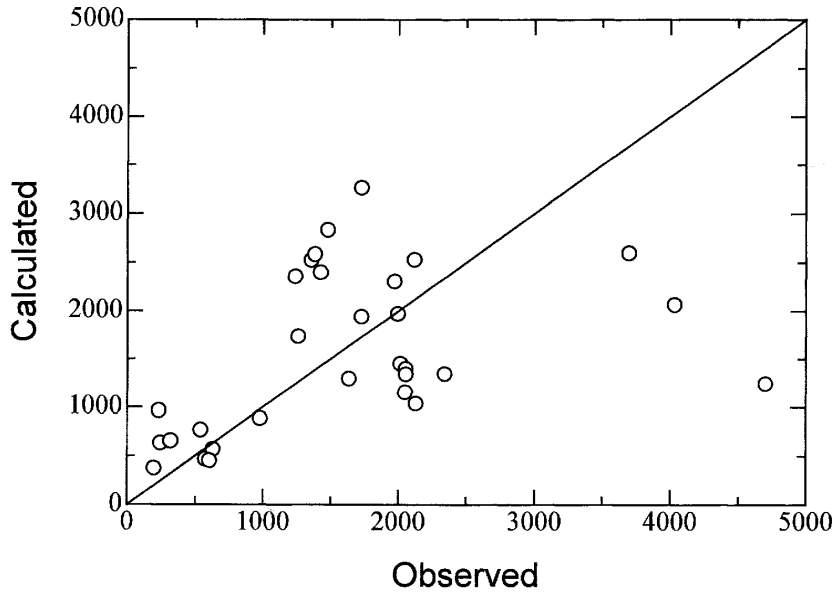

Fig. 3.3b Training Results (Snipes/Curlews).

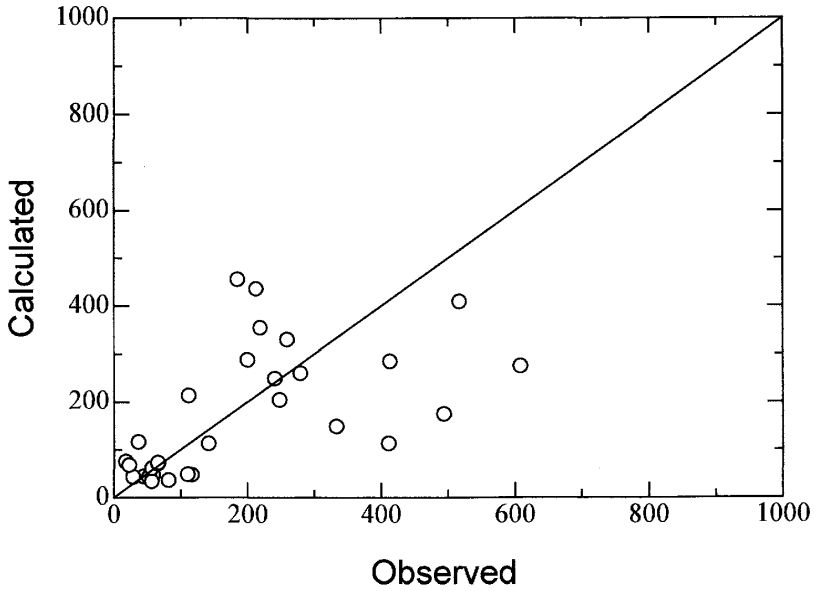

Fig. 3.3c Training Results (Plovers).

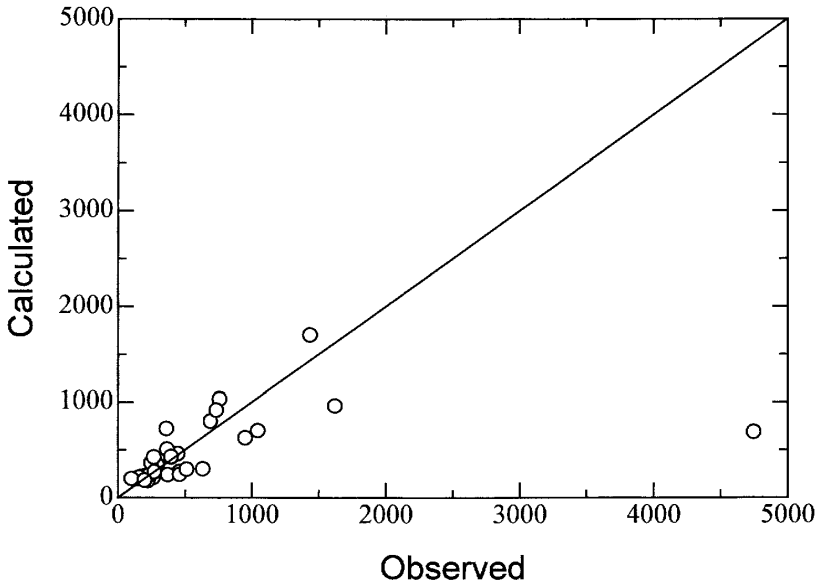

Fig. 3.3d Training Results (Herons/Egrets).

4. Sensitivity Analysis

Sensitivity analysis determines the effect on the output by changing the model input values to some extent. If an input has a direct influence on the output, sensitivity is expected to have positive values and negative if otherwise.

4.1 Methodology

Sensitivity is expressed as the change of the state of an output neuron with respect to that of the corresponding input neuron/s, that is $\partial y_i/\partial y_{k1}$. The sum of the input signals a neuron receives from other neurons of the preceding layer is expressed as follows,

$$v_j = \sum_{k \in L_i} w_{jk} y_k \tag{10}$$

$$v_i = \sum_{j \in L_h} w_{ij} y_j \tag{11}$$

where i, j, and k denote neurons of the output, hidden and input layers, respectively. With the same transfer function as in equation (1), sensitivity of y_i with respect to input y_{ki} is given by

$$\frac{\partial y_i}{\partial y_{k1}} = \frac{\partial y_i}{\partial v_i} \cdot \frac{\partial v_i}{\partial y_{k1}} = (1-y_i)y_i \sum_{j \in L_h} w_{i,j}[(1-y_j)y_j w_{j,k1}] \tag{12}$$

4.2 Results

Shown in **Fig. 4** are the relative sensitivity values of the outputs in relation to the inputs.

It can be seen that all outputs except one have negative sensitivity values with regards to the average temperature; this coincides with the fact that snipes, plovers, and most of the bird population thrive during the cold weather while the positive value for herons/egrets proves of their warm habitat. With respect to rainfall quantities, the negative sensitivities show that the birds' foraging activity does not have a direct correlation with monthly or annual precipitation. Daylight hours show a positive effect only on snipes. Though daylight hours trigger breeding in birds, the length of these hours do not influence their reproductive behavior. In spring, daylight hours are lengthened each day, thus stimulates releasing of hormones for reproduction but this change is a result of evolution and the fact that most birds in temperate regions breed in spring and summer, even having the same length of daylight hours during autumn and winter does not influence reproductive activity. Thus, the negative values are reasonable.

Most birds feed on tidal flat and inter-tidal organisms. However, for the three output parameters, namely, total bird species, snipes and curlews, and plovers sensitivities to tidal flat organisms are negative but at a very small range which is less than 1. This can be associated with the errors of prediction. For inter-tidal organisms sensitivities are positive except that of snipes/curlews. As these organisms increase by about 1%, the increase in the total population of the birds is very small which is about 0.3%, 0.09% for plovers, and 0.6% for herons/egrets and brings about a decrease of about 0.9% for snipes/curlews.

This analysis exhibits bird behavior and its interaction with the state variables.

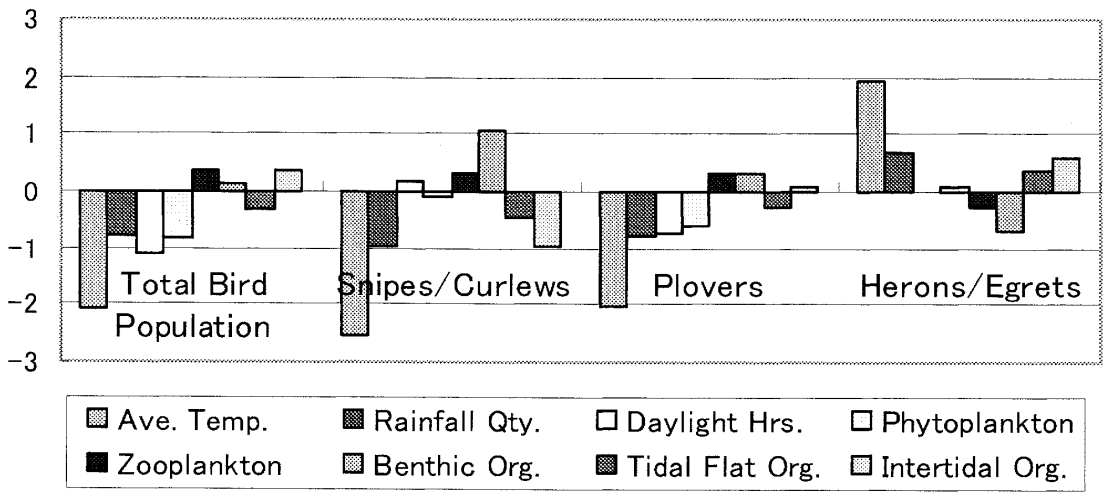

Fig. 4 Sensitivity Results.

5. Time Series Analysis

5.1 Methodology

A simultaneous training, testing, and time series analyses were performed wherein a set of data collected from some past years were used to predict values of the following year. Predictions were continued for each succeeding year until model values for training are exhausted. This simply means that if the present time step is $t = t_m$, previous time steps will be $t \leq t_m$ and the time step that succeeds the present is $t = t_{m+1}$. Therefore, values at $t \leq t_m$ will be used to forecast values at $t = t_m$. For the next time step, $t = t_{m+1}$, values of the previous time steps, $t \leq t_m$, will be the one used for the succeeding prediction and so on. If the test data demonstrates the same tendency with the training data then the test result would be acceptable, otherwise, a notion that some other factors must have an influence on the birds' behavior can be perceived. Since most of the birds roost during winter, it can be seen in **Fig. 5a–5b** that the population is highest during winter and lowest in summer. Digging deeper will eventually lead into another extensive study that is beyond the scope of this paper. The results are intended only to illustrate the effectiveness and usefulness of ANN.

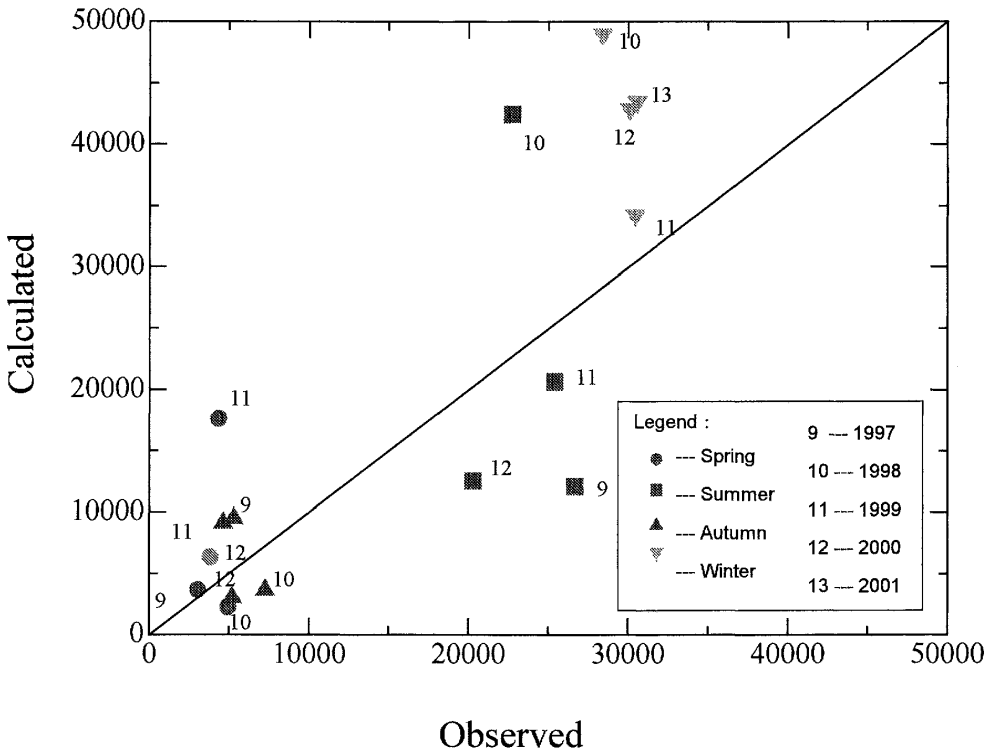

Fig. 5a Time Series Analysis of Total Bird Population at 15% Training Error.

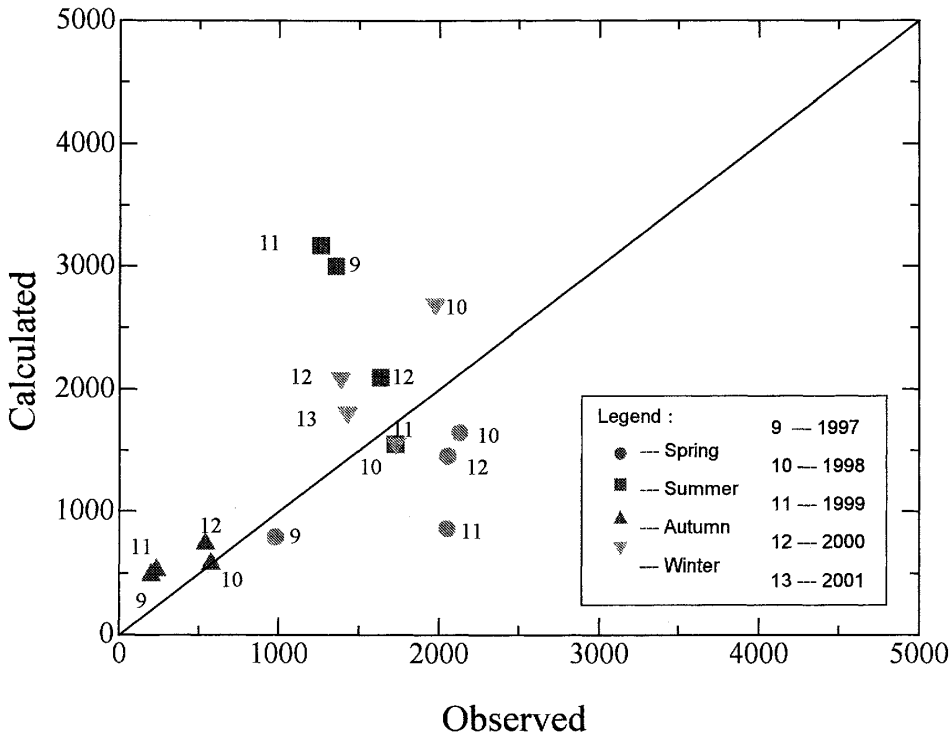

Fig. 5b Time Series Analysis of Snipes/Curlews at 15% Training Error.

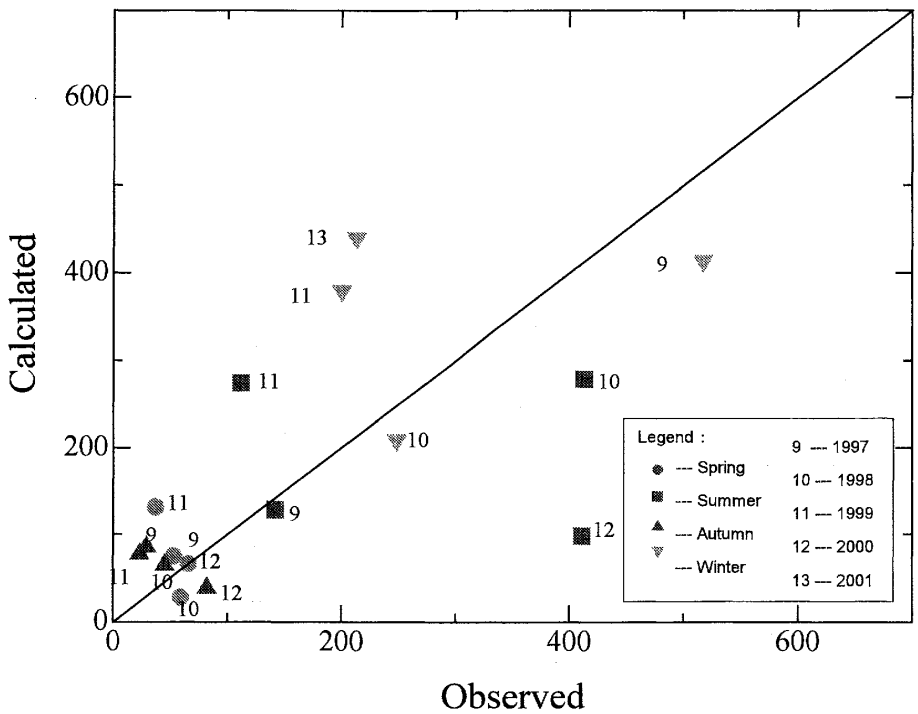

Fig. 5c Time Series Analysis of Plovers at 15% Training Error.

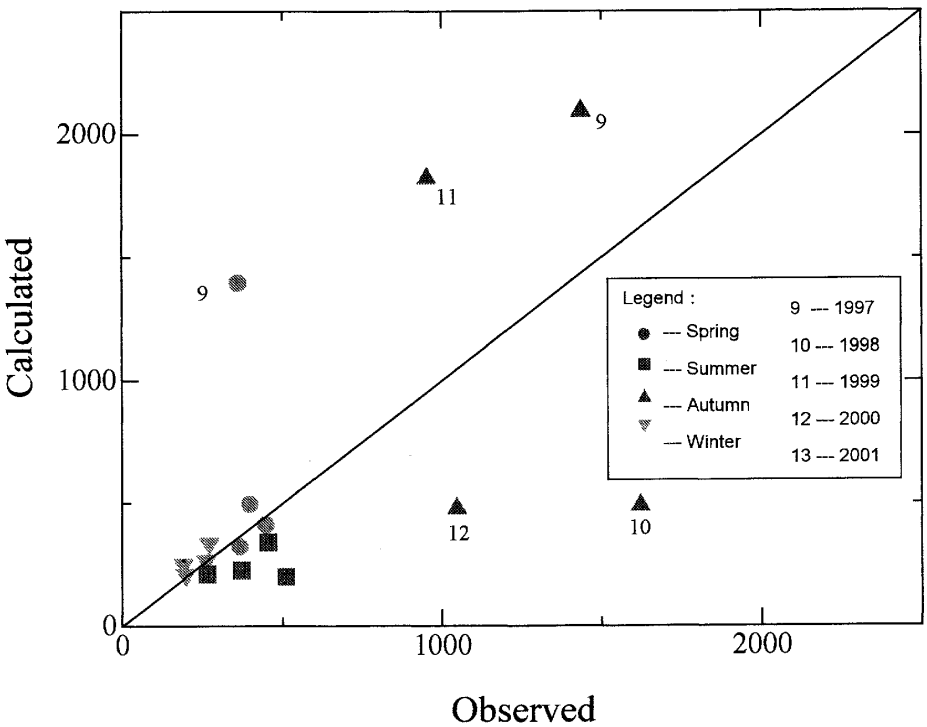

Fig. 5d Time Series Analysis of Herons/Egrets at 15% Training Error.

6. Conclusions

At a 25 percent training accuracy, prediction error is lowest for the overall bird species at 31 percent and highest for plovers at 49 percent while testing errors are 37 percent for the overall bird species and 62 percent for plovers.

Sensitivity analysis illustrated the birds' behavioral tendencies and reactions toward their environment. Time series analysis can also be performed using ANN. The sensitivity graph showed that as temperature decreases by 1%, the total bird population also decreases about 2.0%, snipes/curlews decrease by 2.5%, plovers decrease by 2.0%, while herons/egrets increase by about 1.9%. The relative increase and decrease of the output parameters against the other input parameters can be readily observed.

With a very limited amount of data available ANN modeling has so far been remarkable and increasing the quantity and quality of data can surely bring about more accurate results.

Acknowledgements

We wish to extend our gratitude to the Fukuoka Harbor Bureau and Kyushu Environmental Evaluation Association and their staff for their contribution and cooperation to this study especially for the data that they loaned to us for the analysis. We would also personally thank Professor Kazuhiro Eguchi of the Department of Biology for sharing his knowledge about the behavior of birds and their habitat.

References

1) Data Book of Island City Development Project, Environmental Observation Results, Fukuoka City Harbor Bureau, 2000

2) Bose, N.K. and Liang, P, Neural Network Fundamentals with Graphs, Algorithms, and Applications, McGraw-Hill, Inc., 1996, 162
3) Smith, Murray, Neural Networks for Statistical Modeling, Van Nostrand Reinhold, 1993, 22-23
4) Bose, N.K. and Liang, P, Neural Network Fundamentals with Graphs, Algorithms, and Applications, McGraw-Hill, Inc., 1996, 162-167
5) Wilde, Philippe de, Neural Network Models, Springer-Verlag London Limited 1997, 17, 37, 36-39
6) Bose, N.K. and Liang, P, Neural Network Fundamentals with Graphs, Algorithms, and Applications, McGraw-Hill, Inc., 1996, 162-167
7) Data Book of Island City Development Project, Environmental Observation Results, Fukuoka City Harbor Bureau, 2000