International Journal of GEOMATE, Sept. 2022, Vol.23, Issue 97, pp.146-153
ISSN: 2186-2982 (P), 2186-2990 (O), Japan, DOI: https://doi.org/10.21660/2022.97.3357
Geotechnique, Construction Materials, and Environment

A SENSITIVITY ANALYSIS OF RIVER ENVIRONMENT FACTORS THROUGH DEEP LEARNING

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*Corresponding Author, Received: 14 March 2022, Revised: 25 June 2022, Accepted: 02 Aug. 2022

ABSTRACT: The water environment of the most important watersheds of Japan generally have not improved in a considerable manner in the last two decades although central and local governments have made considerable management and improvement efforts, such as increasing sewerage system coverage rates nationwide and installing advanced wastewater treatment systems. It is believed that the marginal effects of these direct efforts have been diminishing. This study seeks to discover the most effective water environment improvement measures in a wider range other than those direct measures. An artificial intelligence (AI) model has been constructed with Deep Learning technology by applying the watershed information from 104 watersheds as teacher data to train the AI model. The well-trained AI model is used to identify the effectiveness of all the direct and indirect water-environment-related factors, ranging from geological/geographical factors, hydrological/hydraulic factors to socio-economic factors. This study concludes by pointing out that Deep Learning through big data can reveal and simulate the complicated relationships between river management goals and diverse water environment factors. It is hoped that this study will contribute to establishing a more reliable river environment planning and management methodology.

Keywords: Water Environment Evaluation, Sensitivity Analysis, Big Data, Artificial Intelligence (AI) Model, Deep Learning

1. INTRODUCTION

Water environment evaluation and planning have been mainly dependent on 1) mathematic models that simulate all the physical, chemical and biochemical processes leading to water environment changes over time and space, and 2) expertise of planners on a specific river [1]. Mathematic models connect all direct water environment factors to management goals, and the final evaluation and decision-making are usually based on the expertise of planners. In this planning process, most of the indirect environmental factors have not been taken into consideration in a reasonable and proper manner, and expertise tends to put much more weight on the characteristics of a specific river and ignore the common characteristics of all the other rivers in the same region. How to evaluate and apply the experiences and lessons all rivers with some common characteristics can provide is a question that remains unanswered. This study approaches this problem by applying the water environment big data to environment planning.

In Japan, a water quality survey of public water areas focusing on items that are used in environmental quality standards (EQSs) for the prevention of water pollution has been performed since 1971 under the provisions of the "Water Pollution Control Law" (enacted in December 1970). This survey has been conducted by local governments (including prefectures and designated cities) under the Water Pollution Control Law, and also in the case of direct-administrative-control areas of Class-A rivers.

The survey has shown that the requirements of the environmental quality standards for human health have been achieved in almost all monitoring sites for the last thirty years, and the achievement rate was 99.1% in 2018 [2]. As for the environmental quality standards for conservation of the living environment, their achievement rate of BOD improved significantly in the first three decades after the survey started, and the compliance rate reached 90% in 2004 for the first time since the survey started [3].

However, the compliance rate of the environmental quality standards for conservation of the living environment was still only 94.1% in 2018 [2], and the water environment of the most important watersheds, almost all of which are designated as the direct-administrative-control areas of Class-A rivers, generally has not been improved in a considerable manner in the last two decades, although the Japanese government has made significant management as well as improvement efforts, such as increasing sewerage system coverage rates nationwide and installing advanced wastewater treatment systems. It is believed that the marginal effects of these direct efforts have been diminishing [4]. The questions of what are and how to find the most effective river environment improvement measures need to be addressed with urgency.

2. RESEARCH SIGNIFICANCE

This study seeks to discover the most effective water environment improvement measures in a wider range outside of the common direct measures provided by a traditional physically-based or biochemically-based models. An artificial intelligence (AI) model has been constructed with Deep Learning technology by applying the watershed information from the 104 Class-A watersheds as the teacher data to train the AI model. With the well-trained AI model, we have successfully identified 7 river environment factors that have the most significant impacts on the present water environment quality. This result has also been verified by both reality checks and theoretical analyses, and shows an AI model is a reliable river environment planning tool.

3. ARTIFICIAL INTELLIGENCE MODEL

An artificial intelligence model, specifically a neural network model has been adopted to compose a water environment evaluation method for evaluation or prediction problems due to the suitability of neural network models [5], [6].

3.1 Structure of A Neural Network [6]

A neural network is a network system constructed artificially by idealizing the neurons (nerve cells), and consists of a number of nodes and lines that are called *units* and *connections* (or *links*) respectively. Based on the differences in network structures, neural networks generally are classified into two types: layered networks and interconnected networks. It has been shown that a layered network is suitable for evaluation/prediction problems due to its abilities in learning (self-organization) and parallel processing of information.

A typical layered neural network, which has a layer of input units at the top, a layer of output units at the bottom, and a number of hidden layers between the input layer and the output layer. Connections exist only between the units in the adjacent layers, and connections within a layer or from higher to lower layers are forbidden.

3.2 Modelling A Neural Network

For the sake of simplicity, consider a neural network consisting of three layers.

Let the unit numbers of the input layer, hidden layer and output layer be N, M, and 1, respectively. When an input $\{I_i,\ i = 1,2,\cdots,\ N\}$ is given to the units of the input layer, the inputs and outputs of the hidden layer units as well as the output layer units are represented as follows.

$$Y_j = f(X_j),\ \ j = 1,2,\cdots,M \tag{1}$$

$$X_j = \sum_{i=1}^{N} w_{ij} I_i + \theta_i \quad ,\quad j1,2,\cdots,M \tag{2}$$

$$O = f(Z) \tag{3}$$

$$Z = \sum_{j=1}^{M} w_j Y_j + \theta \tag{4}$$

Where Y_j is output from the unit j of the hidden layer, X_j is input to the unit j of the hidden layer, $f(\cdot)$ is unit output function, w_{ij} is connection weight between the input layer unit i and hidden layer unit j, θ_j is threshold value of the hidden layer unit j, O is output from the output layer unit, Z is input to the output layer unit, w_j is connection weight between the hidden layer unit j and the output layer unit, and Θ is threshold value of the hidden layer unit j.

For the unit output function $f(\cdot)$, some expressions have been proposed. The following Sigmoid function has been applied frequently. However, it is not necessarily the best one in terms of learning efficiency. A testing process for different output functions is strongly suggested. In this studied this Sigmoid function has been finally adopted after careful tests.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

Theoretically, the neural network model expressed by Eq. (1) through Eq. (5) is able to approximate any non-linear relationship between inputs and outputs with any degree of accuracy by using enough hidden layer units and setting connection weights and thresholds to be appropriate through proper learning processes [6]. The potential of this model has been verified with similar problem to this study [4].

3.3 Learning Process of Neural Network Model

For a neural network model, the process of setting the connection weights and unit thresholds is called *learning*. The term *learning* here means the self-organization process through which the neural network model automatically adjusts all the parameters (i.e. all the connections and thresholds) to the appropriate values, when a series of samples of input-output data (called teacher data or teacher signals) are shown to the model. If we consider the information processing in a neural network model as a transformation of input data to output data, then model learning can be considered to be a process through which the neural network model gradually becomes capable of imitating the transforming patterns represented by the teacher data.

A lot of learning algorithms have been proposed, and among them the Error Back Propagation Algorithm is the most widely used and most successful algorithm. The following is the summary of the Error Back Propagation Algorithm [7].

Suppose T sets of teacher data are given.

$$\left\{I_1^{(t)}, I_2^{(t)}, \cdots, I_N^{(t)}, O^{(t)};\ t = 1,2,\cdots,T\right\} \tag{6}$$

Notice that the teacher data consists of two parts: the input part $\left\{I_1^{(t)},\ I_2^{(t)}, \cdots,\ I_N^{(t)};\ t\ = 1, 2, \cdots, T\right\}$ and the output part $\left\{O^{(t)};\ t = 1,2,\cdots,T\right\}$.

Now consider an initial value

$$w_{ij}^{[k]}, w_j^{[k]}, \theta_j^{[k]}, \theta^{[k]}\ \ ,\ k = 0 \tag{7}$$

for each of the connection weights and threshold values, respectively. Notice that the superscript [k] indicates the number of learning iterations and [k=0] means the initial values for all the parameters directly preceding the start of the learning process. Then the outputs corresponding to the inputs of the teacher data $\left\{I_1^{(t)},\ I_2^{(t)}, \cdots,\ I_N^{(t)};\ t = 1, 2, \cdots, T\right\}$ can be obtained from Eq. (1) ~ Eq. (5). Let these outputs be $\left\{U^{[k](t)};\ t = 1, 2, \cdots,\ T\ and\ k = 0\right\}$. Clearly, $\left\{U^{[k](t)};\ t = 1, 2, \cdots,\ T\ and\ k = 0\right\}$ are different from the outputs of the teacher data $\left\{O^{(t)};\ t = 1,2,\cdots,T\right\}$, and an error function can be defined with the two different kinds of outputs as follows.

$$R^{[k]} = \sum_{t=1}^{T}\left(O^{(t)} - U^{[k](t)}\right)^2,\ k = 0 \tag{8}$$

Obviously, $R^{[k]}$ is a function of connection weights and threshold values because $\left\{U^{[k](t)};\ t = 1, 2, \cdots,\ T\ and\ k = 0\right\}$ are calculated after all $w_{ij}^{[k]}$, $w_j^{[k]}, \theta_j^{[k]}\ and\ \theta^{[k]}$ are given.

The Error Back Propagation Algorithm makes use of the connection weights and threshold values that minimize the above error function $R^{[k]}$. Usually a non-linear programming method is required to solve the optimization problem along with an iteration process in order to obtain the optimal (but possibly suboptimal) connection weights and threshold values. The final iteration procedures derived from a non-linear programming method known as the Method of Gradient Descent are as follows.

$$w_j^{[k+1]} = w_j^{[k]} - \eta \cdot \sum_{t=1}^{T}\left(\delta^{[k](t)} \cdot Y_j^{[k](t)}\right) \tag{9}$$

$$\theta^{[k+1]} = \theta^{[k]} - \eta \cdot \sum_{t=1}^{T}\delta^{[k](t)} \tag{10}$$

$$w_{ij}^{[k+1]} = w_{ij}^{[k]} - \eta \cdot \sum_{t=1}^{T}\left(\delta^{[k](t)} \cdot w_j^{[k+1]} \cdot \gamma_j^{[k](t)} \cdot I_i^{(t)}\right) \tag{11}$$

$$\theta_j^{[k+1]} = \theta_j^{[k]} - \eta \cdot \sum_{t=1}^{T}\left(\delta^{[k](t)} \cdot w_j^{[k+1]} \cdot \gamma_j^{[k](t)}\right) \tag{12}$$

where the superscript [k] indicates the number of learning iterations as mentioned earlier, and η is a small positive number that indicates the step size of the Method of Gradient Descent for optimization iteration process, and we have set $\eta = 0.25$ in this study. The other variables which occurred in the final learning procedures are defined as follows.

$$\delta^{[k](t)} = (O^{(t)} - U^{[k](t)}) \cdot O^{(t)} \cdot (1 - O^{(t)}) \tag{13}$$

$$\gamma_j^{[k](t)} = Y_j^{[k](t)} \cdot \left(1 - Y_j^{[k](t)}\right) \tag{14}$$

In order to avoid the overfitting (or over-learning) problem, a criterion is usually required to make a judgement when the iterative learning process should be terminated. In this study the learning process will be stopped when the Mean Relative Error (MRE) of the outputs is less than a specified relative error expectation for prediction/evaluation results, which is a common treatment for a learning process of teacher data with random errors (i.e. white noise). Needless to say, this error expectation should be set according to the required accuracy of the problem which is being dealt with. In this study we have set the error expectation to 2%, which is considered an accuracy that is good enough for the expected result.

3.4 Verification of Neural Network Model

The proposed neural network model has been verified by applying it to an urban daily water demand prediction problem [8], which has been studied with several different models, and for which there is clarity regarding what is a good or an acceptable prediction for daily water demand. We will examine whether the proposed neural network model is able to predict daily water demand with the same or even higher accuracy by using the same information as the other prediction models used.

Specifically, the neural network model has been compared with three different prediction models: Multiple Regression Model [9], ARIMA (Auto-

Regressive Integrated Moving Average) Model [10, 11] and Kalman-Filtering Model [11]. All the models used the same daily water delivery records from April 1982 to March 1990 for a city in Japan, the weather information during the same time period and each day's characteristics (weekday or weekend/ national holiday) to calibrate or identify the model parameters. This historical data is used because the comparison models are composed with these data. For the neural network model, these records are used as the teacher data to train the model. As for the weather information, the records of daily high temperature, weather (sunny, cloudy or rainy) and daily precipitation are included.

Three accuracy indexes have been applied to compare the models to identify which model is able to give the most accurate prediction for daily water demands. Mean Relative Error (MRE, %) is a very straight index: the smaller the Mean Relative Error is, the better the predictions are. Correlation Coefficient (CC) between predictions and records indicates how good the predictions are: the predictions are perfect when CC=1.0, and the predictions are totally random when CC=0. Relative Root Mean Square Error (RRMSE) is similar to CC and reflects how good the predictions are: RRMSE=0 for perfect predictions and RRMSE=1 when all the predictions are equal to the mean of the records.

Table 1 shows the prediction accuracies of daily water demands over the course of a year for the same city from April 1991 to March 1992 by different models. The neural network model gave the best predictions by far in terms of all the three accuracy indexes. The improvement magnitudes of prediction accuracy in each index show the reliability and the potential of the neural network model.

Table 1 Prediction accuracy comparison of different models

Model	MRE (%)	CC	RRMSE
Multiple Regression Model	2.90	0.764	0.659
ARIMA Model	2.80	0.794	0.623
Kalman Filtering Model	2.69	0.808	0.599
Neural Network Model	2.13	0.877	0.483

In order to understand the error structure of the predictions given by the neural network model, the prediction error distribution is shown in Table 2, and the possible causes have been examined for the 5 days which have a prediction relative error greater than 10%, which is shown in Table 3. Per Table 3, the largest prediction error was yielded when important information that affected daily water demands was missed. In other words, prediction accuracy is expected to be further improved when this missed information, such as typhoon, continuous rain periods, extreme weather events or atypical days, are taken into consideration by including all of them into the teacher data for neural network training. This demonstrates that careful teacher data hunting is important in artificial intelligence model application research.

Based on these results, it is reasonable to conclude that the proposed neural model is a reliable and capable tool in information processing of data. In the next section we will apply this neural network model to river environment evaluations and predictions to provide more reliable information for water environment planning and management.

Table 2 Relative error distribution of the predictions made by the Neural Network Model

Relative Error Range (%)	No. of Days	Composition (%)
[0.0, 3.0)	278	76.2
[3.0, 5.0)	61	16.7
[5.0, 8.0)	19	5.2
[8.0, 10.)	2	0.5
[10., ∞)	5	1.4

Table 3 The possible causes for the days with a relative error more than 10%

Date	Demand prediction (m^3/day)	Delivery record (m^3/day)	Relative error (%)	Possible causes
May 5	354.5	320.0	10.8	The last day of "Golden Week" holiday and sunny after a rainy week.
Sept. 17	364.9	319.5	14.2	Hit by typhoon.
Oct. 5	362.9	315.0	15.2	Heavy rain. (105.5mm/day)
Oct. 7	361.4	404.4	10.6	Sunny after 5 continuous rainy days.
Jan. 2	358.5	315.0	13.8	New Year Holiday and sunny.

4. TRAINING NEURAL NETWORK MODEL

4.1 Teacher Data

In order to apply the neural network model proposed above to a water environment evaluation problem, the model has to be trained appropriately through a deep learning process by using water-environment-related data.

In this study, the data obtained from the continuous water quality survey conducted for the 109 Class-A rivers of Japan by Japanese central government [12], which are available for publics as an open source, are used for the deep learning process.

After a careful data verification process, only 104 rivers out of 109 are chosen to be included in the teacher data set for deep learning because there are quite a few of data missing for the other 5 rivers that are excluded from the teacher data set. For each river the data includes 58 water environment items from 7 categories as shown in Table 4. The data records used in this study are from 1998 to 2018 with a duration of 21 years long, during which, the compliance rate of the environmental quality standards for conservation of the living environment has not been improved in a meaningful manner for the most important Class-A watersheds.

The 58 environment items are divided into two parts to form a teacher data set, evaluation goal variables and explanation variables. The evaluation goal variables include the five environment items that are used to define The Water Environment Quality Standards (EQSs) for Rivers as shown in Table 5 [13], which are pH, BOD, SS, DO and Total coliform. All the remained environment items are used to explain how the achievement of water environment standards are impacted.

Table 4 Water environment items included in the teacher data for deep leaning

Category(Number of Items)	Water Environment Item	
Time of Sampling(4)	Year Day	Month Hour
River/Flow Conditions(17)	Place of Sampling Water Level Total Water Depth Temperature Vertical Visibility Water Smell Time of Low Tide of Sampling Day Time of High Tide of Sampling Day Visual Appearance: Water Color Turbidity (Muddiness)	Weather Quantity of Flow Water Depth of Sampling Water Temperature Horizontal Visibility Flow Strength Floating Waste/Garbage
Watershed Conditions(7)	Length of Main Stream Catchment Population Annual Average Stream Flow Number of Hydraulic Power Plants	Catchment Area Number of Tributaries Number of Dams
Water Quality Indexes For The Living Environment(10)	pH COD DO Total Coliform The Amount of N-Hexane Extract (Oil) Total Nitrogen	BOD SS Saturation Degree of DO Total Phosphorus
Water Quality Indexes About Human Health(9)	Cadmium Lead Arsenic Alkyl Mercury Dichloromethane	Cyanogen Hexavalent Chromium Total Mercury PCB
Water Quality Index For Inflow Of Domestic Wastewater(1)	Ammonium Nitrogen	
Others(10)	Chromaticity Evaporation Residues Potassium Permanganate Consumption Sodium Manganese Residual Chlorine	Turbidity Total Hardness Iron Aluminum
(7 categories in total)	(58 items in total)	

Table 5 Water environment quality standards for rivers [13]

Item Class	Water Use	Standard Value				
		Hydrogen-ion Concentration (pH)	Biochemical Oxygen Demand (BOD)	Suspended Solids (SS)	Dissolved Oxygen (DO)	Total Coliform
AA	Water supply class 1, conservation of natural environment and uses listed in A-E	6.5≤pH≤8.5	≤1 ㎎/L	≤25 ㎎/L	≥7.5 ㎎/L	≤50MPN/100mL
A	Water supply class 2, fishery class 1, bathing and uses listed in B-E	6.5≤pH≤8.5	≤2 ㎎/L	≤25 ㎎/L	≥7.5 ㎎/L	≤1000MPN/100mL
B	Water supply class 3, fishery class 2, and uses listed in C-E	6.5≤pH≤8.5	≤3 ㎎/L	≤25 ㎎/L	≥5.0 ㎎/L	≤5000MPN/100mL
C	Fishery class 3, industrial water class 1, and uses listed in D-E	6.5≤pH≤8.5	≤5 ㎎/L	≤50 ㎎/L	≥5.0 ㎎/L	-
D	Industrial water class 2, agriculture water, and uses listed in E	6.0≤pH≤8.5	≤8 ㎎/L	≤100 ㎎/L	≥2.0 ㎎/L	-
E	Industrial water class 3 and conservation of environment	6.0≤pH≤8.5	≤10 ㎎/L	Floating matter such as garbage should not been observed	≥2.0 ㎎/L	-

The achievement of water environment quality standards has been scored with an effort to make the final scores for different standard classes that are corresponding to different water use purposes a uniform distribution, which is expected to maximize the score distance between different standard classes. The results of scoring are shown in Table 6.

Table 6 Scoring of achievement degree of EQSs

Water quality class ranked with EQSs for conservation of the living environment	Score
AA	0.9
A with indexes ranked in AA	0.8
A	0.7
B with indexes ranked in A or higher	0.6
B	0.5
C	0.4
D	0.3
E	0.2
Below E	0.1

4.2 Training of Neural Network Model

The neural network model has been trained (put under a learning process) with the collected teacher data explained above. The training process is based on the learning procedures as described prior, but it is still a process of trial and error because there are still many details that remain undecided, such as a suitable step size of optimization, a suitable output function, an efficient order to present the teacher data to the neural network model, and a proper initial network size (layers and units in each layers). The learning process was stopped after the trained neural network model is able to reproduce the entire teacher data with an acceptable error, which was set in this study to be below 2% in terms of the mean relative error.

5. WATER ENVIRONMENT EVALUATION

5.1 Sensibility Analyses of Variables

The well-trained neural network model has been used to carry out a sensibility analysis for all the variables to identify how much each variable impacts on the achievement of water environment standards. The sensibility coefficient of a variable is defined as the partial derivative of the achievement score regarding each variable as follows.

$$S_i = \frac{\partial O(X_1, X_2, \cdots, X_N)}{\partial X_i}\Big|_{at\ a\ given\ variable\ value\ set} \qquad (15)$$

where S_i is the sensitivity coefficient of variable X_i at a given variable value set.

For all the variables, the sensitivity coefficients have been evaluated for the average variable value of the last data year 2018. This sensitivity analyses have identified 7 variables that have the most significant and meaningful impacts on the achievement degree of water environment standards as shown in Table 7. As for all the other variables, the sensitivities were not great enough to treat them as variables with a considerable impact in terms of average variable values.

Needless to say, the sensitivity is defined as the differentiation of the evaluation function with respect to each factors at a given time (the final year of the data records in this study), and just means how sensitive the evaluation function is to the change in each factor. It is reasonable to view the sensitivity as a relative index to compare different factors, but it is

Table 7 The environment items with the greatest impacts on achievement of water environment standards

Environment Item	Sensitivity	Descriptions
Month of Sampling	0.16	It means that water environment has a clear tendency of seasonal change.
Annual Average Stream Flow	0.09	It is reasonable and expected that water quantity has a tremendous impact on water quality.
Catchment Population	0.07	This just reconfirmed that human activity is one of the main factors that are able to make a great difference on water environments.
Visual Appearance: Turbidity (Muddiness)	0.04	Visual turbidity usually gets remarkably worse right after storms that cause landslides or debris flow in mountain areas, soil erosion in farmland and sewage overflow in urban areas.
Total Nitrogen	0.03	Total nitrogen in water environment is mainly contributed by sewage inflow and agriculture drainages.
Dichloromethane	0.02	Dichloromethane is almost entirely from industrial wastewater.
Number Of Hydraulic Power Plants	0.01	Power plants change river flow, consequently water environments

not designed to make a sense in terms of absolute impacts of each factor on the evaluation function.

5.2 Discussions

The environment items with the greatest impacts on the achievement degree of water environment standards can be classified into three categories: natural factors, human factors and mixed factors.

Natural factors include month of sampling and annual average stream flow. The fact that the month of sampling has great impacts means that water environment has a clear tendency of seasonal change. This is because of the subtropical climate pattern in Japan with a clear rainy season and a typhoon season. The seasonal rainfall change is considered the main cause for the seasonal change tendency in river water environment. This is consistent with the fact that the annual average stream flow is ranked as the second most important factor to water environment. This is also a reasonable result expected from the common knowledge that water quantity has a tremendous impact on water quality [14].

Human factors include catchment population, total nitrogen, dichloromethane and number of hydraulic power plants. Catchment population implies that human activity is one of the main factors that can make a significant difference on water environments. Total nitrogen in water environment is mainly contributed by sewage inflow and agriculture drainages (overuse of fertilizers), and dichloromethane is almost entirely from industrial wastewater. Power plants are the most controversial factor. The conflicts between power generation and conservation of river environment have been problems in most basins and a priority problem of river flow for different purposes is remained to be resolved.

The only mixed factor is turbidity or muddiness in terms of visual appearance. Visual turbidity usually gets remarkably worse right after a heavy storm that causes landslides or debris flow in mountain areas, soil erosion in farmland and sewage overflow in urban areas. Both catchment natural condition and farming or urban human activities are contributing indirectly to river flow turbidity during rainy time.

6. CONCLUSION

With the purpose of developing a better methodology for water environment evaluation and management of rivers, an artificial intelligence model has been proposed for water environment evaluation in this study. The artificial intelligence model was trained through a deep learning process with the water environment big data of the most important 104 Class-A rivers that are under direct administrative control.

The well-trained artificial intelligence model was applied to a sensitivity analysis of water environment factors. The sensitivity analysis results have identified 7 variables that have the most significant and meaningful impact on the achievement degree of water environment standards, of which there are natural factors (season and annual average stream flow), human factors (catchment population, total nitrogen, dichloromethane and number of hydraulic power plants) and a mixture of both (visual turbidity). These results are reasonable and are consistent with the expectation derived from common knowledge.

Importantly, the above analysis results have shown that an artificial intelligence model with deep learning technology can treat both numerically continuous variables such as annual average stream flow and categorical variables such as visual turbidity with the discrete values yes/no without substantial effort or hindrance.

With this well-trained neural network model, the next step is to identify the most influential environmental factors for each river, and find the most effective combination of water environment improvement measures.

In terms of modelling philosophy. the biggest difference between a physically-based or biochemically-based traditional water environment model and an artificial intelligence model is what kind of the knowledge base is applied in environment evaluations. Traditional models are mainly based on the knowledge and experiences (or expertise) with regard to a specific target river. Artificial intelligence models, however, are able to utilize the full knowledge and experiences that are hidden in the environment survey data of all rivers with similar characters. More analyses are required to show what kind of new developments this character of artificial intelligence model can make in water environment evaluation and management in the future. These results combined together in their entirety will demonstrate that artificial intelligence is an effective and promising tool for water environment evaluation.

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