Sensors and Materials, Vol. 37, No. 6 (2025) 2631–2649
MYU Tokyo

S & M 4078

Vegetation Index and Ecological Restoration Methods of Quarry Environments through Multitemporal Spatial Image Analysis

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(Received February 14, 2025; accepted June 13, 2025)

Keywords: orthophoto, multispectral, ecological restoration, time-series analysis, vegetation index

Vegetation information is an important index utilized in numerous fields including landscaping, ecological restoration, urban planning, and the environment. We investigated the temporal changes and ecological restoration techniques for damaged quarries using orthophoto images supplied by the National Geographic Information Institute and drone multispectral sensor technology. We examined the area changes of deforestation in quarries and the supervised categorization of photos to produce qualitative and quantitative results based on a temporal background of roughly 24 years from 2000 to 2024. Additionally, different vegetation indices (normalized difference vegetation index, soil-adjusted vegetation index, and modified soil-adjusted vegetation index) and their variation trends were also investigated by analyzing the multispectral images from 2011, 2017, and 2024. The kappa coefficient for orthophoto images through supervised classification was approximately 0.781 on average, indicating satisfactory classification results. The accuracies in 2023 and 2024 were low, which was considered to be due to ambiguous boundary distinctions in the beginning stage of the restoration of damaged areas. The vegetation indices were analyzed for changes over three years in zones A, B, and C. Consequently, the vegetation index for 2017 was lower than those for 2011 and 2024, and it was observed that quarry development in 2017 progressed significantly across all areas. Discussions on the restoration plan for the damaged quarry are presented by comparing the area and vegetation index presented in the time series analysis of this study, therefore rendering information on future vegetation management. This study shows how sensor technology can be usefully applied to ecological restoration, making it meaningful for both environmental and sensor-related research.

1. Introduction

Industrial development significantly impacts the local economy, although it tends to reduce the environmental importance associated with it. Particularly, the development of quarries, such as stone mines, significantly damages natural landscapes and ecosystems. In contrast to that in the past, it has now become crucial to restore the ecosystems of these damaged areas and seek sustainable management strategies. The various quarries scattered across the country were

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https://doi.org/10.18494/SAM5603

ISSN 0914-4935 © MYU K.K.
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under development for a long time, significantly impacting the surrounding ecosystems. Additionally, the destruction of ecosystems and changes in land use due to developmental activities are causing various environmental problems, such as the reduction in biodiversity. Drone technology was used in various fields such as forestry, agriculture, and disaster prevention to assess the health of vegetation. In recent domestic research, Cho *et al.*(1) assessed the classification accuracy of vegetation health using drones equipped with near-infrared sensors to calculate vegetation indices. Similarly, Lee *et al.*(2) compared the accuracies of various vegetation indices derived from optical sensors. Furthermore, research on drones and vegetation indices was conducted, including the rapid acquisition of terrain spatial information, high-precision mapping, and vegetation crop analysis.(3)

Among international studies, Yang *et al.*(4) used Landsat images and the LandTrendr algorithm to detect the dynamics of vegetation disturbance and recovery in the Curragh coal mine area in Australia, and examined the spatial and temporal changes from 1989 to 2014. From 1989 to 2014, 2982.60 ha of the 4573.08 ha Curragh mining area were restored, which corresponds to 59% of the total disturbed area. In the central part, 95% of the restoration was successfully completed. Bonifazi *et al.*(5) conducted a study using Landsat 5 satellite images to distinguish between bare soil and restored vegetation, and evaluated the degree of restoration from bare soil to vegetation using a vegetation index. The numerical values comparing field surveys and remote sensing results were consistent with those within the margin of error, and they quantified the restoration status of the quarry through the integrated restoration quotient.

Ecological restoration research in quarries is being globally conducted through various technological approaches. Particularly, technological advancements are considerably aiding these studies. Orthophotos and multispectral images obtained using drones can provide fundamental information to significantly improve the efficiency of ecosystem monitoring and restoration processes.

This study is distinguished by proposing long-term ecological restoration strategies targeting the environment of a quarry. We precisely monitored changes over an extended period from 2000 to 2024, and on the basis of this, restoration plans were proposed. We proposed specific customized ecological restoration plans and established practical restoration strategies on the basis of the analysis of vegetation conditions. Earlier studies primarily used Landsat satellite images for analysis, although in this study, we utilized high-resolution orthophotos and drone multispectral sensors to analyze the subtle changes in the quarry based on the data. The current work is distinctly ahead of previous studies in that it can specifically monitor not only vegetation changes but also restoration effects through high-precision data.

2. Research Method

2.1 Materials and methods

The study area is located in Gangseo-gu, Busan, where development projects such as industrial complexes are being actively undertaken in the surrounding regions (Fig. 1). The

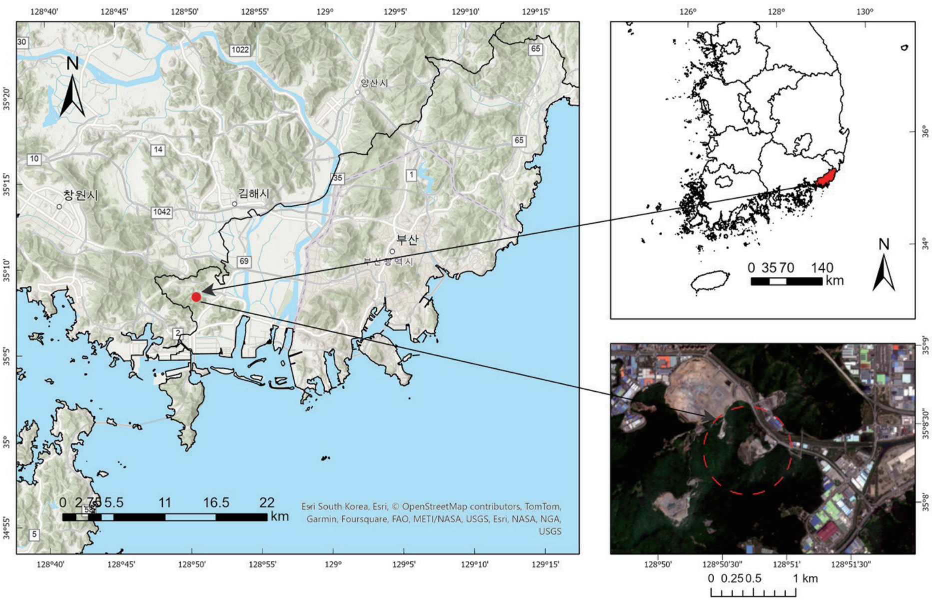


Fig. 1. (Color online) Study area.

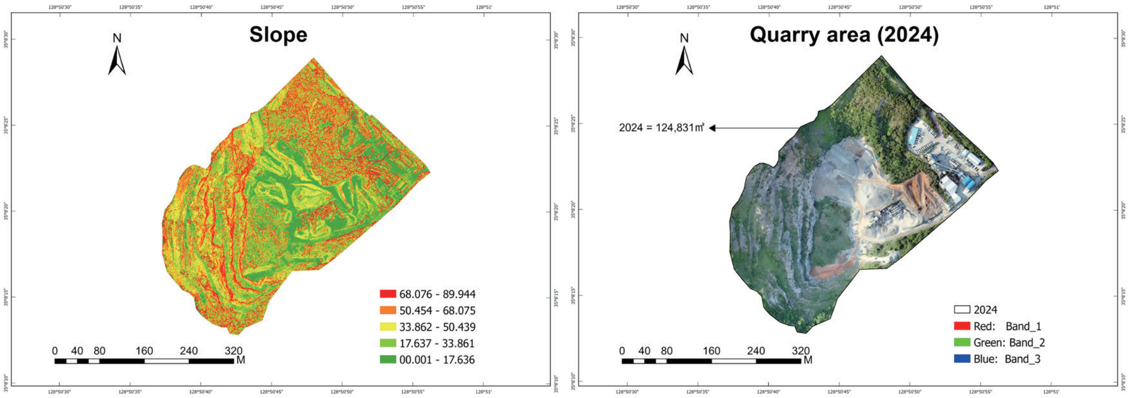
quarry is located in an ecological grade 2 natural green area, with an average slope of approximately 23° and a site area of 124,831 m² (Fig. 2). Figure 3 presents the flowchart of this study.

2.2 Orthophotos and multispectral images

The experimental data were obtained by two methods. Aerial images from the National Geographic Information Institute were collected at five-year intervals from 2000 to 2023. In 2024, it was planned to produce and analyze orthophotos through high-resolution drone footage. As the study area is not very large, it was deemed appropriate to conduct the research using the 0.25 m-grade aerial photographs and drone footage from the National Geographic Information Institute. Drone photography has the advantage of using data reflecting the latest terrain and development conditions, and it is considered appropriate to analyze past changes through aerial photographs (Table 1).

High-precision imaging and multispectral imaging were conducted on May 22, 2024, using the DJI M300 RTK, with the Sentera 6× Multispectral Sensor camera to acquire information about the study area. The shooting time, shooting altitude, ground sample distance, and flight speed were approximately 20 min, 120 m, 1.88 cm/px, and 13.7 m/s, respectively, and the longitudinal and lateral overlap was set to 90%.

To improve the positional accuracy of the study, a DJI-RTK2 was installed near the study area and images were captured, which were processed using DJI Terra. The various outputs derived from this were analyzed in ArcGIS Pro.



(a) (b)

Fig. 2. (Color online) Quarry topographic modeling. (a) Analysis of slope. (b) Quarry area in 2024.

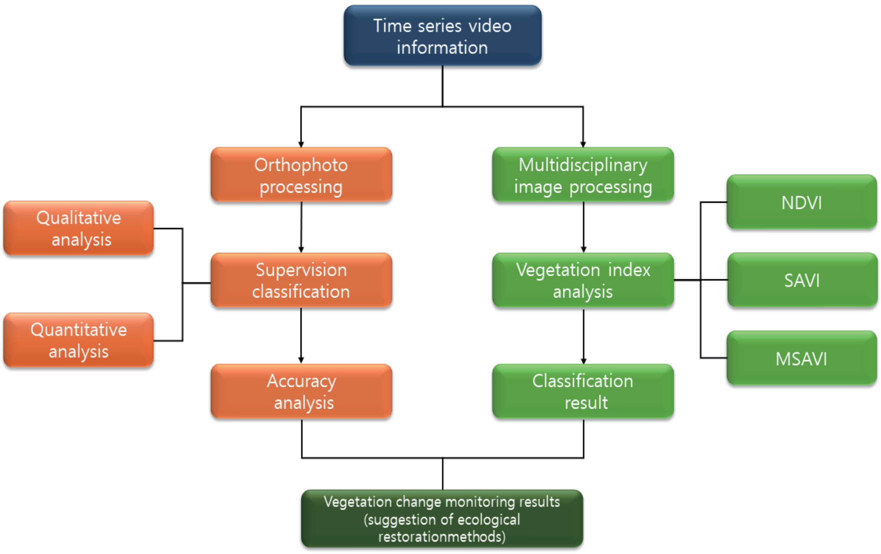


Fig. 3. (Color online) Flowchart.

2.3 Vegetation index

Various vegetation indices are used for assessing the impact of quarrying activities on the surrounding environment and for monitoring the ecological restoration process. The normalized difference vegetation index (*NDVI*) is used to assess the overall vegetation condition quickly and easily, whereas the soil-adjusted vegetation index (*SAVI*) and the modified soil-adjusted vegetation index (*MSAVI*) are utilized to correct for soil exposure in quarries with significant soil exposure, allowing for a more accurate understanding of vegetation conditions. Through the complementary characteristics of each index, it is possible to diagnose the various vegetation changes occurring more accurately in the quarry. These three representative vegetation indices

Table 1
a: Orthophoto data source.

Data information Division		Data type	Time	Resolution
Orthophotographic information	National Geographic Information Institute	Aerial photography	2000.03.01.	1200 dpi
			2004.11.01.	
			2011.04.06.	0.25 m
			2015.05.29.	
			2017.06.04.	
			2021.03.24.	
			2023.02.27.	

b: Multispectral data source.

Data information Division		Data type	Time	Spectral bands
Multispectral information	National Geographic Information Institute	Aerial Photography	2011.04.06	Blue, Green, Red, RedEdge, NiR
			2017.06.04	
	Drones	DJI M300 RTK, (Sentera 6x Multispectal Sensor)	2024.05.22	

(*NDVI*, *SAVI*, and *MSAVI*) are analyzed here. These indices are useful for quantitatively assessing changes in quarry environments and evaluating ecological recovery.

NDVI is one of the most widely used vegetation indices and is excellent at detecting the health status and density of plants. This index is calculated using the difference in reflectance between the near-infrared band and the red band of satellite images. Plants absorb red light and reflect near-infrared light through photosynthesis, and thus, healthier plants show higher *NDVI* values. *NDVI* was developed by Tucker.(6)

SAVI is a modified model of *NDVI*, particularly useful when soil background affects plant reflectance. A correction factor L for *SAVI* was introduced to minimize the soil reflectance effect. This factor is generally set to 0.5, which has the characteristic of reducing the distortion of vegetation signals by soil reflectance.(7)

By further improving *SAVI*, *MSAVI* was developed to provide accurate vegetation information even in areas affected by soil reflectance.(8) This index automatically adjusts the impact of soil brightness changes on the vegetation index by modifying the calculation formula of *SAVI*. Tables 2 and 3 outline the calculation formula for the vegetation index and the distribution of vegetation index values and criteria for healthy vegetation conditions, respectively.

To apply the vegetation index to the study area, aerial images from 2011 to 2017 including multiple bands were first used. In 2024, drone sensor information was obtained to calculate *NDVI*, *SAVI*, and *MSAVI* in ArcGIS Pro. To derive more precise sample vegetation indices, the entire area was divided into grid units (30×30 m^2) rather than using the whole area, and the average values within each grid were calculated. As nonvegetated areas such as development zones and facilities exist, the experimental sites were divided into A, B, and C areas to calculate the average values. Rather than presenting the overall vegetation index, it was determined that dividing the area into three regions would be more effective in minimizing error factors.

Table 2
Vegetation index calculation formula.

Vegetation index	Calculation formula
NDVI	$\frac{NIR - RED}{NIR + RED}$
SAVI	$\frac{NIR - RED}{NIR + RED + 1} \times (1 + L)$
MSAVI	$\frac{2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - RED)}}{2}$

Table 3
Distribution of vegetation index values and criteria for healthy vegetation condition.

Vegetation index	Healthy vegetation threshold	Typical range	Description
NDVI	0.6	0–1	NDVI values above 0.6 typically indicate healthy and dense vegetation
SAVI	1.0	0–1.5	SAVI values above 1.0 indicate good vegetation health, accounting for soil reflectance.
MSAVI	0.8	0–1	MSAVI values above 0.8 are considered indicative of healthy vegetation, particularly in areas with exposed soil.

Figure 4 shows the locations and numbering order of the grids used for analysis among the divided areas, and the grids are designated from the starting point to the endpoint according to the direction of the arrows. To improve the accuracy of the data, areas where vegetation occupies more than half of the area and parts where the shape and vegetation have been altered were excluded. In 2011, 2017, and 2024, 110 out of a total of 172, 101 out of a total of 164, and 107 out of a total of 171 grids were used for analysis, respectively.

2.4 Supervised classification

The image classification task requires distinguishing all the pixels in an image into several land types. The supervised classification method is mainly used when the location or spectral characteristics of the area to be classified are already known, and this method is effective when the user is well acquainted with the area. The user sets up training sites well representing the characteristics of land cover, analyzes all the pixels within the data using the covariance between the centers of each cluster in that area and the bands, and then assigns them to the cluster with the most similar distribution characteristics. For supervised classification techniques, the selection of training sites significantly impacts the classification accuracy, and thus, samples representing the area to be classified should be selected in a diverse and broad manner.(9,10)

For the land cover classification of the study area, the training sites were organized into five main categories. For building, soil, natural vegetation, deforested area, and restored vegetation,

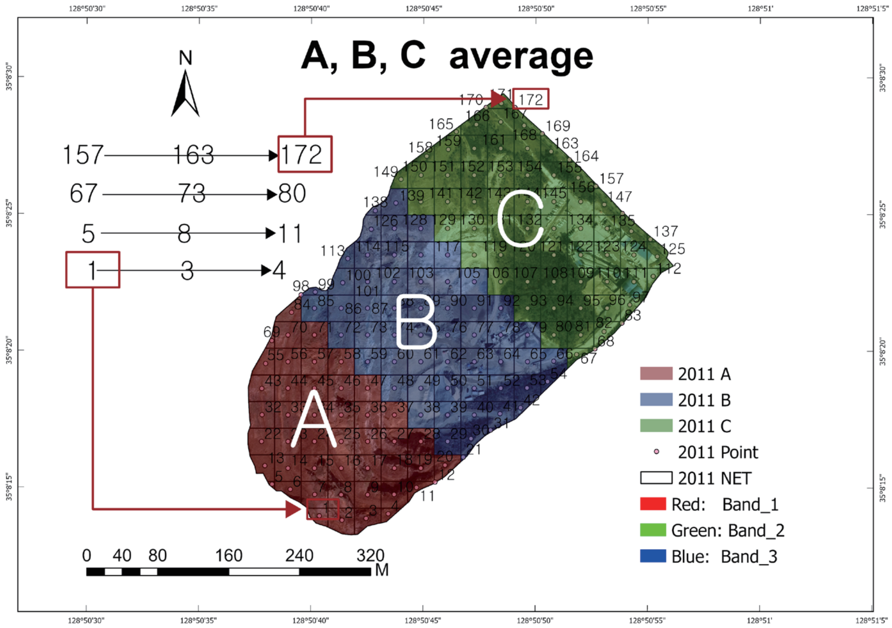


Fig. 4. (Color online) Average values of A, B, and C in 2011–2024.

an average of 150 training sites were selected and classified to categorize the entire study area over five years.

Random trees classification (RTC) was applied as the classification algorithm. Research results suggest that it can achieve good outcomes in ecological restoration monitoring using high-resolution satellite images to address the challenges of classifying high-dimensional spatial data. Additionally, the classification algorithm can effectively manage complex datasets and has the characteristic of offsetting noise with high accuracy and minimized overfitting. The model learns the characteristics of each class and can be applied to new data, with parameters set to optimize the balance between model complexity and prediction accuracy. The results are designed to demonstrate an improvement in classification performance compared with that of the standard classification methods.[11] To track the environmental changes in the quarry over time, data from multiple points in time were collected and compared for analysis. RTC is used for change detection and trend analysis by leveraging the high-dimensional characteristics of such time series data. Although the quarry data itself is not high-dimensional data, it can be considered suitable for applying high-dimensional spatial data classification techniques used for the environmental monitoring and management of the quarry. To evaluate the land cover classification accuracy of the quarry using supervised classification and RTC, the accuracy was calculated using the kappa coefficient, which is expressed as

$$Kappa(\mathrm{K}) = \frac{\Pi_0 - \Pi_e}{1 - \Pi_e}, \tag{1}$$

where Π_0 denotes the probability of the two observed data matching and Π_e denotes the rate at which the two observed data could match by chance. The degree of agreement according to the value range is the same as that shown in the table from a previous study.(12)

2.5 Criteria for distinguishing restored vegetation areas

The criteria for distinguishing restored vegetation areas are primarily identified through land use changes. Restored vegetation refers to an area where vegetation was rebuilt or naturally recovered through artificial or natural restoration efforts after deforestation. This area was originally a land in a degraded state, although over time, it has been restored or is in the process of being restored, and it is generally distinguished from other types of vegetation.(13) On the map, the restored vegetation is highlighted to emphasize the difference from the deforested area, allowing for the identification of changes in the areas where restoration has taken place.

Building: This refers to a structure artificially constructed in the area, indicating the impact of development. During ecological restoration, areas with buildings may be impossible to restore or restoration is limited.

Soil: This refers to an exposed soil area that has not been restored. This area has no vegetation and is considered a priority site for restoration.

Natural vegetation: This refers to an area of natural vegetation that is being maintained healthily. This area protects and manages the existing ecosystem.

Deforested area: This refers to an area primarily damaged by development or natural disasters. This area needs to have its vegetation restored through rehabilitation and is classified as a priority site for restoration.

Restored vegetation: This refers to an area where restoration was conducted or completed, indicating that the restoration work has been successfully accomplished. However, continuous monitoring and management are necessary, as a possibility exists that the health of the ecosystem may decline again over time, and thus, consistent management is required.

3. Result

3.1 Analysis of time series images

The time series analysis of the quarry was conducted to identify the area changes from 2000 to 2024 through quantitative analysis and to analyze the qualitative changes in the images. To align the positions over a long time lag, clear road lines were selected as reference points, and each image was matched at the same scale. Figure 5 presents the results of digitizing and vectorizing the images year by year. From 2000 to 2011, the total area of the region increased from 87732 to 126894 m² and the developed area also increased from 67563 to 80469 m², indicating continuous development. Since 2011, the amount of quarry development has decreased, with the total area slightly decreased to 124831 m² and the developed area significantly decreased to 29838 m². Figure 6 shows the total and developed areas of the quarry site from 2000 to 2024. From 2000 to 2011, both the total and developed areas steadily increased,

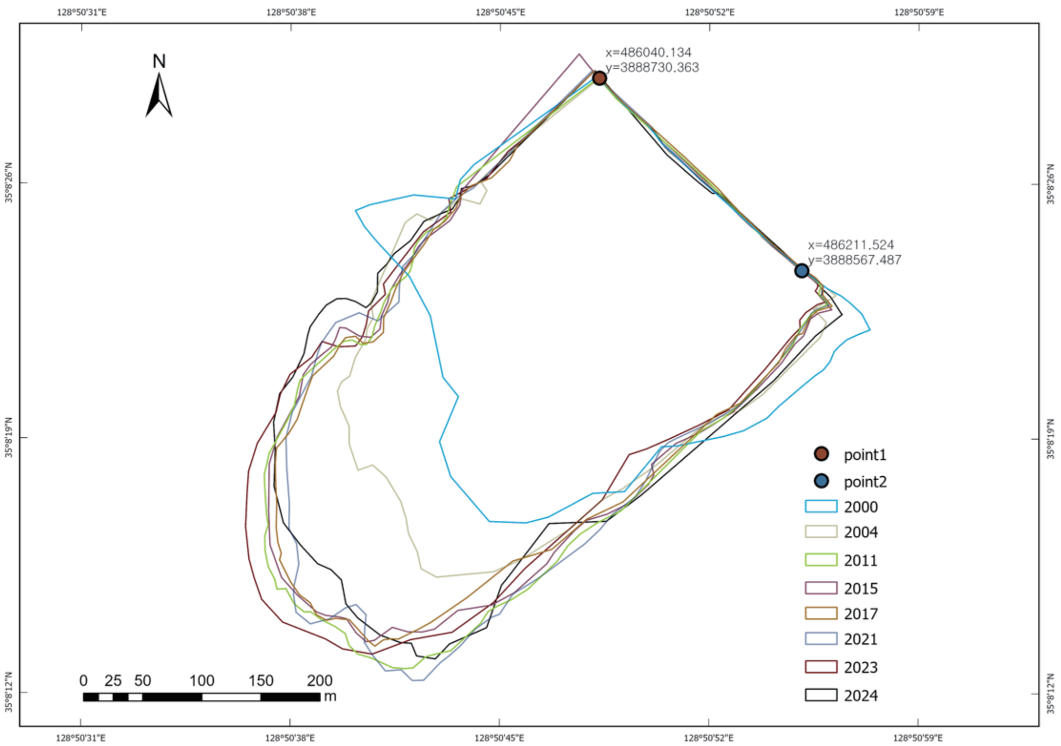


Fig. 5. (Color online) Quarry time series area (2000–2024).

and it was observed that the proportion of the developed area also continuously increased. Later, in 2015, the development pace slowed down and the proportion of developed areas decreased from 28 to 16%. By 2024, the developed area increased again and the development area ratio rose to 24% (Table 4).

3.2 Time series accuracy analysis

Figure 7 shows the analysis results for the study area after applying a supervised classification algorithm with five classification categories. For the final five years (2011, 2015, 2021, 2023, and 2024), the classification accuracy was presented as building, soil, natural vegetation, deforested area, and restored vegetation.

In Table 5, the building category has 4 correctly classified pixels, 2 misclassified as other categories, and an overall user accuracy of 66.7%. Soil has 40 pixels accurately classified, 3 misclassified, and a user accuracy of 93.0%. Natural vegetation has 24 correctly classified pixels, 5 misclassified, and a user accuracy of 82.8%. The deforested area has 43 accurately classified pixels, 7 misclassified pixels, and a user accuracy of 86.0%. Restored vegetation has 19 correctly classified pixels, 5 misclassified pixels, and a user accuracy of 79.2%. In the overall classification accuracy, the total row represents the total number of pixels for each classification and the total U-accuracy indicates the user accuracy for each classification. Here, p-accuracy represents producer accuracy, which implies the probability of being correctly classified from

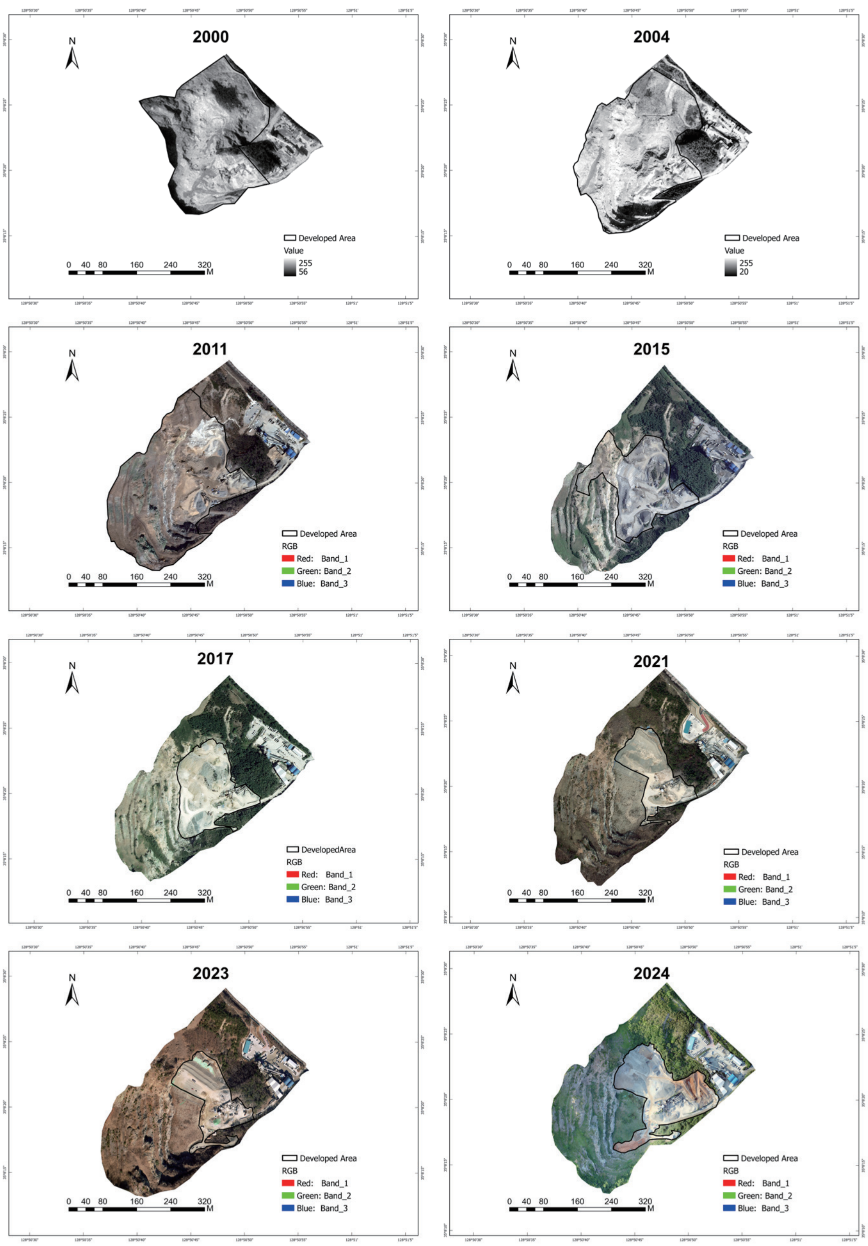


Fig. 6. (Color online) Quarry time series developed area (2000–2024).

Table 4
Quarry area change rate.

Year	Total area	Developed area	Developed area ratio
2000	87732 m^2	67563 m^2	77%
2004	100408 m^2	74102 m^2	74%
2011	126894 m^2	80469 m^2	63%
2015	124074 m^2	35249 m^2	28%
2017	123930 m^2	26722 m^2	22%
2021	124390 m^2	18654 m^2	15%
2023	125841 m^2	19651 m^2	16%
2024	124831 m^2	29838 m^2	24%

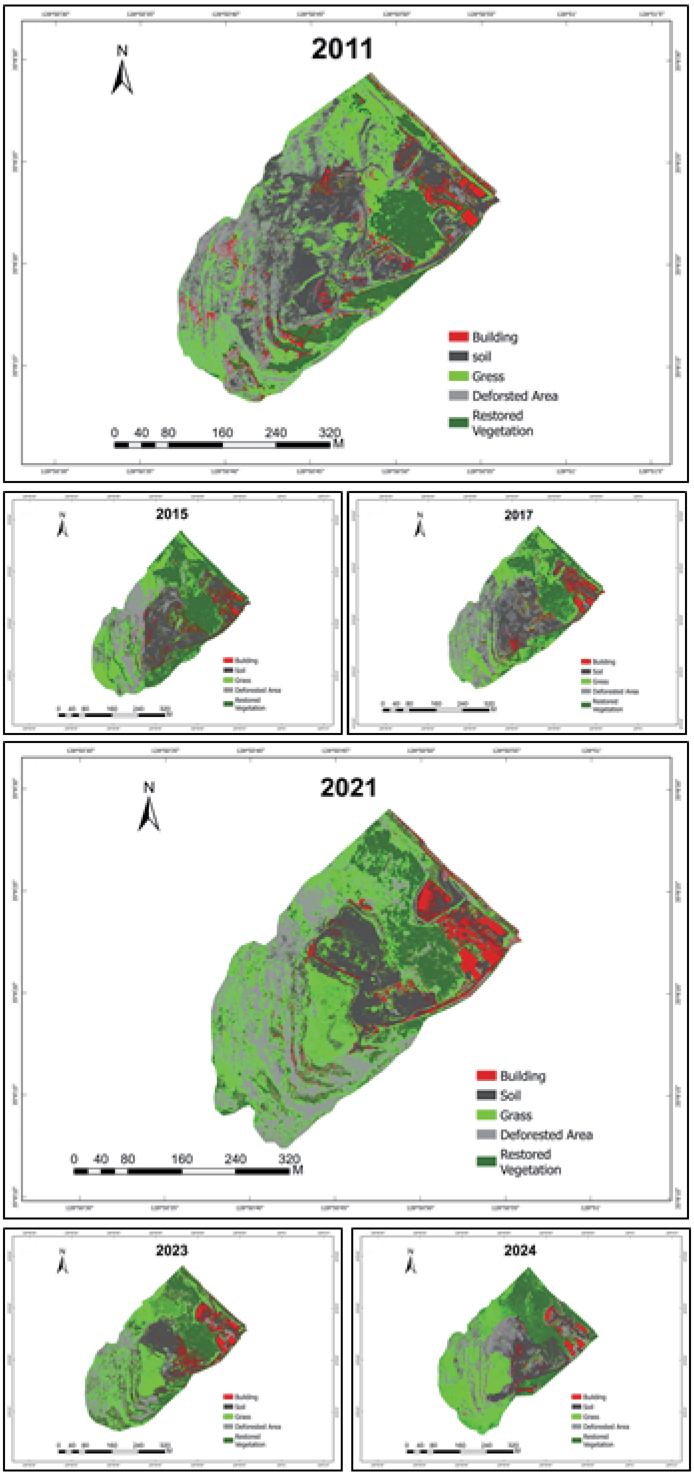


Fig. 7. (Color online) Quarry supervision classification results (2011, 2015, 2021, 2023, and 2024).

Table 5
Kappa coefficient accuracy.

	Building	Soil	Grass	Deforested area	Restored vegetation	Total	U-accuracy
Building	4	2	0	0	1	6	0.667
Soil	1	40	1	1	1	43	0.930
Natural vegetation	1	1	24	1	2	29	0.828
Deforested area	1	2	4	43	0	50	0.86
Restored vegetation	3	0	2	0	19	24	0.792
Total	10	45	31	45	21	152	0
P-accuracy	0.4	0.889	0.774	0.956	0.905	0	0.855

the perspective of the provider. U- and P-accuracies are the proportions of correctly identified instances within each categorized group and correctly classified instances overall, respectively. A Kappa coefficient of 0.808 indicates a high consistency in the overall classification, and the closer the Kappa coefficient is to 1, the better the classification effect. Here, the calculation results of the Kappa coefficient for 2011 are presented, and the final Kappa coefficient results for other years (2015, 2021, 2023, and 2024) are summarized in Table 6.

3.3 Time series vegetation index change analysis

Figure 8 shows the *NDVI*, *SAVI*, and *MSAVI* for 2011, 2017, and 2024. The *NDVI* for 2011 is very high, ranging from 0.703 to 1, and the widely distributed green areas generally indicate a healthy vegetation condition. *SAVI* ranges from 1.04 to 1.497, indicating a good vegetation condition, and *MSAVI* also shows values from 0.805 to 1, confirming an overall healthy vegetation condition.

In 2017, *NDVI* decreased overall compared with that in 2011, from 0.703 to 0.627, and the red areas expanded, indicating a reduction in vegetation vitality. *SAVI* decreased from 1.04 to 0.938, and *MSAVI* decreased from 0.805 to 0.726, indicating an overall reduction in vegetation vitality.

The *NDVI*, *SAVI*, and *MSAVI* for 2024 are 0.758, 1.134, and 0.809, respectively, indicating an increase in vegetation vitality compared with those in 2017. Although the proportion of damaged soil was high in 2017, the restoration of vegetation has been successfully progressing by 2024.

Tables 7 and 8 show that even just considering the *NDVI* values, the average value of region A, which was under restoration in 2024, is 0.556, higher than that of region C (0.468), which has been restored. Accordingly, two observations were made. First, it was observed that the vegetation vitality of the restored area C gradually decreased over time. Second, the current restoration work in area A was progressing very successfully, indicating a higher vegetation vitality than that of the previously restored area C. Figures 9 and 10 show the average vegetation indices for each vegetation zone (A, B, and C). Figure 11 is a trend graph illustrating the changes in vegetation indices for regions A, B, and C in 2011, 2017, and 2024, as shown in Table 8.

These results emphasize the importance of maintaining the restored vegetation, indicating that continuous monitoring and additional management are necessary even after the restoration work. Furthermore, the successful restoration work in region A during the restoration process serves as a model, suggesting that a similar level of management may be needed in region C as well.

Table 6
Kappa coefficient accuracy.

Year	Kappa value
2011	0.855
2015	0.856
2017	0.823
2021	0.769
2023	0.717
2024	0.714

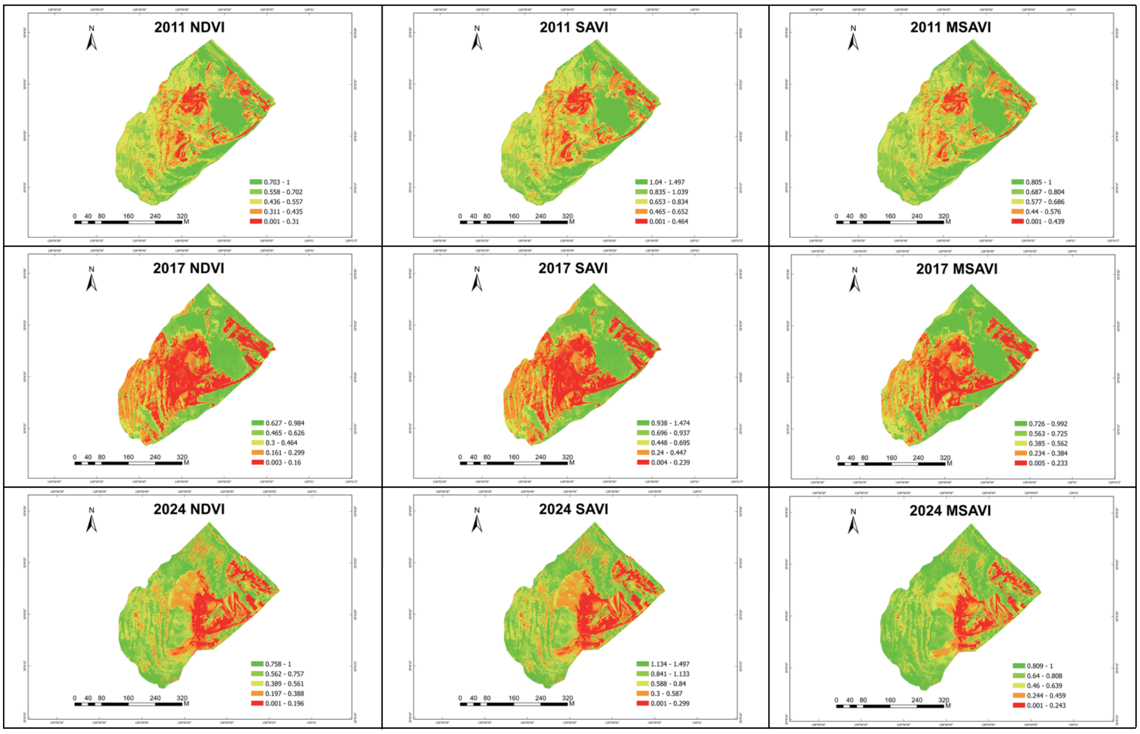


Fig. 8. (Color online) Vegetation index analysis.

3.4 Ecological restoration measures in response to changes in vegetation environment

Customized ecological restoration plans tailored to the conditions of areas A, B, and C based on changes in vegetation index are required. Area A is a region where restoration is in progress, and additional restored vegetation and soil improvement work are essential. Therefore, it is necessary to plant species suitable for the area and set long-term ecosystem restoration goals. For example, by first selecting drought-resistant and cold-resistant species, the survival rate in the initial stages of restoration can be increased.

Area B is a region that has undergone severe damage due to past development, requiring more intensive restoration efforts. It is necessary to plant not only trees but also a combination of shrubs and herbs to ensure ecological stability in the initial stages of restoration.

Table 7
Average *NDVI*, *SAVI*, and *MSAVI*.

Year	Vegetation index	Average vegetation index for each zone						
2011	*NDVI*	8	9	14	15	16	...	167
2011	*NDVI*	0.5976	0.6051	0.5640	0.6149	0.5459	...	0.6245
2011	*SAVI*	8	9	14	15	16	...	167
2011	*SAVI*	0.8950	0.9063	0.8448	0.9208	0.8176	...	0.9352
2011	*MSAVI*	8	9	14	15	16	...	167
2011	*MSAVI*	0.7378	0.7478	0.72	0.7556	0.6989	...	0.7642
2017	*NDVI*	7	8	13	14	15	...	156
2017	*NDVI*	0.3372	0.3305	0.3196	0.3670	0.3800	...	0.4440
2017	*SAVI*	7	8	13	14	15	...	156
2017	*SAVI*	0.5051	0.4950	0.4787	0.5498	0.5692	...	0.6650
2017	*MSAVI*	7	8	13	14	15	...	156
2017	*MSAVI*	0.4867	0.4714	0.4752	0.5210	0.5187	...	0.6087
2024	*NDVI*	8	9	10	14	15	...	163
2024	*NDVI*	0.7268	0.5935	0.6221	0.5230	0.5911	...	0.6382
2024	*SAVI*	8	9	10	14	15	...	163
2024	*SAVI*	1.0883	0.8889	0.9317	0.7833	0.8852	...	0.9556
2024	*MSAVI*	8	9	10	14	15	...	163
2024	*MSAVI*	0.8288	0.7337	0.7522	0.6697	0.7245	...	0.7526

Table 8
Average for A, B, and C vegetation index zones.

A, B, C zone average	Year	*SAVI*	*MSAVI*	*NDVI*
A	2011	0.831	0.705	0.554
	2017	0.429	0.425	0.287
	2024	0.833	0.697	0.556
B	2011	0.685	0.614	0.457
	2017	0.347	0.343	0.232
	2024	0.557	0.499	0.372
C	2011	0.869	0.714	0.581
	2017	0.738	0.624	0.493
	2024	0.702	0.586	0.468

Area C is relatively well maintained, although it should aim to maintain a healthy ecosystem through long-term management and additional restoration efforts. Monitoring the soil condition and existing vegetation in the area and continuous maintenance will be necessary if needed.

Area A generally underwent development while simultaneously progressing with restoration, and thus, no significant changes were observed at this point. The decline in Areas B and C was primarily attributed to changes in artificial terrain due to development.

On the basis of these customized restoration plans, it will be possible to secure long-term ecosystem health by conducting restoration work tailored to the ecological conditions of each region (A, B, and C). In Table 7, by planting the proposed specific tree species based on the restoration data of each region, sustainable ecosystem restoration can be achieved. Table 9 recommends the most suitable vegetation type for ecological restoration planning in quarries in Busan.

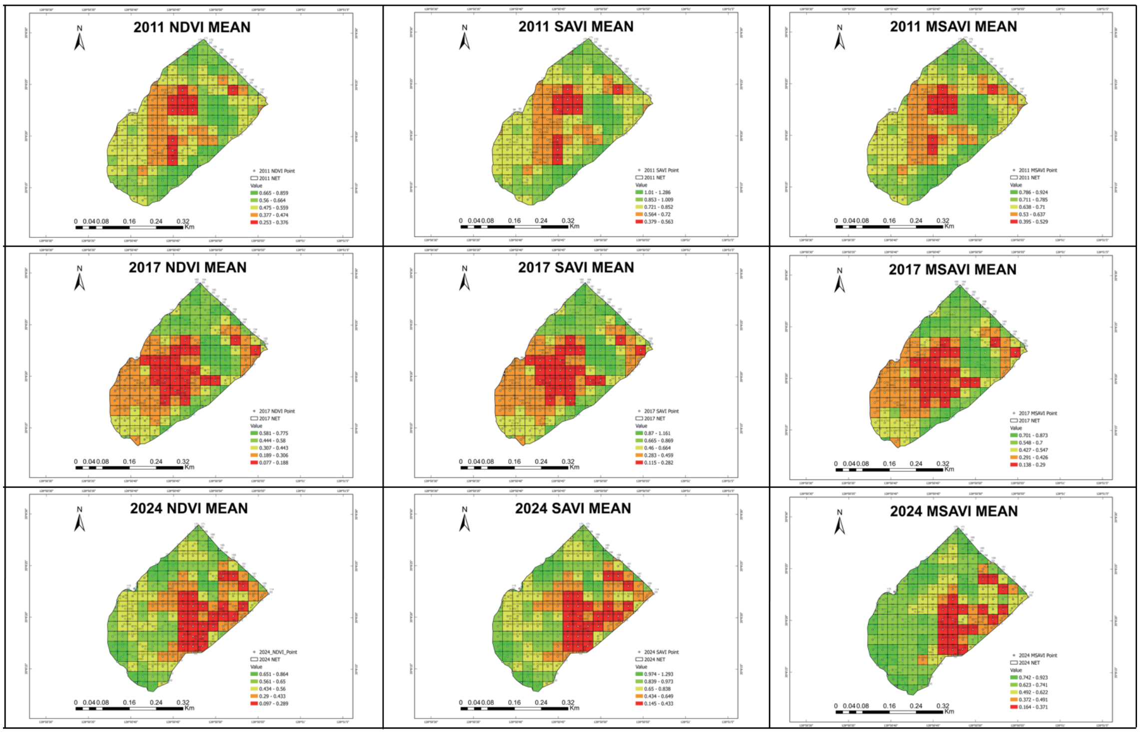


Fig. 9. (Color online) Average vegetation index for the revegetation zone.

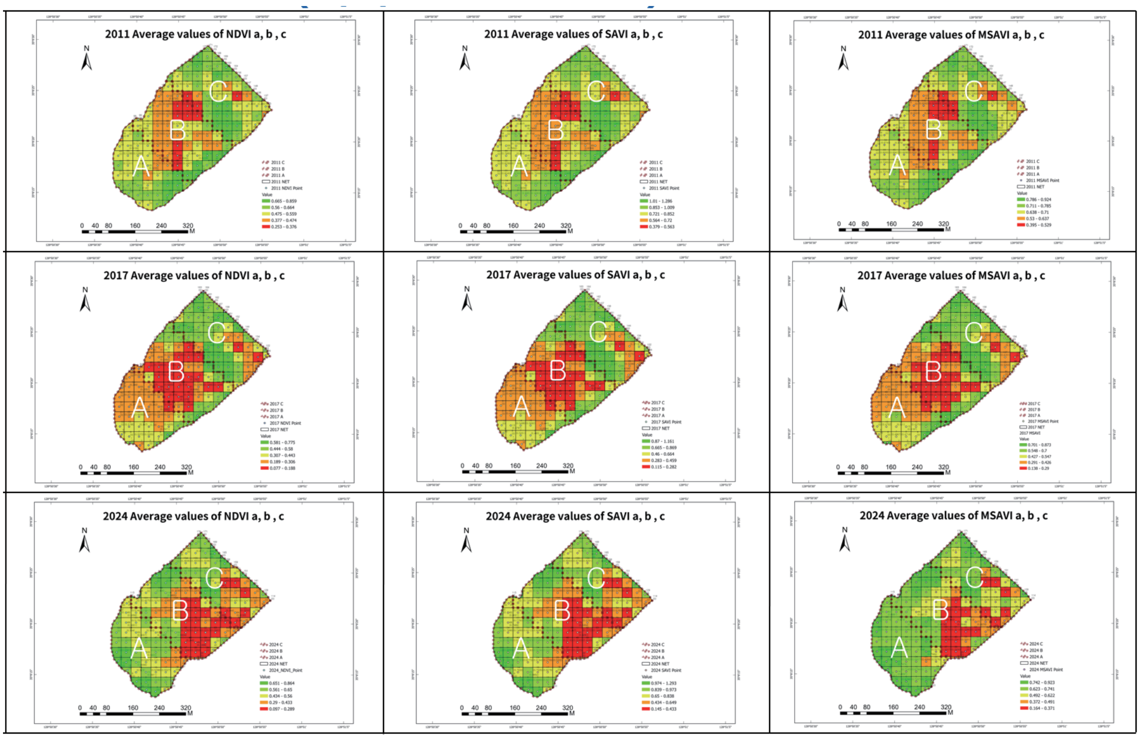


Fig. 10. (Color online) Average vegetation index for each revegetation subzone (A, B, and C).

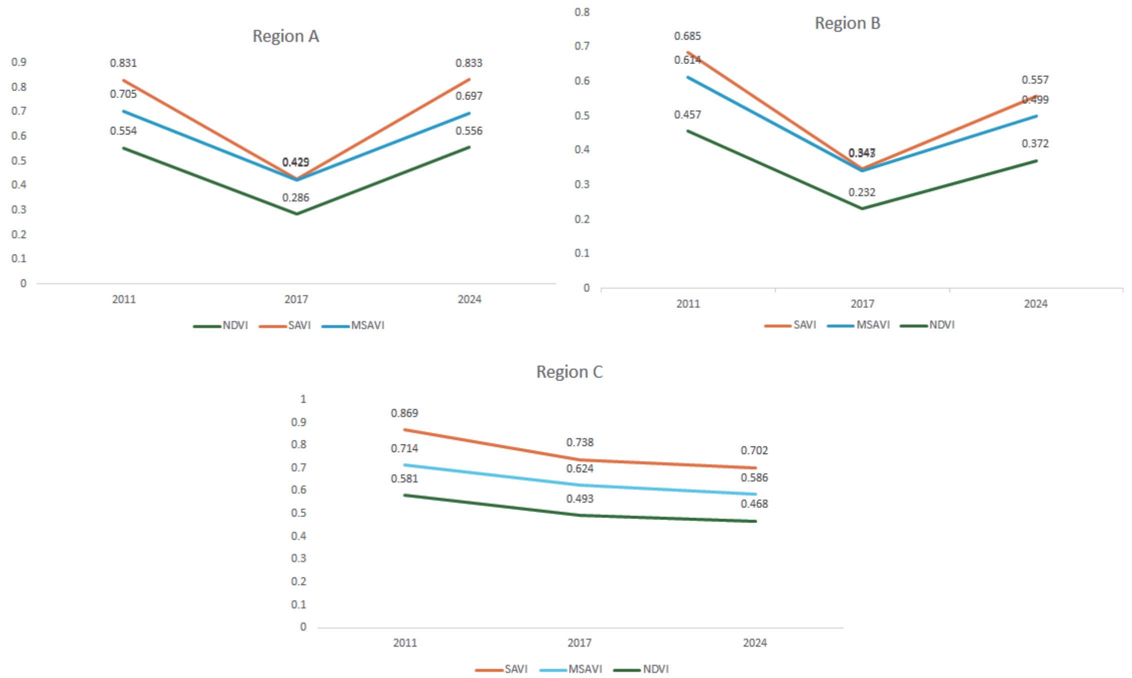


Fig. 11. (Color online) Change trends of regional A, B, and C vegetation indices from 2011, 2017, and 2024.

Table 9
Vegetation type suitable for quarry ecological restoration plan.

Family	Genus	Species
Fagaceae	*Quercus*	*Quercus acutissima*
Pinaceae	*Pinus*	*Pinus densiflora*
Ulmaceae	*Celtis*	*Celtis sinensis*
Sapindaceae	*Acer*	*Acer palmatum*
Ulmaceae	*Zelkova*	*Zelkova serrata*
Ericaceae	*Rhododendron*	*Rhododendron schlippenbachii*
Poaceae	*Miscanthus*	*Miscanthus sinensis*

As a research method for the long-term monitoring of vegetation changes in development areas where deforestation progressed severely, monitoring through remote sensing technology is being used as an effective method. In a previous study,[14] changes in ancient forest areas such as the Sierra Madre were analyzed, identifying issues arising in the restoration areas. Such studies are useful for analyzing vegetation change trends based on satellite data and identifying areas requiring restoration work.

*Basis of recommendation:

(1) Soil stabilization: *Quercus acutissima* and *Pinus densiflora* are necessary for stabilizing areas where the soil is unstable or erosion is a concern, according to vegetation index (*NDVI*,

SAVI, and *MSAVI*) analysis. These species have deep and strong root systems, making them effective in stabilizing the soil and preventing erosion.

(2) Initial vegetation recovery: *Pinus densiflor*a is suitable for initial vegetation recovery owing to their high growth rate. In areas with low vegetation indices, it can be planted first for soil protection and initial vegetation restoration.

(3) Climate change response: *Zelkova serrata* and *Celtis sinensis* exhibit stable growth even in areas where vegetation indices are unstable owing to climate change. They are highly adaptable to various environments and are advantageous for long-term restoration in areas with significant *NDVI* and *SAVI* variabilities due to climate change.

(4) Enhancing biodiversity: *Acer palmatum* is a species that can contribute to enhancing biodiversity. In areas with moderate *SAVI* and *MSAVI* values, it is suitable for improving the landscape and providing habitats for diverse biota, thereby enhancing the resilience of the ecosystem.

(5) Habitat provision and ecological restoration: *Rhododendron schlippenbachii* plays an important role in providing habitats and restoring ecosystems in areas with low *NDVI* values. Evergreen species maintain greenery throughout the four seasons and enhance the biodiversity in areas with low vegetation indices.

(6) Soil protection and restoration: *Miscanthus sinensis* is advantageous for soil protection and initial restoration. In areas with low *NDVI* and *SAVI* values, it quickly establishes itself, stabilizes the soil, maintains biodiversity, and can restore the ecosystem.

(7) Adaptation to extreme environment: Lichen spp. are highly adaptable to extreme environments, making them suitable as the first step for ecological restoration even in areas with low vegetation indices during the initial restoration phase.

4. Conclusions

Here, qualitative and quantitative analyses of changes as well as the analysis of vegetation indices (*NDVI*, *SAVI*, and *MSAVI*) were conducted on the basis of orthophoto images (2000–2024) and multispectral images (2011, 2017, and 2024) to monitor changes in the ecosystem damaged by quarry development activities.

The total area of the quarry and the area of the developed zones showed significant deforestation due to continuous development from 2000 to 2011. Additionally, the developed area also increased. Since 2011, the developed area has not increased further, and some forest restoration has been conducted in the previously developed areas, while the ecological restoration of the recently damaged areas has been observed through video analysis.

On the basis of supervised classification, the study area was divided into five classification categories by land use, and the kappa coefficient of the target image showed a classification accuracy of more than 0.7. After each area was distinguished (A, B, and C) on the basis of the presented classification accuracy, the vegetation index was analyzed at the grid unit level.

Analyses of the vegetation indices (*NDVI*, *SAVI*, and *MSAVI*) in the study area showed that the vegetation index improved after restoration efforts in some regions, although areas (B) exhibiting low vegetation indices were still present. In 2011, the vegetation index was the highest, indicating generally good vegetation vitality, whereas in 2017, the vegetation indices significantly decreased owing to development activities. During this period, the area of soil in poor condition, marked in red, increased, and this phenomenon can potentially lead to soil erosion in the surrounding areas. In 2024, the vegetation index recovered owing to ecological restoration, although it was still not at the level of that in 2011.

By utilizing vegetation indices (*NDVI*, *SAVI*, and *MSAVI*) along with information on the adaptability and growth conditions of various plant species, it is possible to select appropriate vegetation. In particular, selecting plant species that are sensitive to climate change or soil conditions can enhance ecological sustainability and using sensors to monitor ecological changes can help us design more accurate and site-specific restoration plans, especially in areas that are slowly recovering.

Acknowledgments

This research was supported by the Green Restoration Specialized Graduate Program through the Korea Environmental Industry & Technology Institute (KEITI) funded by the Ministry of Environment (MOE).

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