THE APPLICATIONS OF NEURAL NETWORKS TO GIS IN THE CONSTRUCTION OF LAND EVALUATION MODELS

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ABSTRACT

Since the Geographic Information System (GIS) is useful for conducting spatial data analysis and integration, it is often used in land evaluations. To use GIS, logical and accurate criteria must be used to develop evaluation models. An evaluation model should express the entire relationship between all factors related to the evaluation. Though weighting or ranking methods are often used as GIS evaluation models, weight and ranking values are subjectively determined by each evaluator, so it is difficult to objectively prove their validity.

This study uses a neural network as a GIS evaluation model. The neural network is an example of artificial intelligence technology, and it adjusts itself to fit the supervisor. The network, which lets factors relate to results, is represented by a mathematical function like the Sigmoid function.

In this study, neural networks are used in two applications, they are to estimate the suitability of grassland development in Tochigi Prefecture, Japan and to estimate the hazards of land degradation in northeastern Syria.

In the first assessment, the relevant evaluation factors were topography, slope, elevation and soil productivity. An administrative investigation is used to make a supervised data sets for construction of neural network. As the result of trials to construct the network, the neural network, which has 11 units on hidden layer, is highly accurate classified of supervised data sets. Using this network in conjunction with GIS, the land evaluation map for grassland establishment is produced.

In the second application, two networks are constructed to estimate the degree and extent of land degradation. They are evaluated by topography, vegetation, soil category, and present land state.

INTRODUCTION

Since GIS has spatial analysis modules, it is used for urban planning or regional and environmental analysis. Similarly, GIS is useful for land evaluation for agricultural development and for land-use planning.

To make land evaluations on specific area or for specific purpose, all factors should be considered comprehensively, and evaluation models should express the whole relationship between factors related to evaluation. Ranking methods or weighted calculations are often used to make GIS models. Thought they reflect influence and limitation by the factors, the criteria on these methods are decided by each experimenter. Therefore, it is difficult to testify the objectivity of models.

The author remarks Neural Networks(NN) can be used as a method to express the overall relationship between various factors objectively, and for GIS modeling for land evaluation. In this paper, two applications are introduced as GIS models using NN, the land-suitability assessment for grassland/pasture establishment in central Japan; and evaluation of land degradation in northeastern Syria.

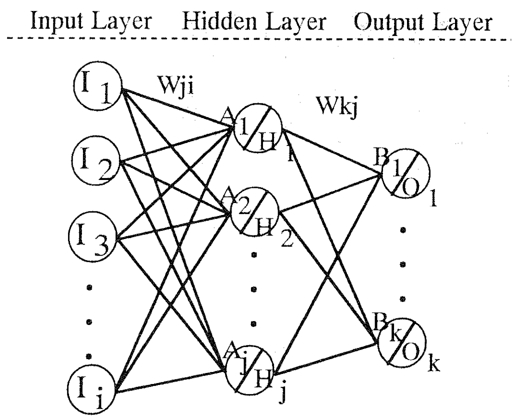
OUTLINE OF NEURAL NETWORKS

NN is a computer system that determines relationships between factors and results as a problem of pattern recognition. Throughout repeated calculations called "learning", the computer adjusts its parameters to reduce estimation errors on data sets automatically. As a result of this process, a network is constructed. The data sets using learning are called "supervisor".

In this study, " NEURO92 " which is the computer program that constructs NN, developed in National Grassland Research Institute in Japan, was used. NEURO92 constructs multi-layer networks with back-propagation algorithms. It is described in C language, so it is available to personal computers and EWS.

Figure 1 illustrates a three-layered neural network and Sigmoid function. The first layer is called input layer, the second or middle layer is the hidden layer and last layer is the output layer. Each layer has some units. Units between layers are interconnected, just as neurons in the human brain. The data or information is propagated next units in forward layer by Sigmoid function.

NEURO92 automatically adjusts network parameters, offsets on each unit and linkage coefficient between units, to minimize the estimation errors compared output layer in the supervisor. After learning, network parameters are saved to files in the computer.



$H_j=f(x)=1/(1+\exp(-2x_1/u))$
$x_1=(\Sigma W_{ji} \cdot I_i)+A_j$
$O_k=f(x)=1/(1+\exp(-2x_2/u))$
$x_2=(\Sigma W_{kj} \cdot H_j)+B_k$

I :Input data
H:Output from Hidden Layer
O:Output from Output Layer
A:Unit Offset on Hidden Layer
B:Unit Offset on Output Layer
W:Linkage Coefficent
u :Inclination of Sigmoid

Figure 1. The model of multi-layers neural network and Sigmoid function f(x).

CASE STUDY 1 : Land Suitability Assessment for Grassland/Pasture Establishment in Central Japan

In this study, an NN to evaluate land suitability for grassland and pasture based on natural factors is constructed. This constructed network is applied to GIS to make an evaluation map of test site, which is Tochigi Prefecture, located in central Japan.

(1) Preparation for the Supervisor

The supervisor for learning by NEURO92 was prepared using the data of " the Land Inquiries for Grassland Establishment (1983 - 1986, The Ministry of Agriculture, Forestry and Fisheries) ". Investigations were conducted for all of sites where it is possible to develop and establish grassland and pasture in the whole of country. 1 74 data sets in Tochigi were extracted from the investigation data sets as the supervisor. Since this study aims at an assessment based on natural factors, four elements were selected as input data, Slope, Elevation, Topography and Soil Productivity. As an output, suitability rankings as evaluated by the person in charge of each investigation were used. To use in NEURO 92, data for the supervisor was standardized, ranging from 0.0 to 1.0. Input and output data were modified using the criteria shown in Table 1.

Table 1. The criteria for supervisor of NEURO92.

Natural Factors	Categories		
Slope	<= 8°	8~15°	15° <=
	Area (ha) /100		
Elevation	Average elevation (m) /1000		
Topography	Foot of Mt.	Moutainous	Hill
	0.2	0.4	0.6
	Plate	Low-land	
	0.8	1.0	
Soil Productivity	Excellent	Standard	Inferior
	1.0	0.5	0.0
Evaluation by Person	Excellent	Good	Possible
	0.875	0.625	0.375

(2) Neural Network Construction using NEURO92

The network was assumed that it had three layers, the input, hidden, and output layers. The network is completed incrementally through learning to reduce estimation errors. However, the effect of learning is influenced by learning times and the number of units in the hidden layer. For this reason, trials altering the number of units in the hidden layer were conducted in order to select the most accurate network.

Figure 2 shows the results of trials after 10000 cycles of learning with 1 to 15 units. It illustrated the accuracy which has been calculated the ratio of classified data correctly to supervisor. In the results, the most accurate ratio was 85.1%. It was marked by two networks with 11 and 15 units in their hidden layer. Though both were considered to be effective as an evaluation model for the assessment, the fewer units network was preferable for the model because of map calculation costs. For this reason, the network which has 11 units in its hidden layer was selected as the evaluation model.

(3) Drafting an Evaluation Map for Grassland Establishment

To draft and produce an evaluation map for grassland establishment, it is necessary to inputmap data to the GIS, which corresponds to the input layer's information of supervisor. Consequently, contour, topography and soil productivity maps were digitized and corrected georeferentially with GIS. Attribute files of each map were made, in accordance with Table1.

Figure 3 and Table 2 show the network model and parameters determined by NEURO92. These parameters were used for map calculations. As a result of map calculation, the evaluation map shown in Figure 4 was drafted.

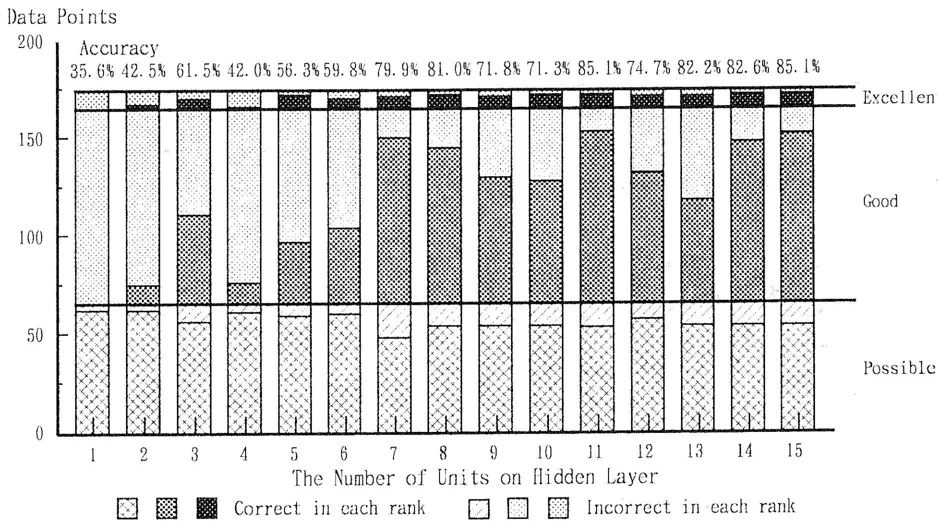


Figure 2. The accuracy of networks with different number of units of hidden layer.

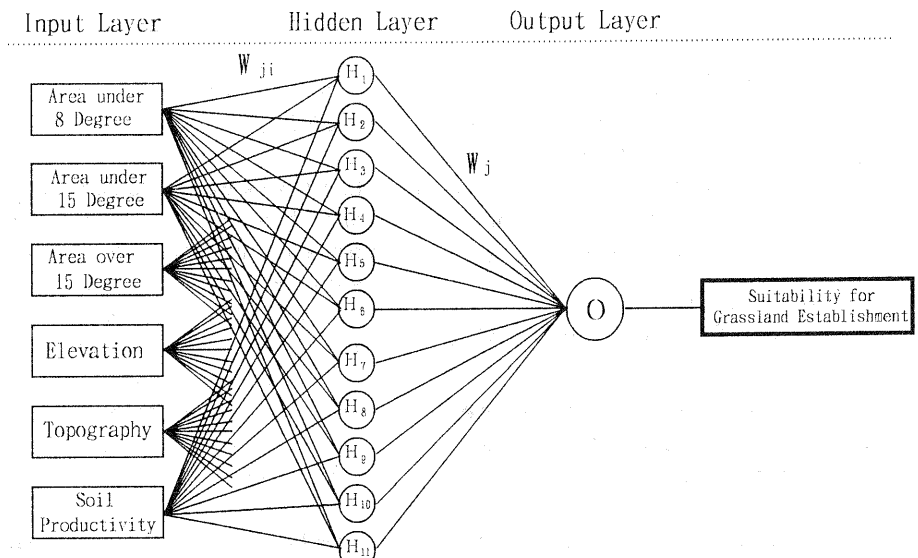


Figure 3. The neural network to assess the suitablity for grassland establishment.

Table 2. Network parameters determined by NEURO92.

Offset of	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Hiddel Layer	1.834	-0.621	-1.279	-0.296	-1.270	3.704	-2.923	-0.225	0.466	0.416	2.941
Link. Coef.	I1	I2	I3	I4	I5	I6					
H1	-1.061	-0.291	-0.427	-4.805	-2.459	2.089					
H2	-0.858	-0.971	-0.126	-0.963	-0.428	-1.388					
H3	-2.859	-13.304	-7.903	0.332	2.558	-2.512					
H4	-3.168	0.673	-2.663	1.720	-0.522	-4.137					
H5	0.608	3.060	3.803	-2.239	-0.561	-3.385					
H6	2.126	-1.874	2.190	-6.164	-6.325	-7.022					
H7	3.305	0.003	-3.463	0.296	0.666	-2.314					
H8	1.108	-0.094	2.972	0.315	-2.641	-4.361					
H9	0.084	-4.605	-7.942	-3.455	-2.058	2.467					
H10	-2.978	-1.585	-6.215	-9.085	0.755	0.713					
H11	0.887	-5.200	-1.446	-2.194	-4.085	-2.961					
Offset of Output layer		-0.264									
Link. Coef.	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
	0.448	-0.649	1.620	0.714	0.535	3.636	0.691	-3.248	0.909	-1.613	-1.438

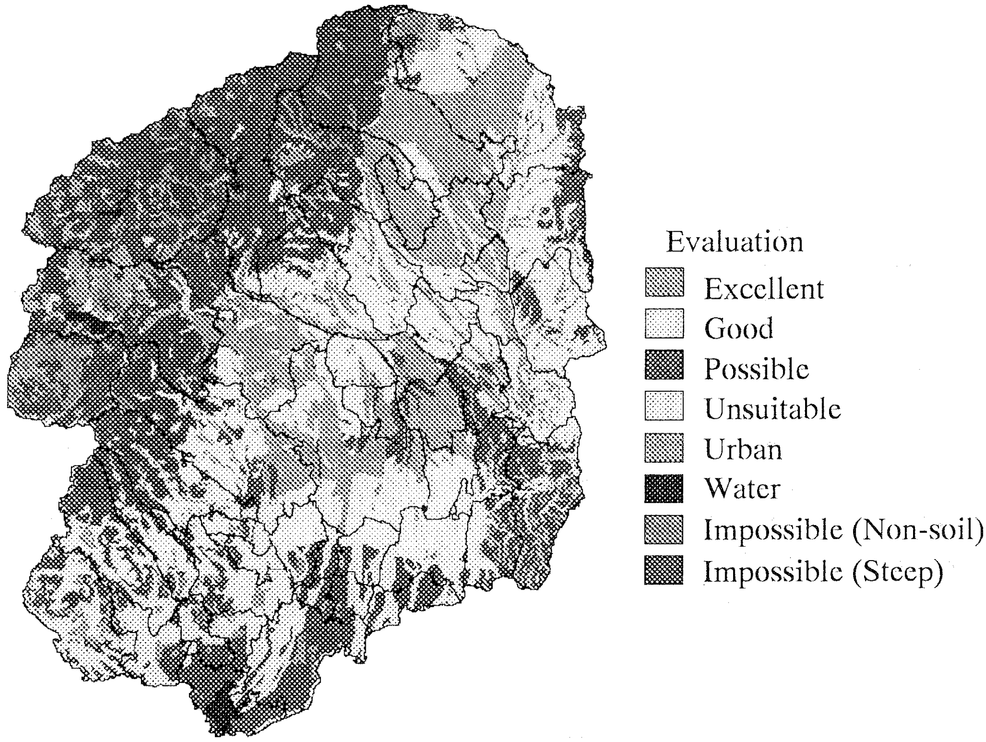


Figure 4. The assessment map for grassland establishment. (*Color Printed)

CASE STUDY 2 : Evaluation of Land Degradation in Northeastern Syria

In the Abdal Aziz region in northeastern Syria, animal grazing on native pasture has occurred for a long time. Grazing has been the typical land-use system in this region; however, land-use is changing due to an expansion of cultivation and forestation recently. These human activities have caused difficulties affecting environmental changes. To maintain sustainable agricultural activity in dry regions, regional resource management in consideration of environmental conservation is necessary.
This study aims to evaluate hazards of land degradation, using NN and a map database of the Abdal Aziz region.

(1) Outline of Evaluation

Figure 5 shows a flow chart for production of a hazard map of land degradation. The operation was divided to two parts; first, to construct NN using NEURO92, and second, to draft a hazard map of land degradation using the constructed network. The supervisor for NEURO92 was made as follows.
First, 214 points data were extracted at random from the map database. From these point data, elevation, slope, direction of aspect, soil category and vegetation coverage were input to the input layer of the supervisor. Output data of the supervisor were degree of degradation and extent scale of degradation. They were input singly. Thus, two supervisor files were prepared, having the same input layer and different output layer.
Using the two supervisors, NN were constructed with NEURO92. To select the most suitable network, 15 trials with different numbers of hidden layer units were performed. The learning cycle was repeated 10,000 times.
After the selection of networks, the output of the whole points in map database were calculated using the network parameters with GIS. The outputs were mapped to express the degree and extent scale of land degradation. These two outputs were integrated by multiplication to produce the final hazard map of land degradation.

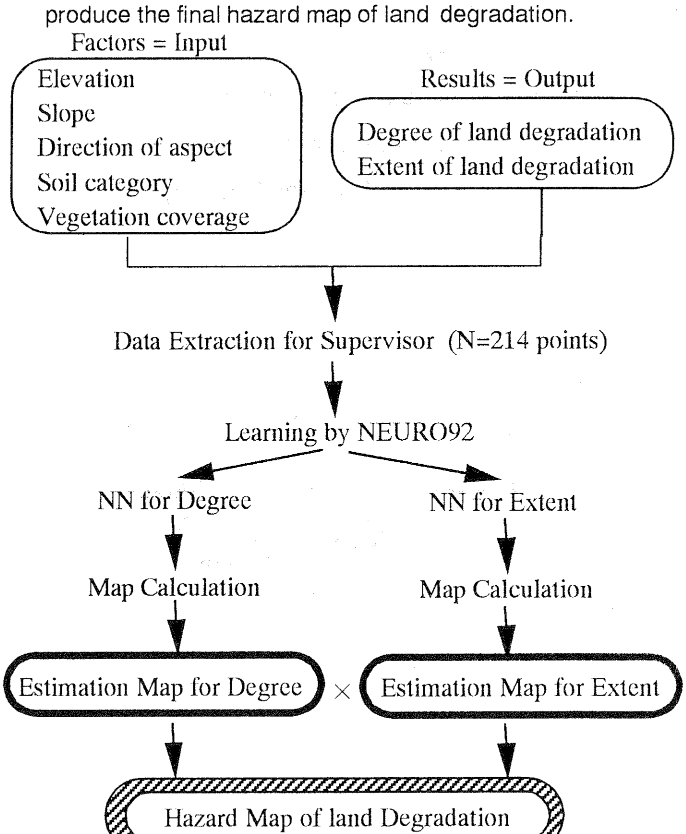


Figure 5. The flow to draft the hazard map of land degradation.

(2) Results

Of the results of the 15 trials with different numbers of units in their hidden layers, networks with 11 units were the best ones for both degree and extent. The accuracies which were evaluated the ratio of points estimated within 0.25 estimation error to supervisor, were 86.4% and 79.4% . They approximately satisfied the accuracy necessary for evaluation.

Figure 6 and Figure 7 are results of map calculation using network parameters for degree and extent of land degradation. Figure 8 shows the hazard ranking as a whole. It was produced by reclassifying outputs of the multiplication.

Characteristics related to natural factors of the hazardous zones are shown in Tables 3 to 7. They are occupied area of different ranks in each category. Specific features were not clear for elevation, slope, direction of aspect and vegetation coverage, because they were distributed in proportion to the ratio of each category over the whole area. On the other hand, features related to soil category shown in Table 6 were unique. Though most of test sites were Calcic Xerochrept (Xero. deep, Xero. slop) and Litic Xerorthent (Xerot.), the hazardous sites were in Gypsic Xerochrept(Gyps.) or Litic Xerochrept (Liti.) categories. Since they were stony soil, soil structures with stone and rock appear to influence land degradation.

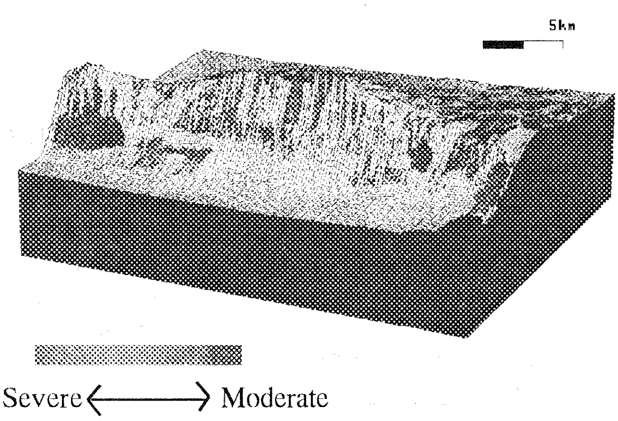


Figure 6. The estimation for the degree of land degradation. (*Color Printed)

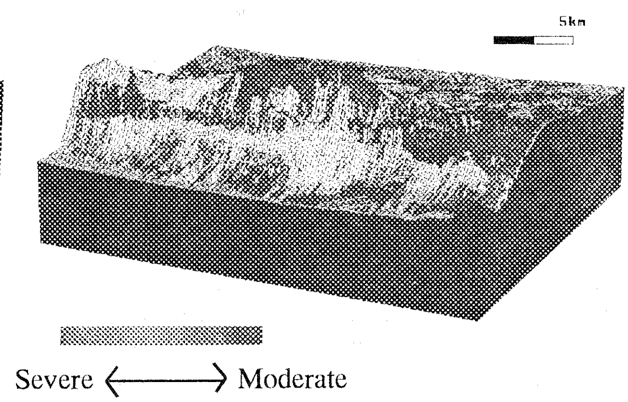


Figure 7. The estimation for the extent of land degradation. (*Color Printed)

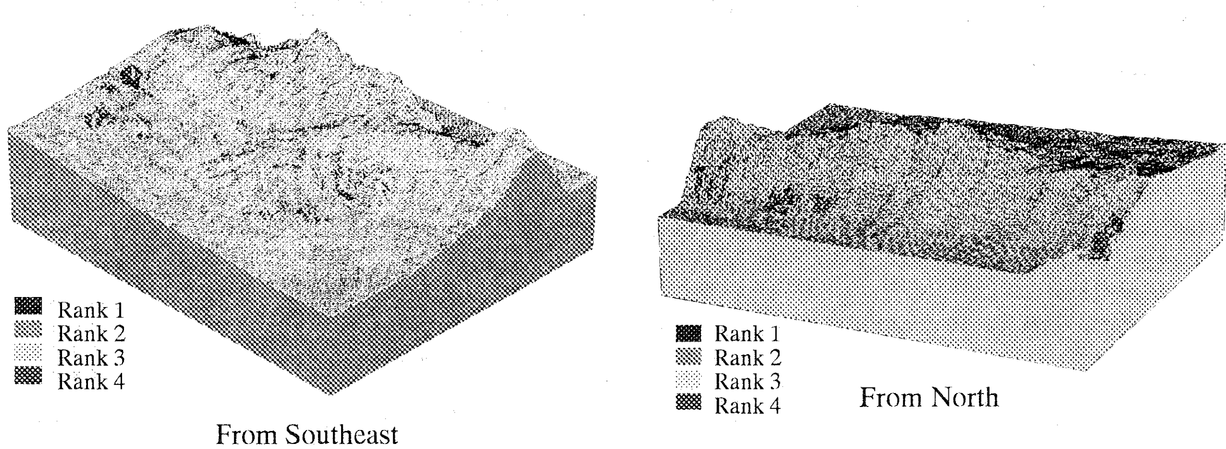


Figure 8. The hazard map for land degradation. (*Color Printed)

Table 3. Distribution of hazardeous zone in different elevation (ha).

	No Hazard	Rank 1&2	Rank 3&4	Total
0-100m	909.54	0.00	0.00	909.54
-200m	36.81	0.00	0.00	36.81
-300m	36.72	0.00	0.00	36.72
-400m	39.60	0.00	0.00	39.60
-500m	34017.57	267.30	689.67	34974.54
-600m	31149.27	667.17	1057.95	32874.39
-700m	17922.06	49.68	202.77	18174.51
-800m	7417.98	18.54	0.09	7436.61
-900m	1577.88	0.00	0.00	1577.88
-1000m	147.24	0.00	0.00	147.24
Total	93254.67	1002.69	1950.48	96207.84

Table 4. Distribution of hazardeous zone in different slope (ha).

	No Hazard	Rank 1&2	Rank 3&4	Total
-5 deg.	41517.18	241.56	514.17	42272.91
-10 deg.	35507.07	633.87	882.45	37023.39
-15 deg.	8945.64	104.85	361.26	9411.75
-20 deg.	4666.50	18.81	116.37	4801.68
-25 deg.	1269.27	1.62	50.22	1321.11
25 deg.-	1349.01	1.98	26.01	1377.00
Total	93254.67	1002.69	1950.48	96207.84

Table 5. Distribution of hazardeous zone in different direction (ha).

	No Hazard	Rank 1&2	Rank 3&4	Total
Level	957.06	0.00	4.32	961.38
N-NE	12925.89	391.86	1094.40	14412.15
NE-E	5647.86	176.49	447.39	6271.74
E-SE	12249.45	373.77	389.07	13012.29
SE-S	20330.37	60.57	15.30	20406.24
S-SW	18120.60	0.00	0.00	18120.60
SW-W	5603.49	0.00	0.00	5603.49
W-NW	6248.07	0.00	0.00	6248.07
NW-N	11171.88	0.00	0.00	11171.88
Total	93254.67	1002.69	1950.48	96207.84

Table 6. Distribution of hazardeous zone in different vegetation (ha).

	No Hazard	Rank 1&2	Rank 3&4	Total
Annual	761.13	0.00	0.00	761.13
Barley	10148.94	10.80	4.77	10164.51
D.O.W.	9312.21	140.40	22.05	9474.66
D.S.D1	45539.28	585.54	1149.84	47274.66
D.S.D2	2647.08	0.00	0.00	2647.08
Wheat	1156.41	0.00	0.00	1156.41
O.Wood.	2922.48	5.94	4.50	2932.92
S.S1	10553.31	106.92	222.21	10882.44
S.S2	5388.66	140.94	411.57	5941.17
S.S3	1880.82	12.15	135.54	2028.51
Total	93254.67	1002.69	1950.48	96207.84

Table 7. Distribution of hazardeous zone in different soil (ha).

	No Hazard	Rank 1&2	Rank 3&4	Total
Gips.	3454.20	371.97	899.82	4725.99
Liti.	3635.91	630.72	1050.66	5317.29
Rock	3242.43	0.00	0.00	3242.43
Xero.deep	37716.03	0.00	0.00	37716.03
Xero.slop	22187.16	0.00	0.00	22187.16
Xerot.	20096.01	0.00	0.00	20096.01
Total	93254.67	1002.69	1950.48	96207.84

CONCLUDING REMARKS

Using NN, the factors in the input layer and the results or phenomena in the output layer are conveniently connected through the learning supervisor. Comparing to other multi-variate analysis methods, the accuracy to the supervisor would be excellent, as both quantitative and categorical data are available with such standardization. This is a significant advantage in constructing GIS models. Furthermore, the network to be used as an evaluation model is constructed semi-automatically, and it is possible to apply parameters to GIS map calculations to draft evaluation maps.

Using this method, however, the priority of factors is not shown directly. Because networks show the relationship between factors and phenomena as a whole. Accordingly, it is not available for the analysis to compare individual factors.

Land evaluations are one of bases for regional planning. To evaluate land objectively, logical models are necessary. Logical models are constructed by data integration and analysis, and since NN is a flexible system for both data and applications, it would be useful method to construct GIS models.

REFERENCES

Yamamoto, Y. (et al.), 1995. The application of the Neural Networks to GIS in the Construction of al Land Evaluation Model : Land Evaluation for Grassland Development in Tochigi Prefecture. J. of Japanese Agriculture System Science, 11(1), pp.14-25.
*Japanese with English Summary

Tsuiki, M.(et al.), 1993. Multilayer Feedforward Neural Networks Construction Program NEURO92. Bull.Computing center for Research in Agriculture, Forestry and Fishery, B(11), pp.1-33.
*Japanese with English Summary