

Article

A Trend Analysis of Development Projects in South Korea during 2007–2016 Using a Multi-Layer Perceptron Based Artificial Neural Network

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Abstract: In Korea, the Ministry of Environment and regional environment management agencies conduct environmental impact assessments (EIA) to mitigate and assess the impact of major development projects on the environment. EIA Big Data are used in conjunction with a geographical information system (GIS), and consist of indicators related to air, soil, and water that are measured before and after the development project. The impact of the development project on the environment can be evaluated through the variations of each indicator. This study analyzed trends in the environmental impacts of development projects during 2007–2016 using 21 types of EIA Big Data. A model was developed to estimate the Korean Environment Institute’s Environmental Impact Assessment Index for Development Projects (KEIDP) using a multi-layer perceptron-based artificial neural network (MLP-ANN) approach. A trend analysis of development projects in South Korea revealed that the mean value of KEIDP gradually increased over the study period. The rate of increase was 0.007 per year, with an R^2 value of 0.8. In the future, it will be necessary for all management agencies to apply the KEDIP calculation model to minimize the impact of development projects on the environment and reduce deviations among development projects through continuous monitoring.



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1. Introduction

An environmental impact assessment (EIA) is a process that can be applied to predict, analyze, and evaluate the environmental impacts of development projects [1–5]. It is implemented as a policy measure to prevent environmental damage and pollution. Since the United States first introduced the EIA concept in the National Environmental Policy Act of 1969, the EIA process has been applied worldwide, with considerations given to the social environment and national specificity of different regions [6,7]. In Korea, strategic EIA and EIA must be performed on 18 development projects, including urban and industrial sites, energy sources, harbors, roads, water resources, railroads, airports, rivers, reclamation, and tourism complexes, under the Environmental Impact Assessment Act. [8]. Various studies have been conducted to quantitatively evaluate the effectiveness of the EIA. This has been achieved by developing a quantitative index that can determine how well a development project reflects the results of the EIA.

The EIA for a development project is conducted by comparing the environmental conditions before and after the project. Generally, an EIA is divided into air, soil, and water categories, and the methods and procedures used to conduct an EIA are determined at the

discretion of researchers. Wood (1992) proposed a procedure for applying the EIA system to Victoria, Australia, and conducted a study to evaluate its effectiveness [9]. Ramanathan (2001) suggested that an EIA should be performed using an analytic hierarchy process (AHP) approach to development projects [10]. Cloquell-ballester et al. (2006) conducted a study to analyze and validate indicators used in the process, enabling a quantitative evaluation of the EIA process [11].

Recently, methods have been proposed to synthesize each environmental indicator and express them as one composite index. Zhou et al. (2006) developed an index that comprehensively represented sulfur dioxide, nitrogen dioxide, and fine particulate matter (PM10) from development projects in China [12]. Blanc et al. (2008) integrated sub-indexes, such as air quality, soil loss, water quantity, ocean quality, fragmentation, and wilderness, into air and soil indexes, and studied the determination of the weightings required to synthesize each index [13]. Carvalho et al. (2014) conducted a study of the framework used to calculate a composite index for an EIA [14]. Sadeghfam et al. (2020) determined the weightings of seven layers and produced a composite index for subsidence vulnerability [15]. Previous studies have shown that environmental indicators may vary depending on the researcher's definition and considerations. To produce a composite index, various indicators affecting the environment should be considered, and weightings should be assigned after determining their impact on the environment [12–15].

In South Korea, various EIA methods have been introduced and implemented to prevent environmental problems that may arise with development projects [16–21]. In addition, after the development projects were completed, post-environmental impact investigations were conducted to validate the effectiveness of the EIA systems. The Korean Environment Institute (KEI) developed an index (KEI's EIA index for development projects, KEIDP) to comprehensively evaluate the environmental impact of development projects initiated during 2010–2015 [22,23]. The index was built on the results of approximately 1600 development projects and revealed how much the projects considered three important environmental aspects (ecology, resource conservation, and amenities). A total of 11 detailed indicators, the methods for calculating each indicator, and indicator weightings were determined through two public hearings and an AHP approach conducted by environmental experts. The AHP approach is a widely used decision-making method based on the measurement of relative weights [24,25]. KEIDP was applied to 150 development projects to prove the usefulness of the index.

However, because the Korean government's environmental data production policy has changed over time, some environmental data required for KEIDP calculations are no longer measured. It is therefore difficult to calculate the KEIDP for recent development projects. In particular, the Degree of Green Naturality (DGN) map, which is essential for the calculation of KEIDP, was discontinued in 2009 and is no longer available. If KEIDP is calculated by treating all DGN-related indicators as missing data, there are problems that may occur due to limitations of the AHP technique [26–30]. The AHP method determines the weight of each indicator by constructing a comparison matrix that evaluates all possible indicators with relative importance. If it is necessary to forcibly exclude specific indicators like KEIDP in the current situation, the relative importance must be re-evaluated from the highest criteria to the lowest indicators [31]. The biases and errors of AHP results can be larger [32]. Moreover, re-evaluating their relative importance for current development projects also requires costly and time-consuming public hearings. Thus, a new approach and data are needed to comprehensively evaluate the impact of the development project on the environment like the existing KEIDP.

EIA Big Data are the result of field surveys to evaluate environmental impact statements for development projects. EIA Big Data consist of materials related to air quality, water quality, and soil quality and have been produced since 2007 by government EIA policies [33]. Since EIA Big Data have recently been provided in conjunction with a geographical information system (GIS), its usefulness is high. The measurement results can fully reflect the environmental aspects considered in the existing KEIDP, so they can be

used to compare the impact of a development project, before and after the project. However, there is a limit to providing a comprehensive index by synthesizing them due to independent EIA Big Data characteristics. They cannot be used as input data for KEIDP calculation because they do not directly match.

The aims of this study are (1) to develop a model that could provide values similar to existing KEIDP results using EIA Big Data, which are new environmental data for recent development projects, and (2) to analyze the trend of environmental change that occurred during the development project process using the environmental index produced from the developed model. This is to analyze how effectively Korea's EIA policy works with development projects. For the study, development projects carried out during the transition period of the EIA policy change (2010–2015) were selected. Both the environmental data used for the KEIDP calculation and EIA Big Data were available for the selected development projects. The KEIDP results were used as the reference set for the model. The EIA Big Data were used as the input set, and a multi-layer perceptron based artificial neural network (MLP-ANN) approach was used to develop a relationship between the input and reference sets. Despite the use of the new EIA Big Data, it was expected that the model results would be similar to the existing KEIDP results.

In addition, an environmental index was calculated and used to analyze the environmental changes that occurred during the development projects.

2. Data

2.1. The KEIDP Based on an AHP Approach

During the period from 2010 to 2015, the KEI, the only environmental policy evaluation institute in Korea, conducted a study to produce the KEIDP, which can be used to evaluate the impact of development projects on the environment [22,23]. Through two public hearings attended by environmental experts, the study determined 11 types of indicators that considered three significant environmental aspects (ecological, resource conservation, and amenity). In addition, how to calculate the value of each indicator using environmental data measured before and after the development project was determined. The relative weighting of each indicator was determined by experts using the AHP approach, and the resulting KEIDP was then applied to 150 development projects.

Table 1 provides a description of the indicators, the equations used, and the weighting suggested by the KEI. Each indicator was quantified using its equation, as shown in Table 1, based on the EIA results before, during, and after development. Each quantified indicator was multiplied by its weighting, and the KEIDP was calculated by summing each indicator, as in Equation (1) [22].

$$KEIDP = \sum_{i=1}^k W_i \cdot I_i \quad (1)$$

where W_i is i -th indicator's weight and I_i is the i -th quantified indicator.

Each indicator can be classed as positive or negative for the environment, depending on its characteristics. For a negative indicator the weighting is multiplied by a negative number. Thus, a larger indicator value indicates that the development project is environmentally-friendly, and a smaller value indicates that the development project will harm the environment. If it is assumed that a development project has no impact on the environment (all indicators with positive weight have 1 and all indicators with negative weight have 0), the ideal is 0.308 according to Equation (1). Therefore, KEIDP can evaluate how much the development projects minimize the environmental impact based on ideal value.

In Table 1, the key indicators with the highest weight, "Phytomass" and "Degree of green naturality over 6 grades", are calculated from the DGN map. The DGN map of Korea has provided 10 grades of human interference with nature [34]. However, as the government's environmental policy paradigm changed from simple monitoring of green areas to environmental conservation, the production of DGN maps stopped after 2009. Instead, the Environmental Conservation Value Assessment MAP (ECVAM) for the national land of

Korea is being produced, which provides five grades of environmental importance [35]. The grade of the ECVAM is used as a criterion for permitting the development project, so it is impossible to calculate KEIDP to reflect the EIA of the new development project using ECVAM.

Table 1. Indicators, equations and weights for calculating traditional KEI's environmental index for development projects (KEIDP) (translated from Korean to English).

Criteria	Sub-Criteria	Indicator	Equation	Weight
Ecological aspect	Ecosystem conservation	Phytomass	Phytomass before and after development	0.074
		Degree of green naturality over 6 grades	Ratio of green naturality over 6 grades before and after development	0.139
	Promotion of biodiversity	Topography change	Ratio of total earthwork volume and development area	-0.013
		Green belt	Ratio of green belt area before and after development	0.040
Resource conservation aspect	Land water conservation	Rainwater storage basin	(Settling basin + detention pond)/development area	0.011
		Wastewater treatment	Capacity of wastewater treatment/(settled population + full-time employment)	0.035
	Minimize fossil fuel use	Amount of waste	Amount of waste during development and operation time/development area	-0.033
		Greenhouse gas emissions	Amount of greenhouse gas emission during development and operation time/development area	-0.020
Amenity aspect	Resident protection	Amount of net production	Ratio of net production amount before and after development	0.009
		Noise pollution	Number of calmness facility/development area	-0.035
		Atmospheric environmental material emissions	Emissions during operating time/development area	-0.027

In this study, KEIDP was calculated for 150 development projects conducted during 2010–2015, and the calculation results were used as a reference set to construct the MLP-ANN model that connects KEIDP with EIA Big Data.

2.2. The EIA Big Data

An EIA Big Data database was created in 2007 from the EIA results for major development projects [33]. The database provides the location where the data were measured, and attribute information, such as project information, measurement time, and measurement value. The EIA Big Data used in the current study consisted of 25 air quality-related measurements, two noise-related measurements, 64 water and marine quality-related measurements, 23 odor-related measurements, and 21 soil quality-related measurements. Each sub-dataset was measured before and after the development project, and, for each project, multiple measurement results could exist depending on the measurement location, time, and frequency [33].

This study used EIA Big Data for 611 development projects, for which an EIA had been completed more than four years before and after the project. Figure 1 shows the temporal distribution of the development projects used in this study. The x-axis of the figure is the year in which the EIA was conducted before the project. There were EIA Big Data available for more than 35 projects every year, except for 2016. In 2016, there were fewer projects available because, for many projects, no post-project EIA had yet been completed.

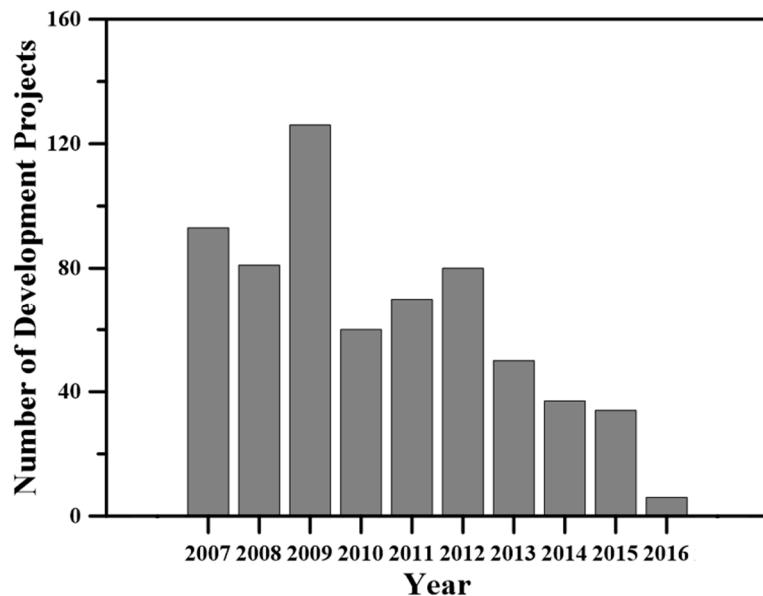


Figure 1. Temporal distribution of the development projects used in this study.

For each sub-dataset, based on guidance from environmental experts, data with a measurement frequency of more than 40% were selected as the input set for making the MLP-ANN model. The selected sub-datasets were five air quality-related datasets (PM10, nitrogen dioxide, sulfur dioxide, carbon monoxide, ozone), eight water and marine quality-related datasets (hydrogen ion concentration, dissolved oxygen, suspended solids, chemical oxygen demand, biochemical oxygen demand, total nitrogen, total phosphorus, total coliforms), and eight soil quality-related datasets (cadmium, copper, arsenic, mercury, lead, zinc, nickel, fluorine). Table 2 shows the EIA Big Data selected to produce the KEIDP calculation model.

Table 2. EIA Big Data selected to produce the new index.

Category	Number of Data	Used Data
Air quality	5	Particulate matter-10 ($\mu\text{g}/\text{m}^3$), nitrogen dioxide (ppm), sulfur dioxide (ppm), carbon monoxide (ppm), ozone (ppm)
Water quality	8	Hydrogen ion concentration, dissolved oxygen (mg/L), suspended solids (mg/L), chemical oxygen demand (mg/L), biochemical oxygen demand (mg/L), total nitrogen (mg/L), total phosphorus (mg/L), total coliforms (MPN/100 mL)
Soil quality	8	Cadmium (mg/kg), copper (mg/kg), arsenic (mg/kg), mercury (mg/kg), lead (mg/kg), zinc (mg/kg), nickel (mg/kg), fluorine (mg/kg)

3. Methods

A flow chart of the analysis procedure is shown in Figure 2. The study proceeded in the following four stages: (1) Selection of the target development projects. (2) Normalization of the EIA Big Data. (3) Development and validation of the KEIDP calculation model using MLP-ANN. (4) Application of the KEIDP calculation model for development projects after 2007.

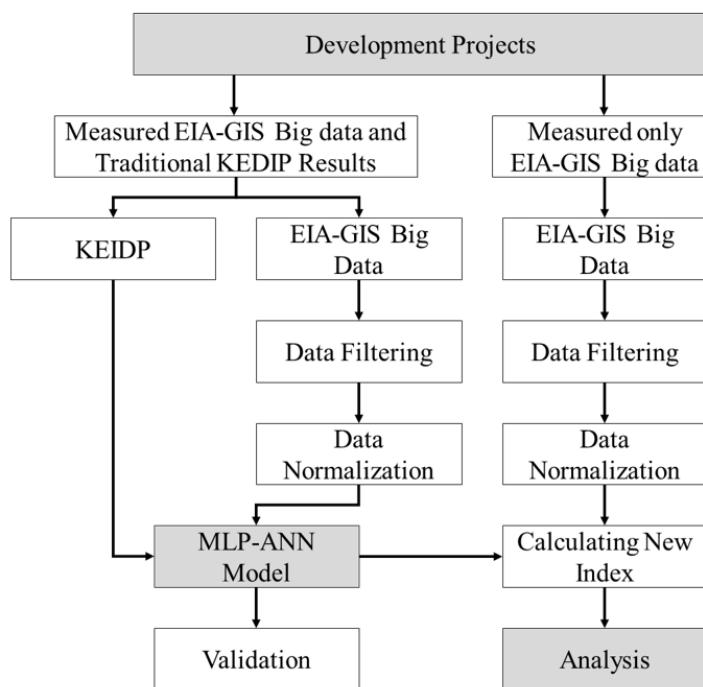


Figure 2. Research flow chart.

3.1. Selection of the Target Development Projects

Korean development projects measure environmental data according to their EIA results. Some development projects have measured environmental data that can be used to calculate the KEIDP, and projects since 2007 have also measured EIA Big Data. Thus, to produce the model for calculating KEIDP using EIA Big Data, it was necessary to select projects in which both KEIDP-related data and EIA-GIS Big data were measured. In this study, development projects were divided into those in which both types of data were measured and projects in which only EIA Big Data were measured. Then, a model capable of simulating the KEIDP value from EIA Big Data for projects in which both types of data were measured was produced and verified. The KEIDP values were calculated and analyzed by applying the model to the projects that measured only EIA Big Data.

3.2. Normalization of EIA Big Data

Because KEIDP is calculated as one value for one development project, EIA Big Data are also required to be expressed as a value that can represent one development project. However, unlike the data used to calculate KEIDP, multiple values of EIA Big Data are measured for one project. For example, in a project to collect and process stone from the Geumgang River Basin in Korea that began in 2010, PM10 was measured 16 times before the project and 80 times after the project. Mean values were calculated as representative values of the periods before and after the project. The means were calculated iteratively at a 99% confidence level to exclude errors in the measuring instrument or mistakes by the recorder.

Normalization was performed for the 21 selected types of EIA Big Data because the units and data sizes were different. The normalization of the EIA Big Data was conducted using Equation (2), with consideration of the before and after periods.

$$I_i^n = \frac{I_i^b - I_i^a}{I_i^b - I_i^a} \quad (2)$$

where I_i^n is the i -th normalized indicator, I_i^b is the i -th indicator measured before the project, and I_i^a is the i -th indicator measured after the project.

Through the normalization process, all EIA Big Data were expressed as values between -1 and 1 . If the normalization result approached 1 , it indicated that the indicator value decreased significantly after a project. This could be interpreted as indicating that the project was environmentally friendly and/or the constructor actively accepted the results of the EIA. In contrast, if a normalization result was less than 0 , it signaled that the indicator value increased compared to the situation before the project, which meant that the EIA results pointed to some degree of environmental damage.

3.3. Development and Validation of the KEIDP Calculation Model Using MLP-ANN

The MLP-ANN is one of the most popular available machine learning methods. It has been widely used by many researchers to predict or forecast specific environmental indicators [36–39]. The MLP-ANN algorithm consists of three layers, i.e., an input layer, hidden layer, and output layer. The hidden layer of the MLP-ANN algorithm solves the limitations of the linear regression of conventional perception. The MLP-ANN algorithm performs the prediction and estimation tasks by adjusting the connectivity between layers using an error backpropagation algorithm. This involves repeating the way the signal is transmitted to the hidden layer to output the result. The error is evaluated by comparing the output value with the true value. The weighting obtained for reducing the error by the backpropagation algorithm is then corrected.

In this study, 21 types of EIA Big Data were used as input neurons. The sigmoid function was chosen as the activation function to adjust the predicted value to a value between the minimum and maximum KEIDP so that the result could be calculated as a KEIDP value. The neural network was iterated for 1000 cycles per epoch, and a total of 1000 epochs were processed, with a learning rate of 0.01 . The hidden layer consisted of 42 neurons and one linear output layer was created. The neural network training was performed by randomly selecting half of the data as training data and half as validation data. The aggregated data were validated using the root mean square error (RMSE) and R^2 value for the relationship between the true and estimated KEIDP.

4. Results

4.1. The MLP-ANN Model Results

Among the targeted development projects, 48 provided environmental data that could be used to calculate the KEIDP and also measured EIA Big Data. The KEIDP was calculated from the environmental data of selected development projects, and 21 mean values before and after the projects were calculated from the 21 types of EIA Big Data. The 21 types of EIA Big Data were normalized using Equation (2).

Figure 3 shows an error convergence graph, model validation graph, and the distribution of factor weightings for the MLP-ANN model. The result was considered to be good because the mean squared error (MSE) was close to 0.1 (Figure 3a). Although the MLP-ANN model performance was not visually impressive, the correlation coefficient from Figure 3b was high ($R^2 = 0.957$). The R^2 value is an indicator of the correlation of the input parameters to the output parameters and is used to determine and select the optimized MLP-ANN inputs. If the value of the correlation coefficient is close to 1 the model is considered to be good. The MLP-ANN model was therefore acceptable. Furthermore, the RMSE results showed that the error was low (0.024). The weight distribution (Figure 3b) followed a normal distribution and, therefore, no factor specifically influenced the production of the MLP-ANN model.

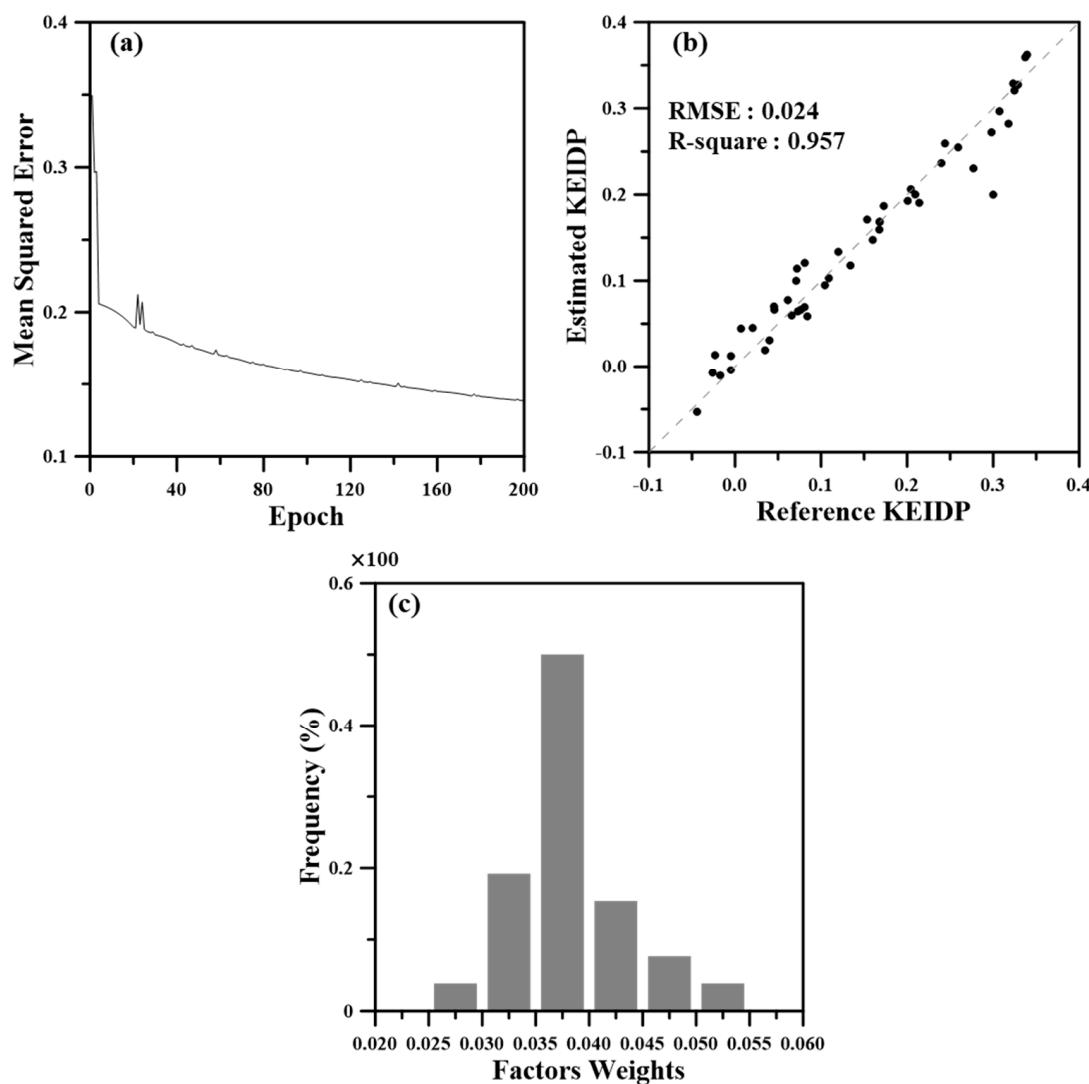


Figure 3. Error convergence, validation and distribution of factors weights results of produced MLP based ANN model: (a) error convergence graph; (b) model validation graph; (c) distribution of factor weightings.

4.2. Application of the KEIDP Calculation Model

Figure 4 shows the trend in the proportion of environmentally friendly projects according to each indicator. Here, environmentally friendly means that the normalized index result calculated from Equation (2) presented a positive value. These projects reduced the value of indicators affecting the environment after their completion, and it could be assumed that the project outcomes reflect the EIA results. The proportion of projects with reduced PM10, nitrogen dioxide, sulfur dioxide, ozone, hydrogen ion concentration, suspended solids, total nitrogen, total phosphorus, total coliforms, cadmium, copper, arsenic, lead, zinc, and fluorine indexes increased by more than 2% per year. The proportion of projects with reduced carbon monoxide, dissolved oxygen, chemical oxygen demand, biochemical oxygen demand, mercury, and nickel indexes increased by less than 2% per year. Overall, the percentage of environmentally friendly projects according to each indicator steadily increased compared to the past. It was found that the percentage of environmentally friendly projects did not exceed 50% in 2007, but exceeded 50% by the end of the study period.

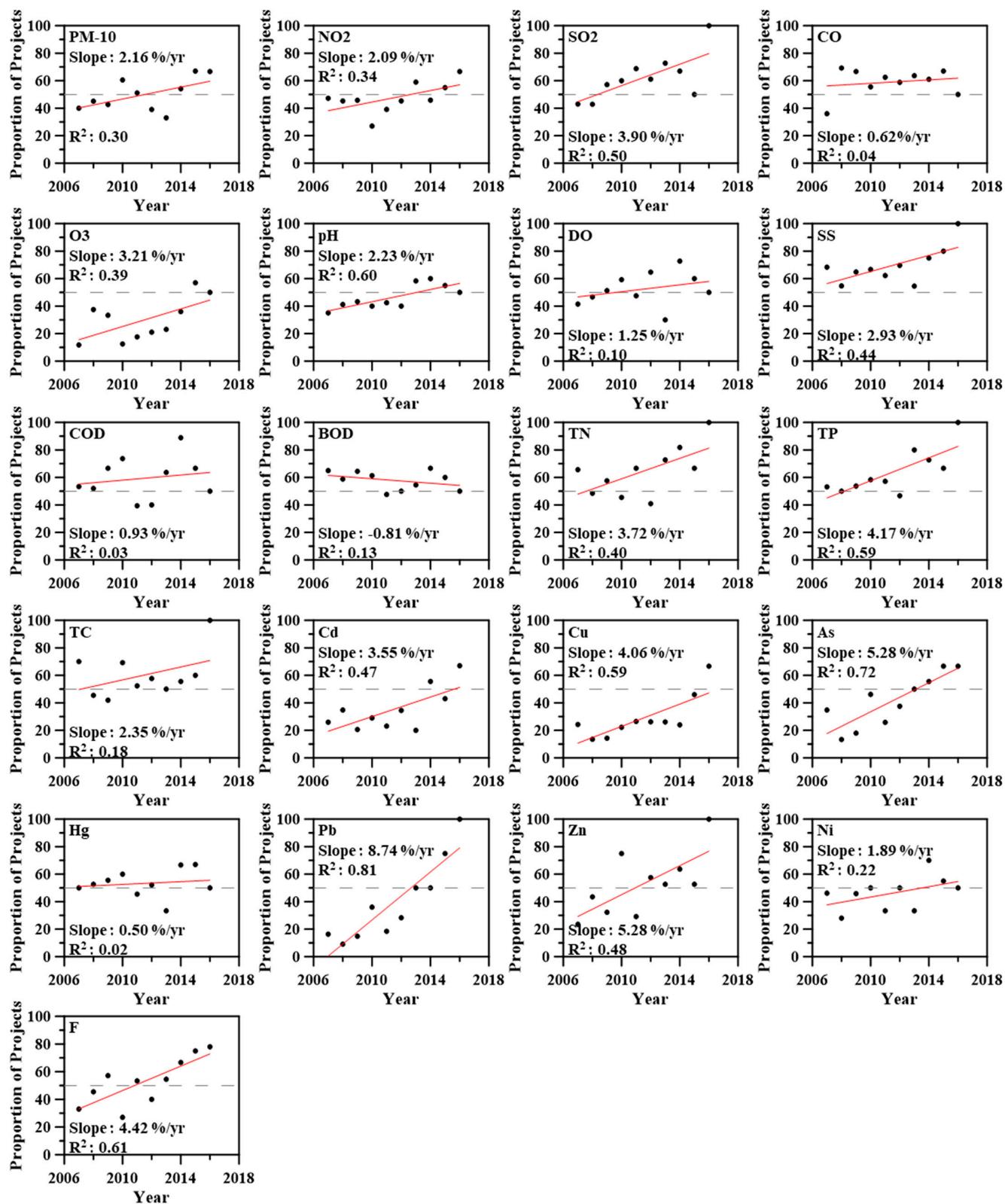


Figure 4. Proportion of environmentally friendly projects trends according to each indicator. The y-axis means proportion of environmentally friendly development projects.

Figure 5 shows the mean KEIDP trend calculated using the MLP-ANN model with EIA Big Data for all 611 projects. The error bars shown in Figure 5 represent one standard deviation of the mean value for the projects carried out each year. Because the input data of the MLP-ANN model were normalized indicators, an increase in the proportion of projects with positive values was reflected. The mean value of KEIDP gradually increased. The rate of increase was 0.007 per year, with an R^2 value of 0.8. This means that the number of environmentally friendly projects (which worked to minimize their environmental impact) gradually increased during the study period. Although there is still a difference from the ideal KEIDP, it has increased from about 0.1 in 2007 to about 0.18 in 2016.

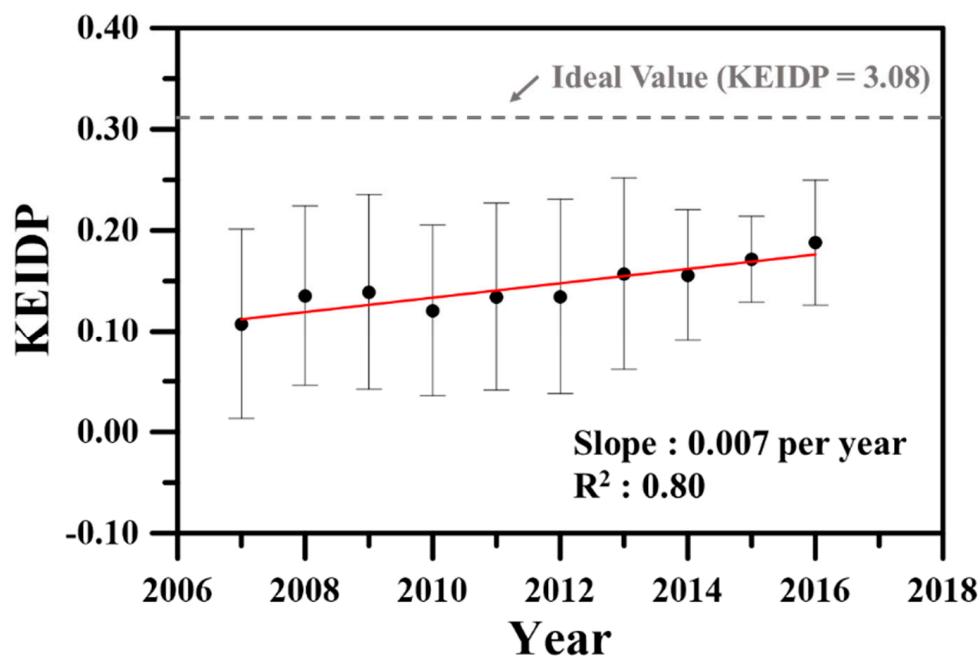


Figure 5. Development projects trend calculated using the MLP based ANN model with EIA Big Data for all 611 projects.

Figure 6 shows a graph of the overall KEIDP trends by organization. The organizations that were analyzed were the Ministry of Environment, Daegu Province Environmental Agency, Han River Basin Environmental Agency, Geumgang Basin Environmental Agency, Jeonbuk Province Environmental Agency, Nakdong River Basin Environmental Agency, Wonju Province Environmental Agency, and Yeongsan River Basin Environmental Agency. Because these organizations performed an EIA and measured environmental data, it was possible to confirm which institution's EIAs most strongly considered the environmental impact of the development project. As a result of the analysis, the KEIDP trends managed by the Ministry of Environment, Han River Basin Environmental Agency, Jeonbuk Province Environmental Agency, and Yeongsan River Basin Environmental Agency were found to increase by more than 0.007 per year. However, the KEIDP trends managed by the other agencies were found to change only slightly or not at all. There was even a decrease in the KEIDP for projects managed by the Daegu Province Environmental Agency.

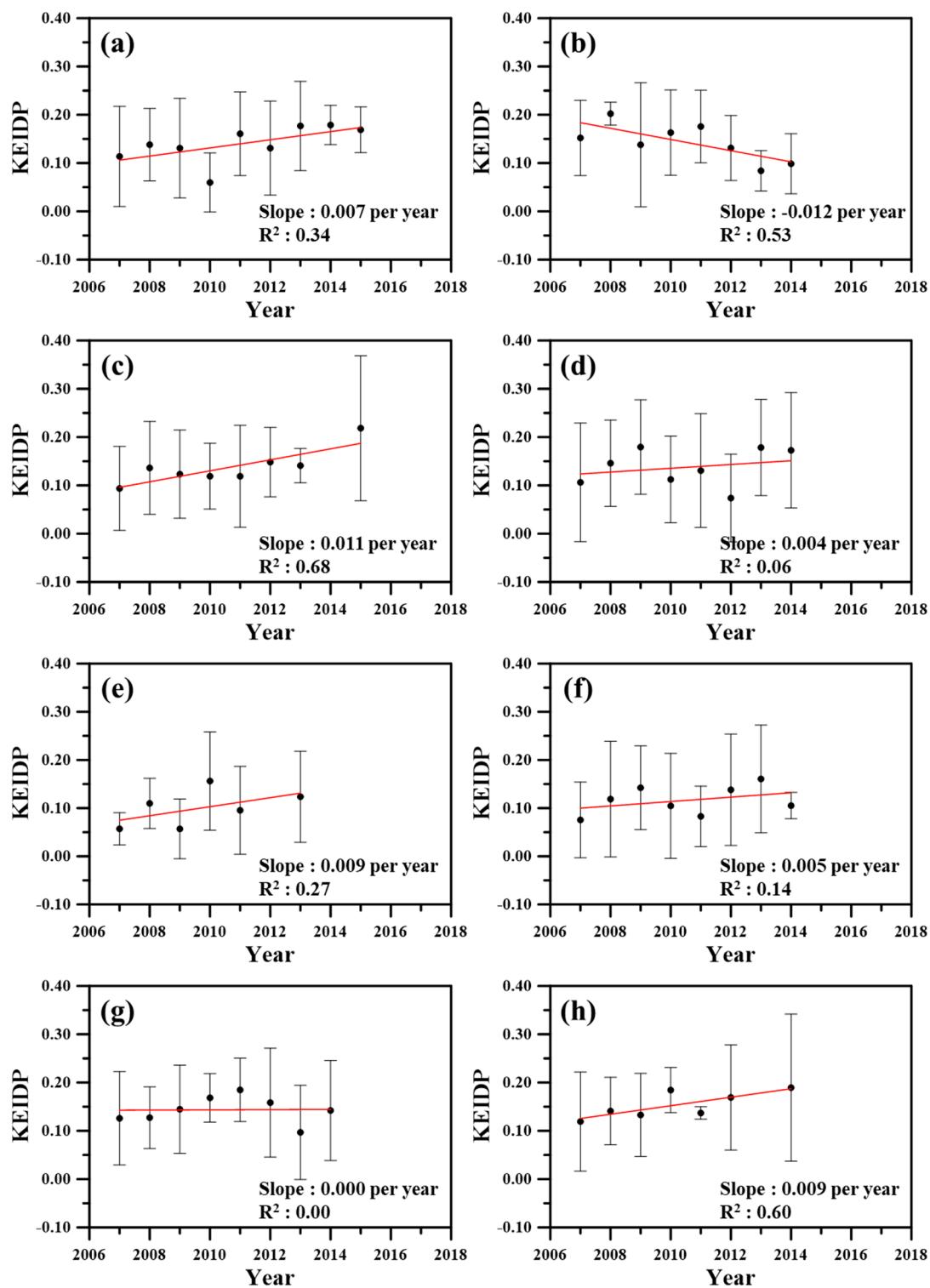


Figure 6. Development projects trends by EIA agency: (a) direct management by the Ministry of Environment; (b) Daegu Province Environmental Agency; (c) Han River Basin Environmental Agency; (d) Geumgang Basin Environmental Agency; (e) Jeonbuk Province Environmental Agency; (f) Nakdong River Basin Environmental Agency; (g) Wonju Province Environmental Agency; (h) Yeongsan River Basin Environmental Agency.

5. Discussion

AHP is an analysis method that calculates relative importance by categorizing multiple evaluation criteria into a hierarchy when they are complex. In the case of complex evaluation criteria like EIA, the use of AHP is appropriate and has been effectively used in many studies [9,40–43]. The KEIDP is also produced using the AHP approach, and it was the result of reflecting the various opinions of many experts (Table 1). However, as input data for KEIDP calculation were no longer produced, there was a limit to the EIA for the development projects using KEIDP. Although it is possible to indicate the impact of a development project on the environment from the conditions before and after the project using EIA Big Data, there is a limit to the scope of the analysis due to the characteristics of the independent EIA Big Data. Following the proposed normalization method, it was possible to analyze the proportion of environmentally friendly projects, but it was also difficult to show the overall trend. Therefore, to comprehensively analyze the impact of development projects on the environment, it was necessary to utilize the existing KEIDP.

The MLP-ANN approach that learns the relationship between input data and reference data with multiple nodes and layers can be used to learn or predict AHP results [44,45]. In this study, the KEIDP calculated from the AHP method was learned by producing the MLP-ANN model using EIA Big Data as input data (Figure 2 and Table 2). There were few development projects with KEIDP and EIA Big Data, but the trained data can explain the whole development project with a margin of error of about 7% at a 95% confidence level [46]. After completing the learning, it was confirmed that the MLP-ANN model to calculate the KEIDP using EIA Big Data was effective. Comparing the estimated KEIDP and the true KEIDP, the correlation coefficient was 0.957 and the RMSE was 0.024 (Figure 3b).

The application of KEIDP is steadily increasing, indicating that development projects are considering their environmental impacts by taking their EIA results seriously (Figure 5). However, despite the upward trend in KEIDP values for each year, the KEIDP deviations for each development project and management agency were high (Figure 6). It was found that about 68% of the projects (the standard deviation of the KEIDP distribution was within 1) each year had KEIDP values that changed over a range of about 0.2. The reason for this is likely to be because the items and criteria used by each management agency for evaluating the environmental impact of development projects are different when performing an EIA. In the future, it will be necessary for all management agencies to apply the KEDIP calculation model to minimize the impact of development projects on the environment and reduce the deviations between development projects through continuous monitoring. In addition, it is necessary to analyze the cause by evaluating the EIA performed for the projects with low KEIDP, and further research is needed to improve or effectively apply the EIA according to the characteristics of the development projects.

Although the scope of the study was limited to Korea, the methodology can be applied to development projects in other countries as well [47,48]. If data such as EIA Big Data can be obtained in other countries (even if they do not perfectly match all the data types used in this study), it is expected that EIA can be performed through this methodology.

6. Conclusions

In this study, a trend analysis of the KEIDP from 2007 to 2016 was conducted using EIA Big Data. The calculation of the true KEIDP requires large amounts of time and money, and it is not always possible to be calculated due to the discontinuation of some data sets. However, in this study, KEIDP values were calculated for current development projects using EIA Big Data and an MLP-ANN approach. In conclusion, this study can be signified in the following aspects: (1) the proposed MLP-ANN approach can continuously produce the KEIDP, which was no longer calculated, (2) in situ-based EIA is possible by producing KEIDP using EIA Big data, which have been measured since 2007, (3) the impact of the development project on the environment can be quantitatively analyzed by comparing it with the ideal KEIDP (0.308), and (4) it was possible to determine the

proportion of environmentally friendly projects that reflected their EIA results through the KEIDP trend analysis.

The EIA Big Data used in this study were measured in EIAs conducted before the development and in the post-project EIA conducted after the development was completed. The EIA Big Data were stored in the KEI-managed Environmental Impact Assessment Support System (EIASS), and data on new projects were continuously being produced. Through a trend analysis of 21 different indicators, it was proven that the KEIDP can quantitatively represent the effects of development projects on the environment. As the trend of KEIDP values showed, the proportion of environmentally friendly projects in Korea is continuously increasing. In future EIAs, the impact of development projects on the environment could be minimized by using calculated KEDIP values in the assessment of their impacts.

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