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A regional assessment of ecological environment quality in Thailand special economic zone: Spatial heterogeneous influences and future prediction

Can Trong Nguyen[1,2] | Rungnapa Kaewthongrach[2] | Sittiporn Channumsin[2] | Mitchai Chongcheawchamnan[1] | Thanh-Noi Phan[3] | Damrongrit Niammuad[2]

[1]Faculty of Engineering, Prince of Songkla University (Hatyai campus), Songkhla, Thailand

[2]Space Technology Research Center, Geo-Informatics and Space Technology Development Agency (GISTDA), Chonburi, Thailand

[3]Department of Geography, Ludwig-Maximilians University of Munich, Munich, Germany

Correspondence
Can Trong Nguyen, Faculty of Engineering, Prince of Songkla University (Hatyai campus), Songkhla 90110, Thailand.
Email: trongcan.ng@gmail.com

Rungnapa Kaewthongrach, Space Technology Research Center, Geo-Informatics and Space Technology Development Agency (GISTDA), Chonburi, Thailand.
Email: rungnapa.kae@gistda.or.th

Abstract

"Eastern Economic Corridor" is a development plan under the Thailand 4.0 scheme to revitalize the economy. However, it has influenced the environment through numerous infrastructural and industrial projects. The ecological environment is the most fragile component since it is susceptible to land use, land cover changes (LULCC) and rapid development. Meanwhile, there is currently a lack of comprehensive studies on spatial heterogeneity and future simulation of ecological environment quality (EEQ). Therefore, this study aims to analyze changes in EEQ and controlling factors and to predict near-future EEQ by adopting an integrated approach of remote sensing and spatial analyses. It revealed that the regional EEQ has considerably fluctuated in the period 2013–2021. The dynamic areas, accounting for nearly half of the area, include ecologically degraded areas in coastal urban and surrounding areas and ecologically improved areas in the eastern forest and perennial plantations. Chonburi is the most vulnerable province due to its long coast with extensive urban infrastructures and industrial estates. These changes are an integrated consequence of natural and socioeconomic impacts. Particularly, LULCC, infrastructural projects, and climate are the most crucial contributors since they directly regulate the functions of the ecological environment, which will amplify the future changes of EEQ reflected via the near-future prediction. This research identified key controlling factors and spatial heterogeneities that are useful for policymakers and local authorities to have appropriate local-oriented plans for each area relevant to their uniqueness. Besides, regional plans should be also considered along with regional concerns such as LULCC, crop structures, water management, and green infrastructure, as well as legal interventions to promote sustainable development in this special economic zone.

KEYWORDS
eastern economic corridor, ecological environment, future prediction, land use and land cover changes, spatial heterogeneity, special economic zone, sustainable development

1 | INTRODUCTION

"Eastern economic corridor" (EEC) is a special economic zone in eastern Thailand to stimulate the economy through high-value-added industries (Bhrammanachote, 2019; EECO, 2018; Niyomsilp et al., 2020). It has attracted vast international and private investments in export-oriented products and heavy industry (Ngampramuan & Piboonsate, 2021). The development of the EEC has markedly improved regional development in terms of economy, gross domestic product (GDP), and poverty alleviation (Hutasavi & Chen, 2022). The average income in this region exceeds that in Bangkok and becomes the region with the highest income in Thailand (Tontisirin & Anantsuksomsri, 2021). However, this project also poses various challenges, such as incentive investment policies, synchronous and connectible infrastructures, job opportunities and benefits for local people, and environmental protection strategies for sustainable development toward environmentally friendly export products (Cheevapattananuwong et al., 2020; Lunsamrong & Tippichai, 2022; Nguyen et al., 2021; Tipayalai, 2020).

The rapid and intensive development forces this region into a context of considerable urban agglomeration, land use and land use changes (LULCC), and environmental degradation (Boonyanam & Bejranonda, 2022; Diep et al., 2022; Mekparyup & Saithanu, 2020; Thongphunchung et al., 2022). The region has seen a more prominent urbanization in coastal areas during 2007–2016, and this trend will continue in the future at a rate of 2.40% per year (Tontisirin & Anantsuksomsri, 2021). The urban agglomeration and industrial development have induced several environmental problems from vegetation loss, to biodiversity reduction, air pollution, and harmful chemicals in atmosphere, water, and even food chains (Boonkaewwan et al., 2021; Boonyanam & Bejranonda, 2021; Saetang, 2022; Thongphunchung et al., 2022; Wongsa et al., 2020). These adverse impacts ultimately affect the health of residents, workers, and the sustainable development of the region.

Ecological environment is a key approach in nature-based solutions (NbS), which provides cost-effective and co-benefit interventions through biodiversity conservation, seamless ecosystem services (e.g., air purification, pollutant retention, noise, and temperature reduction), and cultural and aesthetic values. A healthy and diverse ecological environment is crucial for regional development to address environmental challenges, promote sustainability, and ensure human well-being. Previous studies indicated that the natural ecosystems (i.e., paddy fields, horticulture, and forest) in the EEC have experienced a reduction in both area and economic values (Boonyanam & Bejranonda, 2021, 2022; Tontisirin & Anantsuksomsri, 2021). If this trend continues in the future, it will be challenging to balance the tradeoffs between urban-industrial agglomeration and nature losses, especially under a high demand on land budget, increasingly intensive production, high water demand, and severity of drought and climate change (Mon et al., 2022; Nitivattananon & Srinonil, 2019; Promping & Tingsanchali, 2021; Samanmit et al., 2022; Wongsa et al., 2020). Therefore, monitoring and evaluating the ecological environment quality (EEQ) become even more important to serve as a reference for planning and environmental protection for long-term development. Particularly in the dynamic context of regional development, there is currently a dearth of comprehensive studies addressing the regional environment and EEQ of this region.

Remote sensing facilitates the monitoring of EEQ by observing individual components and indicators of ecosystems, such as vegetation, moisture, desertification, and surface energy balance (Li et al., 2017; Song et al., 2020; Wang et al., 2016; Xu, Li, & Li, 2021). It should be noted that an ecosystem encompasses many components that complicatedly interact with each other in a system. Therefore, assessment using a single indicator cannot adequately reflect the ecological environment conditions (Yuan et al., 2021). Remote sensing-based ecological index (RSEI) was proposed to include the principal components of an ecological environment in order to quantify its quality (Hu & Xu, 2018). The RSEI is able to monitor the EEQ under various conditions, such as urban agglomeration, LULCC, land consolidation, mining activities, and geohazards (Airiken et al., 2022; Nie et al., 2021; Shan et al., 2019; Xu, Zhao, et al., 2021; Yan et al., 2021; Zhao et al., 2021). The EEQ depends on disparate factors at different extents, such as climate, terrain, soil properties, landscape patterns, and socioeconomic and anthropogenic elements (Geng et al., 2022; Tang et al., 2022; Wang, Ding, et al., 2022; Zhang, Feng, et al., 2022; Zhang, She, et al., 2022). However, the impacts of a certain factor on the EEQ in different regions and subregions may not be the same. For example, the influence of topographic features on EEQ in plains and mountainous areas can be contradictory.

The current approaches to analyzing EEQ (e.g., Pearson correlation, linear regression, and geodetection) may not adequately depict the spatial heterogeneity effects leading to underestimation, particularly over a large area (Geng et al., 2022; Pan et al., 2022; Tang et al., 2022). Geographically weighted regression (GWR) can take spatial heterogeneity into account to better reveal the relationship variations and local influence mechanisms compared to overall regression models (Wang, Wang, & Li, 2019; Zhi et al., 2020). The previous studies frequently analyze controlling factors of RSEI for each individual year (Sun et al., 2020; Zhang, She, et al., 2022). It would be more comprehensive to consider the environmental dynamics for the entire period to know how these factors influence long-term progress rather than individual contributions. Moreover, future simulation of EEQ is critical for environmental planning to anticipate potential challenges, minimize negative impacts, better manage resources, and promote sustainable development. Attempts to predict EEQ have been made based on impervious surfaces and population distribution (Xu et al., 2018). It should be noted that EEQ is controlled by a wide range of aspects. Some of them (e.g., climatic factors, LULUC) are even more important that should be involved to get more accurate future prediction of EEQ.

This research therefore aimed to investigate the changes in EEQ dynamics and the key factors driving the transitions following the regional reinvestment privileges implemented in the mid-2010s, and how its future trajectory will be in the coming years. We examined the EEQ dynamics and controlling factors for the whole period instead of individual years, as well as, scrutinize the spatial heterogeneities to reveal local environmental hindrances. We strived to simulate the future EEQ more comprehensively by including more related predictors compared to the previous model. Simultaneously, this study proposed a conventional clustering method based on degradation and improvement proportion to robustly evaluate environmental problems to determine the priority of vulnerable regions. The research findings are expected to be a useful reference for future regional planning and to suggest an assessment framework for the regional EEQ.

2 | METHODOLOGY

2.1 | Study areas

The EEC covers three eastern provinces (Chachoengsao, Chonburi, and Rayong) with approximate areas of 13,226 km^2 (Figure 1). Its topography is characterized by coastal plains alternating with highlands and low mountains (Aman et al., 2019). The major soil texture is sandy loam and clay loam (according to Thailand Land Development Department), which contributes to the difficulties in water retention. This region is dominated by the tropical humid climate with influences of the monsoons, with average rainfall is about 2085 mm. The winter and summer months (October–April) are considered as regional dry period with water deficit and the highest temperature often exceed 40°C (Aman et al., 2019; Phan & Manomaiphiboon, 2012; Promping & Tingsanchali, 2021).

These provinces are set up to be the strategic region since it is nearby the greater Bangkok metropolitan and the Gulf of Thailand with suitable topography for deep seaport and near to natural gas resources at Map Ta Phut (Rayong). Many industrial estates and logistical infrastructures have been established, such as the deep seaports and industrial estates of Laem Chabang, Sattahip, and Map Ta Phut (Muangpan & Suthiwartnarueput, 2019). Each province has been oriented to develop according to its advantages. For example, Rayong and Chonburi have been positioned to be industrial zones, Chachoengsao has been a hub for high-quality agriculture and aquaculture products. Therefore, the environmental quality and degradation in these territories are expected to be much disparate and even dominated by different driving forces, because they develop in divergent orientations.

2.2 | Data sources

Landsat 8 (OLI/TIRS) level 2 of surface reflectance images were the principal data source for EEQ monitoring as it provides both multispectral and thermal data, related to environmental severities such as drought and water shortage. The images were acquired within the

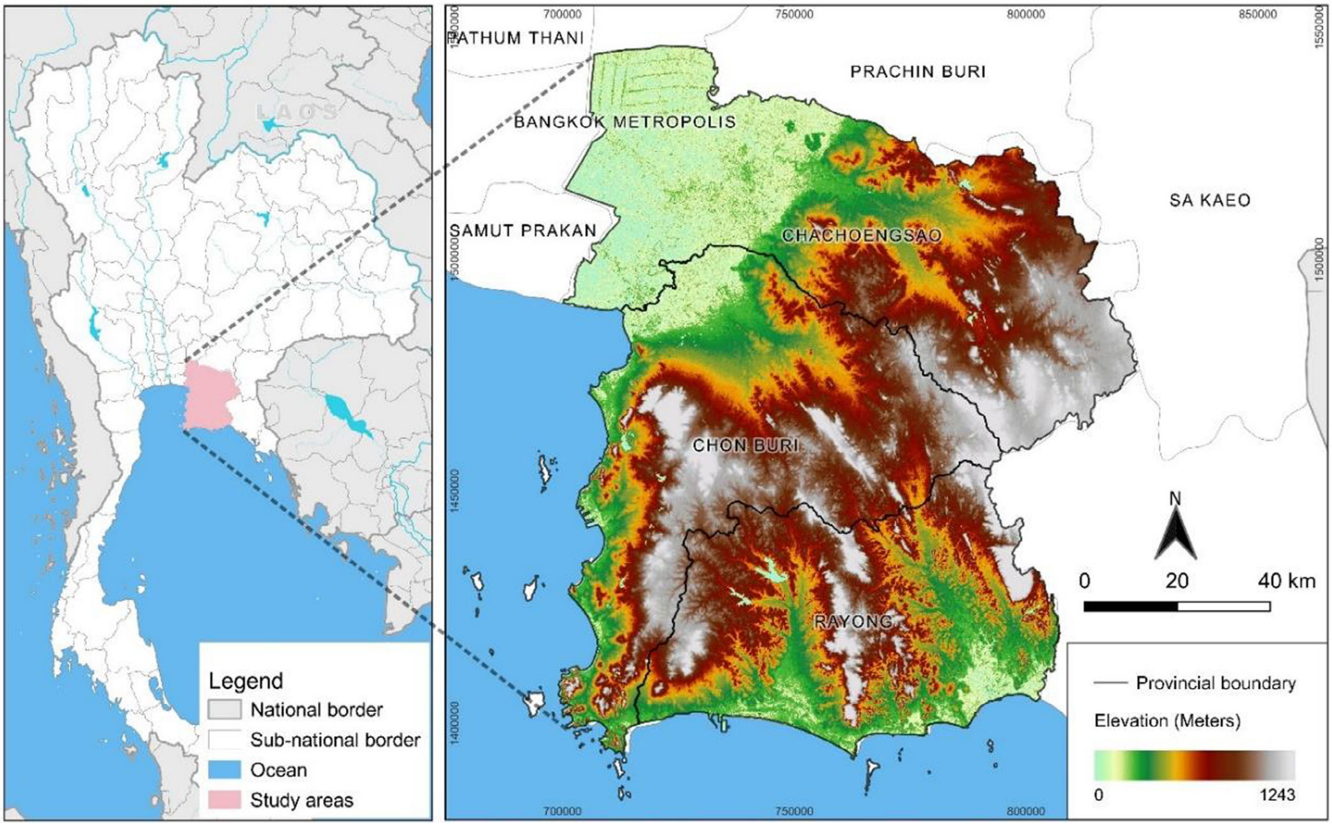

FIGURE 1 Location of the EEC in eastern Thailand and elevation in three provinces of Chachoengsao, Chonburi, and Rayong. [Colour figure can be viewed at wileyonlinelibrary.com]

period of 2013–2021. Specifically, an annual free-cloud composite was generated for each milestone based on cloud quality bitmask. The images were also processed by terrain correction to limit topographic effects due to elevation difference within the EEC. Water surfaces were also removed from the original images to avoid biased weight for the wetness indicator between the large water bodies and other areas (Xiong et al., 2021; Zhang, She, et al., 2022). In this study, water surfaces were masked by the consistent water mask, which is homogeneous water bodies detected by modified normalized difference water index (MNDWI) with a frequency of higher than 80% (Xu, 2006).

Land use and land cover (LUCC), especially the green and vegetation-rich categories, provides a variety of ecosystem services with high EEQ. Therefore, land use and land cover changes (LULCC) are the main artificial causes that substantially affect the EEQ (Airiken et al., 2022). We acquired land use maps in 2013 and 2021 from Thailand Land Development Department (LDD) to quantify and evaluate these impacts. The vector land use maps specify over 40 land use units ranging from forest to agriculture, mixed purposes, urban uses, and water bodies. These maps were then reclassified into six main land cover categories (Table 1) before converting to LULC raster maps at 30-m resolution for conventional comparison with Landsat data.

TABLE 1 Main LULC categories adopted from land use units of the LDD.

Land cover categories	Land use unit (level 2)
Forest and perennial plants	Forest: evergreen forest, deciduous forest, forest plantation, and agroforestry. Perennial plants: orchards, and perennial.
Grassland	Pasture and farmhouse, rangeland, and golf course.
Wetland and water bodies	Aquaculture, aquatic plant, mangrove forest, swamp forest, marsh, and swamp.
Cropland	Paddy fields, field crop, and horticulture.
Construction	Transportation, city, town, village, institutional land, industrial land, and other built-up.
Others	Mine, pit, salt flat, beach, garbage dump, and other miscellaneous land.

The ecological environment is influenced by various natural and anthropogenic agents. We selected the factors included in this research by drawing upon expert knowledge and a comprehensive literature review of empirical studies, ensuring the acquisition of realistic parameters in a cost-effective manner (Gardner et al., 2020; Kuhnert et al., 2010; Martin et al., 2005). This study collected a set of supporting data related to controlling factors (Table 2), which expected to affect the EEQ changes. These controlling factors embrace both natural and socioeconomic aspects to generalize the main drivers for EEQ changes in this region. The natural factors include topographic features, annual precipitation, mean temperature, and distance to major rivers. Topographic features such as elevation and slope can regulate the EEQ through related factors, for example, it is better in higher elevations with fewer disturbances from human activities (Geng et al., 2022; Yan et al., 2021). The topographic features are expected to substantially differentiate the EEQ in the EEC as it is an area with diverse and complex topography (Figure 1). Temperature and precipitation represent climate factors, which greatly influence the ecological systems by affecting water availability, phenology, and ecosystem productivity (Sun et al., 2020; Wang, Ding, et al., 2022). For example, an increase in temperature and decrease in rainfall can lead to high barren land and degradation of EEQ (Bi et al., 2021). Along with natural rainfall, the hydrological systems also play a very essential role in providing water for ecosystems, especially for agricultural landscapes in the EEC. Therefore, we considered accessibility to the main rivers for EEQ.

Anthropogenic impacts embrace human activity inputs through the manners they use and manage landscapes (i.e., LULCC) and infrastructure projects. As a logistics and industrial hub, the EEC is promoted with extensive transportation projects, which imply severe impacts on ecosystems. Therefore, we also involved proximity to towns and transportation systems in the analysis to represent human accessibility and direct impacts on ecosystems and, to some extent, reflect the rapid development in this region compared to others (Nguyen et al., 2021; Lapuz et al., 2021). We also endeavor to include socioeconomic factors in the analyzes to obtain a diversely

TABLE 2 Spatial data acquired for controlling factors analysis.

Data	Extracted variable	Data format	Data source*
Open Street Map	Hydrological system (river), transportation system (road), and town location (town)	Vector shapefile	OSM
DEM (Digital Elevation Model)	Elevation (elv), slope (slope)	Raster/30 m	GISTDA
Globally harmonized nighttime light	Nighttime light density (NTL)	Raster/1000 m	Li et al. (2020), Li and Zhou (2017)
Thailand Population density	Population density (pop)	Raster/1000 m	WorldPop
Historical climate data	Precipitation (prep) and mean temperature (Tmean)	Raster/ ~5000 m	WorldClim

*OSM: Thailand Open Street Map data was downloaded at https://download.geofabrik.de; GISTDA: Geo-Informatics and Space Technology Development Agency; WorldPop: the research program based in the University of Southampton (https://www.worldpop.org); WorldClim: the database of high spatial resolution global weather and climate data (https://www.worldclim.org).

representative set of factors. Population density is a widely adopted variable to reveal the contributions of social aspects to EEQ because urbanization is always associated with population growth and adverse impacts on environment (Cui et al., 2022; Geng et al., 2022).

The economic development, industrial development in the EEC, is one of the biggest levers to deterioration of EEQ and environmental pollution. In previous studies, it has been described by GDP (Gross domestic product) (Geng et al., 2022; Zhang, She, et al., 2022). However, the influence of GDP is relatively modest compared to other factors (Geng et al., 2022; Sun et al., 2020; Yuan et al., 2021). It can be traced back to the fact that most current GDP data are collected and synthesized at the subdistrict administrative level, so it is difficult to capture the local dynamics of EEQ changes. Meanwhile, nighttime light (NTL) can reflect economically active agents, population distribution, and density of urban socioeconomic activity (Cai et al., 2021). In the context of lacking direct economic values, NTL is proposed to be an appropriate variable to characterize the economic development, industrial growth, and poverty alleviation that even sufficiently reflects socioeconomic development specifically for the EEC (Hutasavi & Chen, 2022). Experts in ecology and artificial light at night (ALAN) have also confirmed the negative impacts of nighttime light pollution on the environment and ecology (i.e., from cell to ecosystems) because of the disrupted natural illumination cycle (Barentine et al., 2021; Gaston et al., 2013; Wang, Lv, et al., 2022). NTL is widely adopted in EEQ studies, and it is even a critical input in the coupling coordination degree (CCD) model to explore the coupling and coordination between ecological environment and development instead of GDP or other economic variables (Cai et al., 2021; Zheng et al., 2020). Therefore, we used the Harmonization of DMSP (Defense Meteorological Satellite Program) and VIIRS (Visible Infrared Imaging Radiometer Suite) nighttime light dataset to represent for socioeconomic aspect in our analyses. Only DN values of greater than 7.0 on NTL data were retained to limit uncertainty (Li et al., 2020; Li & Zhou, 2017).

2.3 | Remote sensing ecological index (RSEI)

The EEQ is characterized by four components including greenness, dryness, wetness, and heat (Hu & Xu, 2018). First, vegetation coverage representing greenness was detected by normalized difference vegetation index (NDVI) (Tucker, 1979). Dryness is represented by sealed impervious surfaces and bare soils, which are frequently dry due to lacking vegetation coverage. Normalized difference built-up and bare soil index (NDBSI) was introduced to enhance bare soil in peri-urban by adding soil index (SI) into the index-based built-up index (IBI) (Hu & Xu, 2018; Xu, 2008). The wetness component of Tasseled Cap's components is adopted to reflect land surface moisture (LSM), which is obtained by an empirical formula for Landsat-8 data (Hu & Xu, 2018). Land surface temperature (LST) represents the main heat fluxes in the environment, which is estimated from thermal infrared band by converting measured DN values to at-satellite spectral radiance and brightness temperature (T_B). The brightness temperature is then adjusted using NDVI-based land emissivity (ε) to obtain LST. The detailed steps to obtain LST from Landsat-8 image can be found in corresponding references (Ermida et al., 2020; Nguyen et al., 2022; Van De Griend & Owe, 1993).

A normalization procedure is applied to each spectral Index to solve the problems of uneven scale between indices and transform them into unitless quantities. Then, principal component analysis (PCA) is conducted on the four normalized indices to construct RSEI based upon only the first component (PC1—Equation 1) as it always presents higher than two-third of overall variance compared to other components (Xu et al., 2022).

$$\mathrm{RSEI} = \mathrm{PC1}[f(\mathrm{NDVI}, \mathrm{NDBSI}, \mathrm{LSM}, \mathrm{LST})] \tag{1}$$

Subsequently, each annual RSEI image was normalized between 0 and 1 for peer comparison between different periods. Higher the normalized RSEI values, better the EEQ is. The continuous RSEI images were divided into five equal intervals corresponding to five EEQ classes. Specifically, they include poor (0.0–0.2), fair (0.2–0.4), moderate (0.4–0.6), good (0.6–0.8), and excellent (0.8–1.0), which reflect the general EEQ, vegetation coverage, biodiversity, temperature, and wetness (Hu & Xu, 2018; Tang et al., 2022; Zhang, She, et al., 2022).

2.4 | Detection of EEQ changes

Changes in EEQ were analyzed by reference year base and trend detection. The year of 2013 was considered the reference year basis as it marks the beginning of the period. Given the gradual decline in the quality of the EEQ over time, comparing subsequent years with the first year helps to minimize differences between periods and facilitate comparisons. The RSEI values in later years were in turn compared to the values at reference year to detect the major EEQ dynamics. More explicitly, the difference in RSEI between the considered year $\left(\mathrm{RSEI}_i^y\right)$ and the reference year $\left(\mathrm{RSEI}_i^{ref}\right)$ at pixel i is calculated by Equation 2.1. The threshold value of ±0.1 was proposed to identify the EEQ dynamics of significant degradation (2.2), no significant change (2.3), and significant improvement (2.4) (Wang, Ding, et al., 2022; Xu et al., 2019).

$$\Delta \mathrm{RSEI}_i^y = \mathrm{RSEI}_i^y - \mathrm{RSEI}_i^{ref} \tag{2.1}$$

$$\begin{cases} \Delta \mathrm{RSEI}_i^y \leq -0.1 & (2.2) \\ -0.1 < \Delta \mathrm{RSEI}_i^y < 0.1 & (2.3) \\ \Delta \mathrm{RSEI}_i^y \geq 0.1 & (2.4) \end{cases}$$

With respect to trend analysis, the RSEI time series was analyzed by Mann–Kendall test and Thiel-Sen slope to quantify its monotonic trend over years. The positive slope represents ecological improvement, while the negative slope shows the ecological degradation (Yan et al., 2021). These two analyses were considered at pixel based.

2.5 | Determine controlling factors of ecological environment changes

2.5.1 | Data preparation

This study assessed the influences of controlling factors on the EEQ changes throughout the period instead of individual assessments for each year. RSEI trend slope (dependent variable) and 11 independent variables were consistently converted to raster with a pixel size of 1000 m regardless of whether the original data format was vector or raster. It should be noted that the location-based elements from the OSM (e.g., transportation, major rivers, and towns) were first utilized to estimate Euclidean distance to transform from vector to raster format before using their values for further analysis.

In essence, the independent variables can be separated into dynamic and static factors. The physical factors (e.g., hydrological systems, transportation, distance to towns, and topography) are relatively stable over time. We directly extracted these values for the analysis. In contrast, the remaining elements of NTL, population density, temperature, and precipitation vary over years depending on location specific. The time series of these dynamic elements were subjected to trend detection analysis as general trend synthesis for the whole period before taking them into the controlling factor analysis instead of using their values directly.

Although the LULC maps have been reclassified into six categories, assessing each LULC category separately is challenging because of the increase in the number of variables and the dispersion of their influences. The impacts of LULCC are quantified by a composite index of BAI (biological abundance index), which takes all land use types to indirectly reflect the abundance of ecological in a certain area (Tang et al., 2022; Wang, Jiang, et al., 2019). The higher the BAI values, the better the ecological environment is. In other words, BAI gives prominence to natural ecologies such as forest and wetland. Besides, this study considered the contributions of urban expansion on EEQ, which is represented by urban density estimated from LULC maps.

2.5.2 | Controlling factor detection

Firstly, all potential factors were analyzed their interrelationships by Pearson correlation test before significant variables were identified by multiple linear regression model. Bayesian Model Average (BMA) was applied to reveal all possible models with different sets of controlling variables instead of a single model as is often found by stepwise regression (Tran et al., 2018; Zhao et al., 2013). The importance of explanatory variables was identified by variable importance analysis, which reflects the contribution of each individual variable to the model (Luo et al., 2022). The higher the importance level, the more important the explanatory variable is.

The global regression model facilitates the detection of the general effect of each variable on EEQ changes, whether it is favorable or adverse. However, the effects of each factor may be substantially different among subregions within the EEC. For example, topographical effects on the EEQ may be opposite between highland and low-flat areas. Therefore, we applied geographic weighted regression (GWR) to analyze spatial heterogeneity and local effect of each variable to RSEI changes at commune/village level (Chen et al., 2022). Local regression models were evaluated by absolute variable coefficient values. The higher the absolute variable coefficient, the stronger the impact of the variable is.

2.6 | Simulation of ecological environmental changes in near future

Foremost, the LULC map in 2029 was predicted using Patch-generating Land Use Simulation (PLUS) Model (Liang et al., 2021). Specifically, the 2013 LULC map was taken as a reference year to simulate the LULC in 2021. The performance of model was then evaluated by comparing the simulated LULC map in 2021 to the actual map. The overall accuracy of the LULC simulation achieved a confidence value of 80%. The simulated LULC map in 2029 was adopted to estimate BAI values and urban density in the corresponding year for RSEI estimation.

Subsequently, the model with the highest probability from BMA model selection (i.e., the first model in Section 2.5.2) was applied to quantify RSEI values in 2029. The static variables were directly adopted, while the dynamic variables should be replaced (Figure 6). Future precipitation and mean temperature were acquired from future climate data from CMIP6 scenarios. Besides, NLT is also an important dynamic variable in the selected model, however, there is no future prediction for this variable at present. Therefore, this study proposed a simple logarithm regression to get assumed values for NTL.

The simulated RSEI map was also reclassified into five EEQ classes and compared to the reference year to detect the EEQ trend in the near future. The EEQ changes were then analyzed at district level to detect the vulnerable hotspot of EEQ changes in the near future by a conventional clustering method based on mean values of degradation and improvement proportion. It was also applied for land use, land cover categories to study the environmental vulnerability of different land cover classes. This clustering method splits a group of districts (or land cover) into four main clusters with unique EEQ properties, which is meaningful for regional and environmental planning.

3 | RESULTS

3.1 | EEQ from 2013 to 2021

Ecological environment quality in the EEC was quantified by RSEI, which was classified into five classes corresponding to poor quality to excellent EEQ (Figure 2). In general, the poor EEQ mainly distributes along the coastal urban areas of western and southern parts. In Chachoengsao, the poor EEQ mostly centralizes in middle of the province.

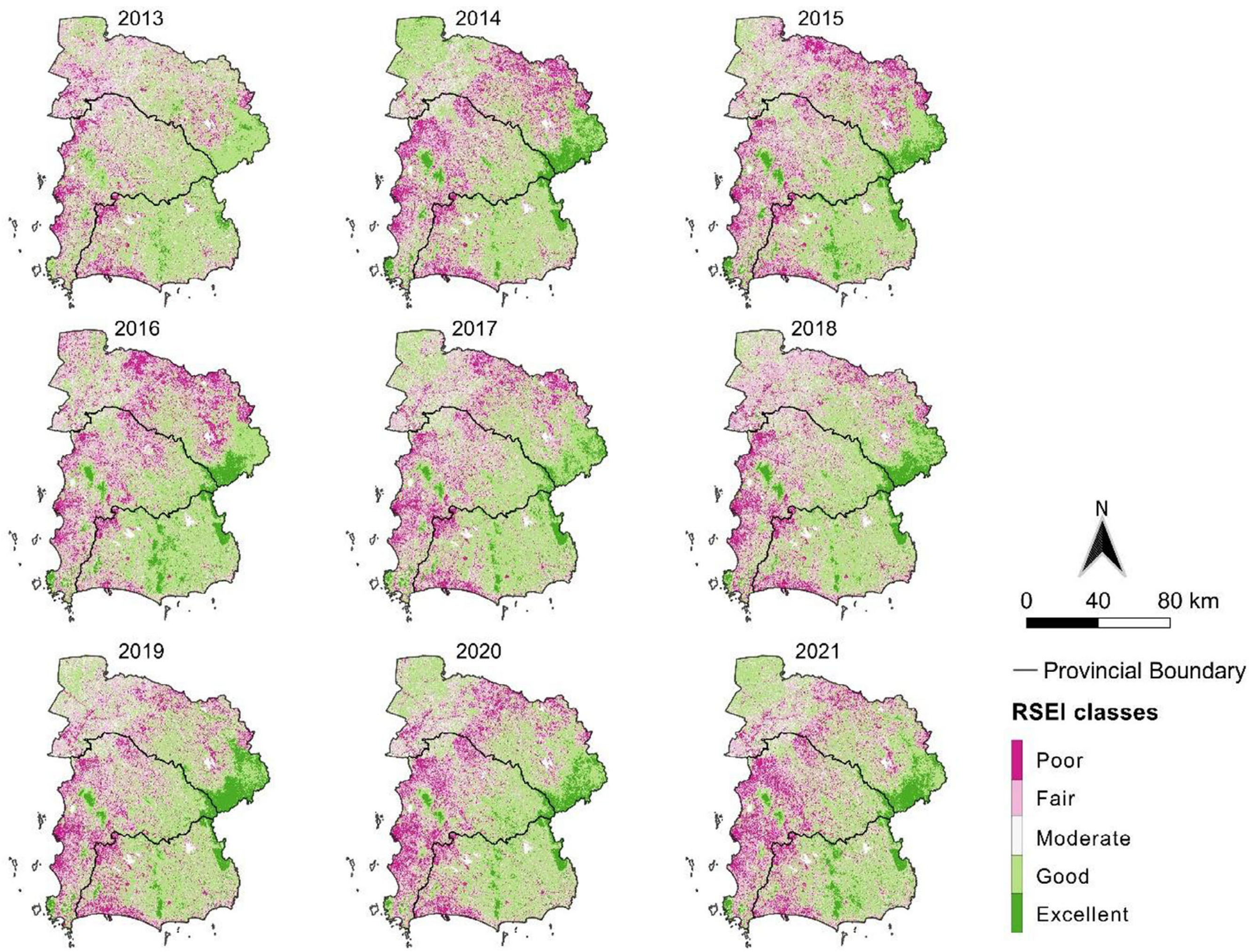

FIGURE 2 Spatial distribution of five RSEI classes ranging from poor to excellent in the EEC provinces from 2013 to 2021. Chachoengsao, Chonburi, and Rayong are the top, middle, and down provinces. [Colour figure can be viewed at wileyonlinelibrary.com]

In contrast, the better EEQ is located on the west side on higher terrain with extensive forest and evergreen vegetation.

Quantitatively, majority of the area is dominated by good and excellent EEQ (Table 3). The good (0.6–0.8) and fair (0.2–0.4) EEQ are the two largest areas, accounting for 44.1%–51.0% and 19.9%–22.3%, respectively. These areas were usually found in the adjacent regions between moderate and poor eco-environment.

3.2 | Spatiotemporal changes in ecological environment

The development of the EEC has been rapidly revived due to resurgent economic policies since the middle of the last decade. There are considerable changes in EEQ observed by trends of RSEI alongside this development. Although there is an insignificant change over the years for RSEI values of the entire EEC ($p > 0.1$), the RSEI fluctuations are more prominent for each individual province (Figure 3). The EEQ in Rayong province is better than the regional, and it improves over time. Although the EEQ in Chachoengsao is not significantly different compared to the regional average, it has positive signs of improvement, especially in the end of the period. On the contrary, the EEQ in Chonburi has encountered a significant decrease in the last 3 years ($p < 0.05$).

Spatial distribution of EEQ changes was identified by comparing with RSEI values in 2013 (Figure 4). About half of the EEC area has a relatively stable EEQ over the period, yet this proportion tends to significantly narrow from 55.5% to 47.5% in 2014 and 2021 ($p < 0.05$), respectively. It is apparent that the deterioration of EEQ extensively distributed along the northeast-southwest corridor in Chonburi and Chachoengsao provinces, especially highly concentrated in the central north of Chachoengsao province (Figure 4a). In 2013, about 22.2% of the total area encountered environmental degradation, and it dramatically increased to 25.7% in 2021 ($p \approx 0.03$), corresponding to an area of 3320 km^2. However, it has also seen ecological amelioration in west side of Chachoengsao province, and east of the EEC on the highland areas. It rose significantly from 22.4% (2014) to 26.8% (2021) with $p \approx 0.02$. It implies that, in parallel with the environmental deterioration, an area of about 3457 km^2 has a positive change.

TABLE 3 Proportion of five EEQ classes based on RSEI during the period of 2013–2021 (Unit: Percent).

EEQ classes	2013	2014	2015	2016	2017	2018	2019	2020	2021
Poor (0.0–0.2)	9.5	13.2	12.3	13	11.8	10.8	12.4	13.4	13.3
Fair (0.2–0.4)	20.9	20.4	22.3	21.9	20.9	21.3	21	19.9	20.4
Moderate (0.4–0.6)	16.5	13	14.1	13.5	14.4	15.3	14.7	13	13.1
Good (0.6–0.8)	51	46.4	44.6	44.6	47.9	46.2	44.1	47.5	46
Excellent (0.8–1.0)	2.2	7.1	6.7	7	5.1	6.4	7.9	6.2	7.2

Note: The shades reflect proportion difference between EEQ classes.

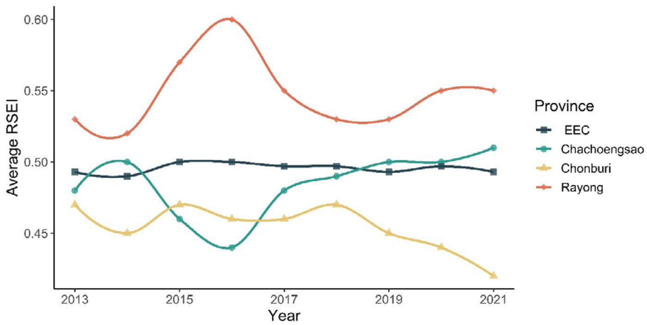

FIGURE 3 Variations of average RSEI in the EEC and three provinces. [Colour figure can be viewed at wileyonlinelibrary.com]

3.3 | Controlling factors of ecological environment changes

The trend of RSEI over the period was quantified by trend detection of the RSEI time series (Figure 5). The RSEI trend is relatively consistent with the individual changes in each period in the previous section. It reflects the general trend in EEQ changes, in which high improvement is in the east Chachoengsao and high degradation along the coastal urban areas, especially in Chonburi. More explicitly, the significant change areas with *p-value* approaching 0 distributed in two margins of the region (Figure 5b).

3.3.1 | Principal controlling factors of RSEI changes

The static indicators and dynamic factors were considered their contribution to the EEQ trend. The BMA model selection suggests four highest probability models (Figure 6a). All the selected variables achieve free-multicollinearity with VIF <4 (Variable Inflation Factors). Seven variables consistently control the EEQ trend in the EEC, including distance to hydrological system (RIVER), distance to major transportation (ROAD), topography (SLOPE), land use/cover (BAI), socioeconomic representative (NTL), precipitation (PREP), and mean temperature (TMEAN). Besides, distance to town and urban density also regulate EEQ in two out of four models. Specifically, distance to road, distance to town, slope, BAI, urban density, and temperature are positively proportional to RSEI trend. Distance to river, NTL, and precipitation are inversely proportional to RSEI trend. On the contrary, population density and elevation have no direct contribution to RSEI trend. The first model reflects approximately 64.2% of the dataset, it is therefore the best model compared to others.

Among the static and dynamic indicators, the most important factors regulate the EEQ trend are land use/cover (BAI), precipitation, distance to transportation, mean temperature, and distance to river, which importance level is always higher than 20% (Figure 6b). It is worthy to consider that LULCC is the most critical element influencing EEQ changes.

3.3.2 | Local heterogeneity of controlling factors

The global linear regression provides a general mechanism of RSEI changes over the period of the entire EEC. Every indicator apparently varies spatially across the region, and it ultimately affects the relationship between RSEI and explanatory variables. Therefore, GWR model for each variable was adopted to explore specific location where each element meaningfully stimulates or limits the EEQ through spatial clusters (Figure 7). Particular attention should be paid to areas that exhibit high R-squared values for both positive and negative effects, as identified by the right side of the bivariate scatter plot displaying dark-pink and dark-green hues. These regions indicate a crucial influence from the corresponding element.

More explicitly, increased precipitation dramatically encourages environmental improvement in two isolated regions in the central north of Chachoengsao and along the shared boundary of Chonburi and Rayong. Changes in average temperature are meaningful in the southwest-northeast corridor of the EEC. Elevation and slope especially dominate EEQ in two parts, where high elevation and slope intend to boost the EEQ, including the southernmost cliff of Chonburi and middle terrain of central Chachoengsao and Chonburi. Urban development characterized by built-up and impervious surfaces deteriorates environment extensive areas in the EEC. It is apparent in the coastal city chain, adjacent area in Chonburi, and southeast Chachoengsao. LULCC substantially affects the environment of the entireEEC, especially in coastal areas, central Rayong, and southeast Chachoengsao. Impact patterns of distance to river are relatively similar to terrain, which are symmetrical in relation to southwest-northeast and northwest-southeast corresponding to positive and negative effects, respectively. The patterns of infrastructures such as distance to towns and major roads are also relatively analogous, which strongly positive impacts in Chachoengsao at connecting point with Bangkok's metropolitan and southwest-northeast corridor. Additionally, increasing population density is convinced to impair the environment in major areas of Chachoengsao and the contiguous area of western Chonburi. Whereas socioeconomic development represented

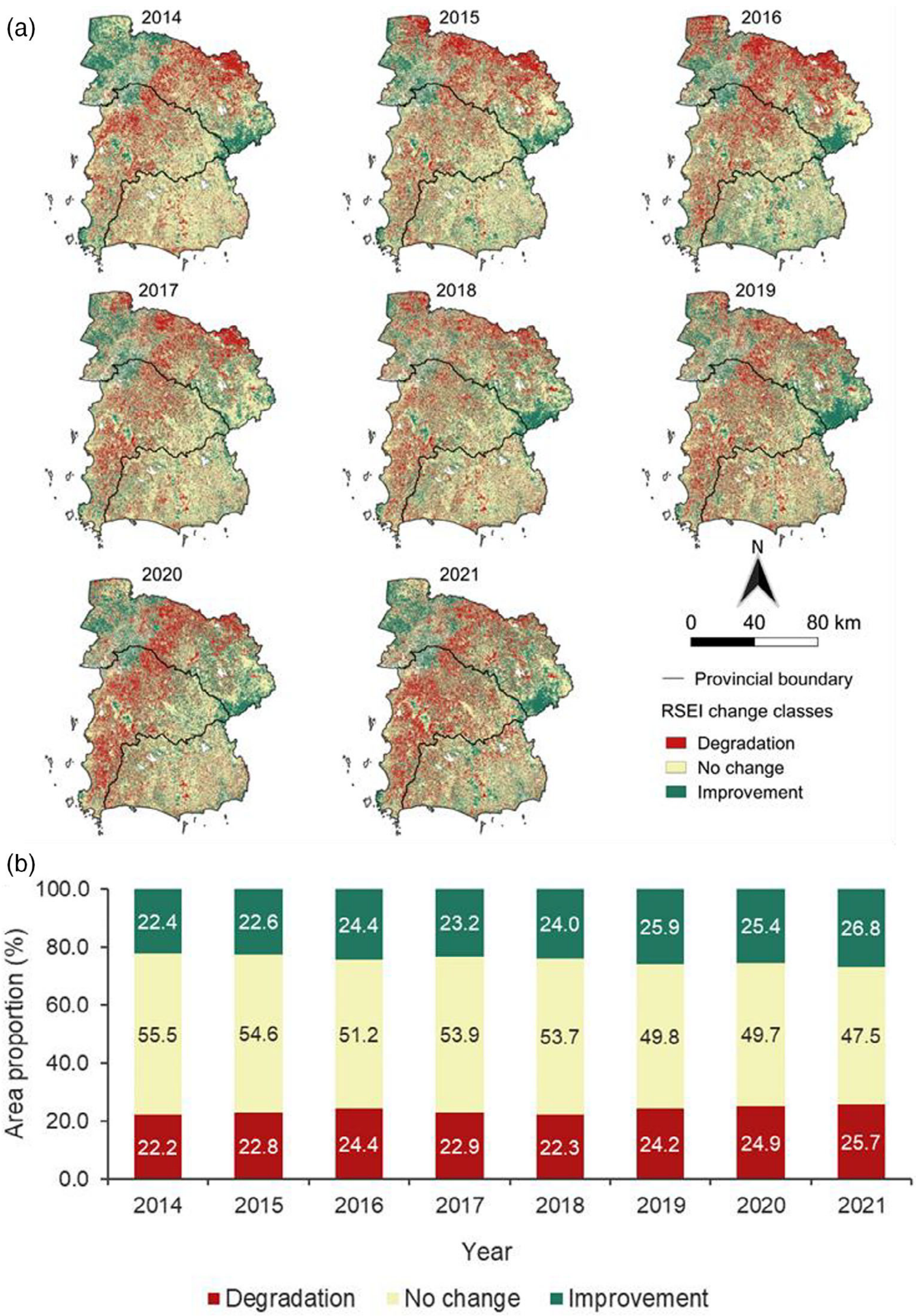

FIGURE 4 (a) Spatial distribution of ecological environment fluctuations of the entire EEC region and (b) corresponding area proportion in three classes of no change, degradation, and improvement. [Colour figure can be viewed at wileyonlinelibrary.com]

by NTL density considerably aggravates ecology in the east and south coastal cities and along the southwest-northeast route.

3.4 | Ecologically vulnerable regions under near-future LULCC

Based on LULC data from 2013 to 2021, this study simulated LULC in 2029, applying the concept of "business as usual" without considerable changes in a short period of time. Subsequently, the simulated LULC data in 2029 was adopted to estimate potential changes in EEQ changes (Figure 8). Under these assumptions, LULC in the EEC will continue to vary in 2029, that is, 28.2% of current areas will be transformed into other LULC categories relevant to 3759 km^2. Specifically, about 24.5% of land cover change area will be converted into grassland. It will be then followed by orchards and perennial gardens (21.3%). Built-up and grassland areas will account for about 20% of each type.

Under this LULCC scenario, it is apparent that BAI values will mostly improve in both west and east sides of Chachoengsao.

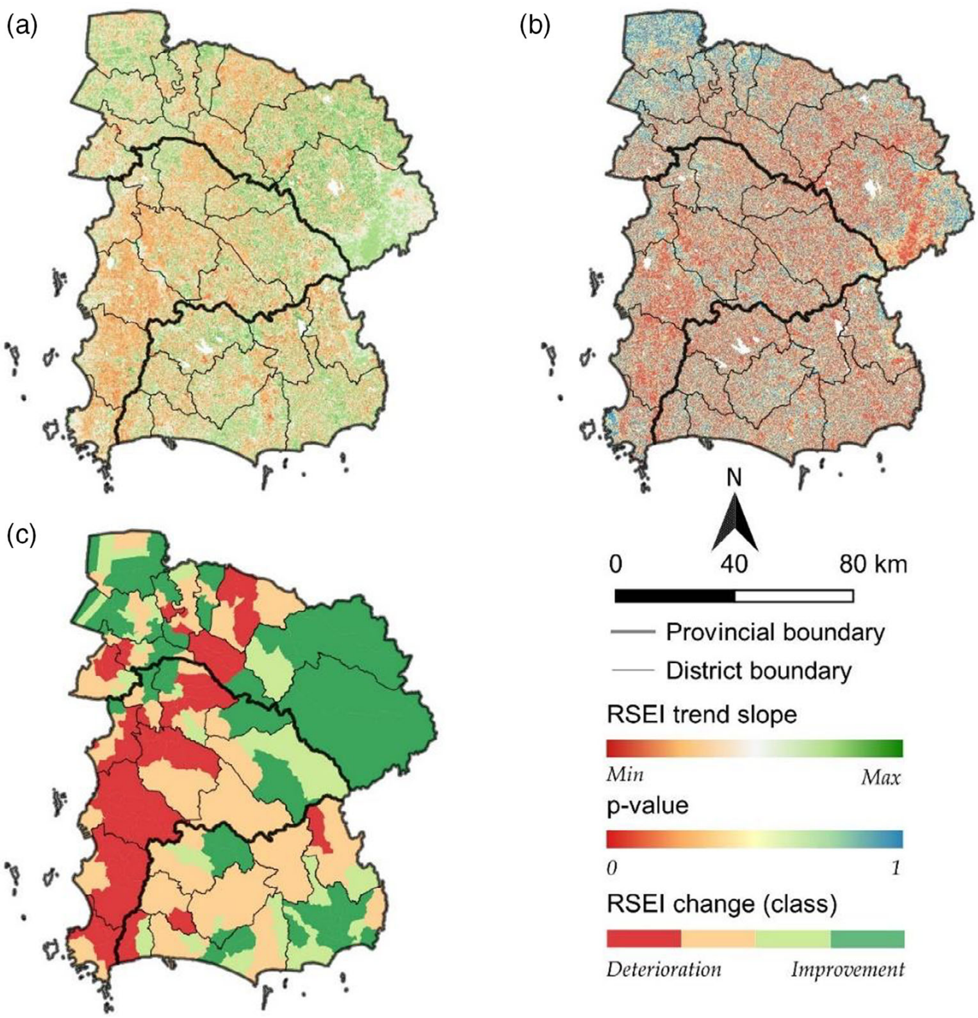

FIGURE 5 (a) RSEI trend analysis over the period, red and orange represent deterioration trend, green is amelioration trend, and white is insignificant change; (b) significance level of trend detection, dark-red and red are statistically significant regions; (c) changing classes of ecological environment, red is significant deterioration and green is significant improvement. [Colour figure can be viewed at wileyonlinelibrary.com]

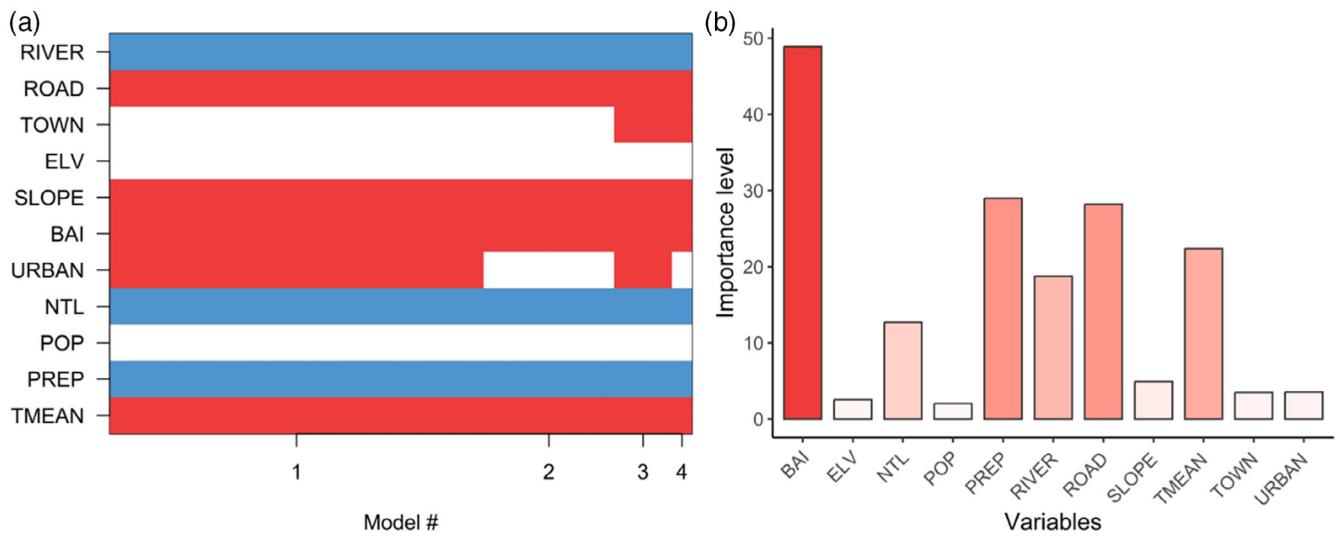

FIGURE 6 (a) Four possible models selected using BMA, red shade is positive variables, blue shade is negative variables, and white is insignificant variables, width of horizontal axis is proportional to model probability; (b) variable importance analysis, shading opacity is proportional to importance level. [Colour figure can be viewed at wileyonlinelibrary.com]

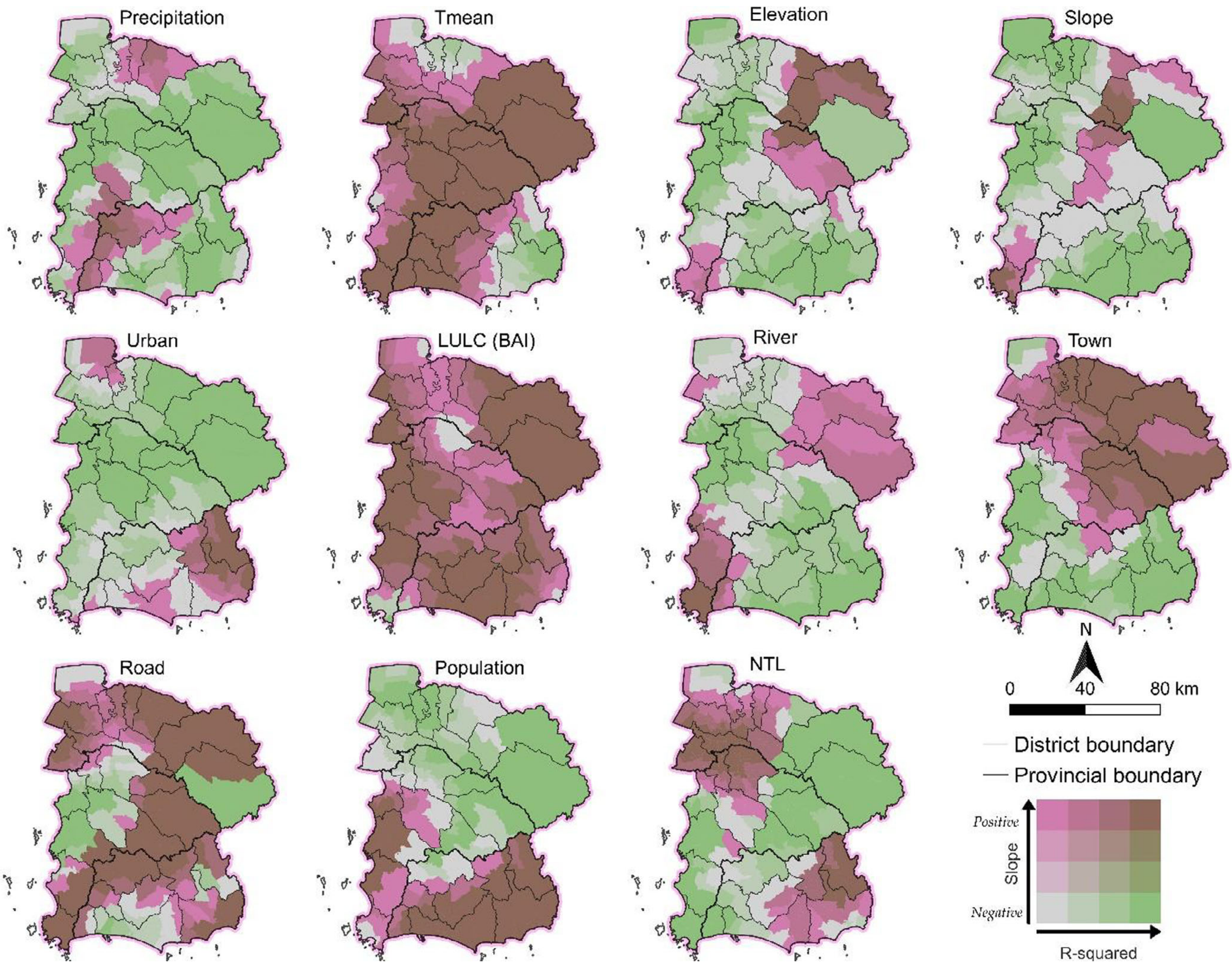

FIGURE 7 Spatial distribution of GWR for each controlling factor in the entire EEC region based on subdistrict data. Bivariate maps illustrate data fit and influence trend. [Colour figure can be viewed at wileyonlinelibrary.com]

However, the major trend is still deterioration in the entire EEC at different extents, especially in adjacent and emerging urban areas. The RSEI classes will therefore continue to be declined along the coastal curve in city chain and these impacts will gradually dominate adjacent areas in both area and severity level. Specifically, only 0.1% of total area will improve EEQ, while 24.1% will expect to be worse in the future (Figure 8f).

It is worthy to note that the EEQ changes in the EEC are varying. Chachoengsao is relatively stable, with 43.4% of the unchanged EEQ. Chonburi is highlighted with 49.8% of degraded environment, while 79.1% of Rayong tends to be improved in the future. Two axes representing for mean area proportion of degradation and improvement classify 29 districts into two clusters (Figure 9). A district with a degradation value of higher than the mean value is a high degradation district, conversely a district with a low degradation level. It is also applicable for improvement. Based on this concept, the districts on the second quadrant (e.g., Bo Thong, Sanam Chai Khet, Rayong, Klaeng, and Chachoengsao) are the most unstable districts with a high proportion of degradation and improvement EEQ. A cluster of nine districts in the bottom-right quadrant (e.g., Phanat Nikhom, Ban Bueng, Si Racha, Bang Lamung, Bang Nam Priao, Phanom Sarakham, Plaeng Yao, Pluak Daeng, and Ban Khai) will tend toward degradation rather than ecological improvement. Tha Takiap (Chonburi – top-left quadrant) will be the only district showing ecological improvement. In contrast, the EEQ in the remaining districts (bottom left) will be less stable compared to other entities.

4 | DISCUSSION

4.1 | Rapid and unstable changes in ecological environment

The development of the EEC has essentially been revived by a chain of tourism–logistic–industrial cities along the coast. Therefore, it is apparent that EEQ has changed dramatically compared to the time before its revival (Figure 4). The EEQ along this corridor has been strongly differentiated with low EEQ. It is increasingly better along

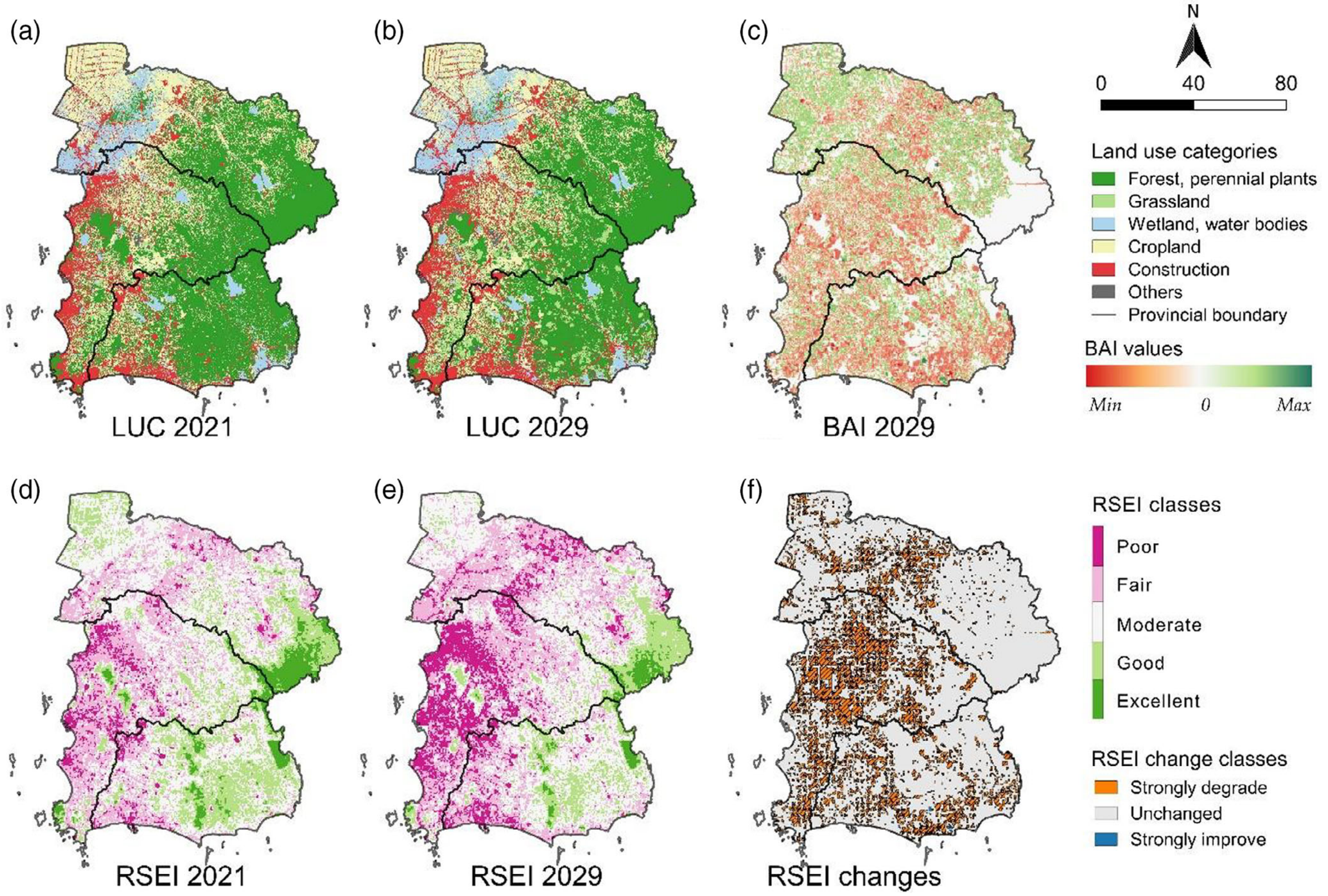

FIGURE 8 Predicted LULC in 2029 compared to 2021 and difference BAI values between 2021 and 2029, corresponding ecological environment index (RSEI), and ecological environmental change classes in 2029. [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 9 Area proportion of ecological environment changes in districts of the EEC under future scenario. Horizontal and vertical lines present mean values for environmental degradation and improvement values, respectively. [Colour figure can be viewed at wileyonlinelibrary.com]

the coastal-inland gradient, where artificial impacts such as land use transformation, industrial productions, and infrastructure projects are gradually declined in both quantity and intensity (Figures 2 and 5).

Although this region holds higher a half of total area with good and excellent environment accumulatively, it should be noted that the low EEQ has extended (about 0.48% per year, Table 3). Improvement signs

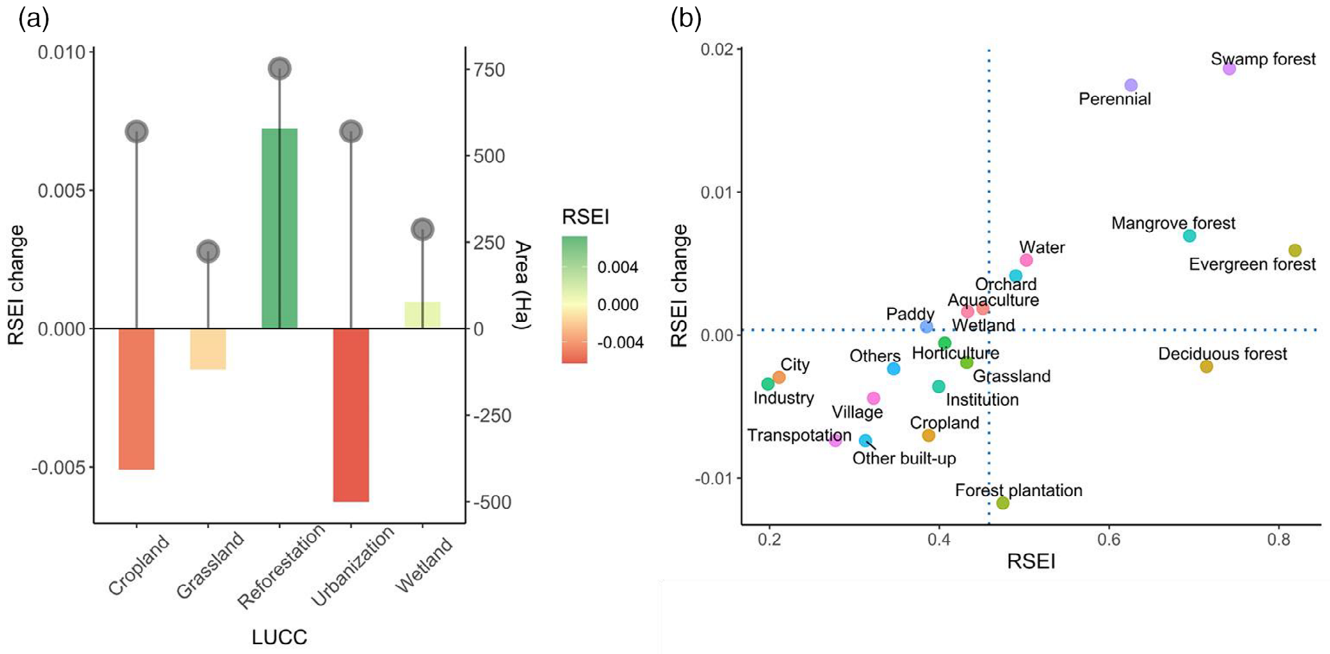

FIGURE 10 (a) Area of major LULCC and RSEI change magnitude for each LULCC class. Columns represent RSEI magnitude, and lollipop sticks are changing area; (b) RSEI values and trends for different LULC categories. [Colour figure can be viewed at wileyonlinelibrary.com]

were also found in the EEC, however, it is mainly distributed in the eastern forest and highland areas. It implies a great geographical heterogeneity of EEQ and its controlling factors, which was only detected by the GWR instead of general monotonic impacts by linear regression (Figure 7).

The regional EEQ has slightly changed, while each province has unique characteristics driven by each provincial context. Chachoengsao is relatively stable with cultivation practices fostered by the Bangpakong river (Wongsa et al., 2020). However, extensive cropland in the central area is more sensitive than elsewhere, especially after the harvesting period when barren land is exposed to high temperature (Yaung et al., 2021). It is amplified during the strong El-Niño year (2015–2016), when RSEI dipped below the average in 2016 (Figure 3). The EEQ in Chonburi has strongly decreased because this is the province with the longest coastline and dense industrial estates. It also holds three of five rapid developing cities in the coastal corridor. Rayong is an opposite case when the EEQ has gradually improved. It was even stable in the 2015/2016 El-Niño year. Inland areas of Chachoengsao and Chonburi may often face water deficit due to low precipitation, while Rayong is irrigated by five reservoirs and irrigation projects. These projects have released water stresses, and the role of water management has been convinced during this severe drought. The high improvement areas are mostly distributed within the Rayong and Phrasae irrigation projects (Vannametee et al., 2022), where efficient water management is assumed to greening these areas.

4.2 | High dependency of ecological environment on LULC and natural conditions

The EEQ is dominated by a range of elements from nature to anthropogenic factors. The dominant factor varies widely among the regions because of regional unique characteristics such as climate, topography, major LULC, and development levels (Figure 7). For example, Wang, Ding, et al. (2022) indicated the importance of climate factors to EEQ, while these influences were relatively fuzzy in a coal mining area (Nie et al., 2021). However, LULCC and natural conditions are the major agents influencing the EEQ that have been consistently detected in many studies (Wang, Ding, et al., 2022; Yuan et al., 2021; Zhang, Feng, et al., 2022; Zhang, She, et al., 2022). Our findings are in line with the previous studies on the contributions of these two factors.

LULCC is the most important controlling factor to EEQ changes (i.e., the highest importance level across the models—Figure 6, Section 3.3.1). Its effect is also relatively consistent throughout the region than other elements (Section 3.3.2). Specifically, reforestation and wetland restoration alleviate ecological stresses in the regional environment (Figure 10a). It has witnessed the forest restoration in the east side. In this study, the broad forest class embraces forest categories and perennial plantations (e.g., orchards and industrial plants). The joint effect of forest restoration, development of geographical identities of tropical fruits and perennial agricultural products that contributes to greening the fallow lands and facilitatesa better EEQ (Tontisirin & Anantsuksomsri, 2021). It somehow weakens the negative impacts from urbanization on EEQ in general. Additionally, swamp forest and perennial plantation are the most contributors to improve EEQ, while deciduous forest, and forest plantation are relatively sensitive (Figure 10b). The severely degraded areas are distributed in urban areas, while the moderately degraded areas are mainly spread over arable land (e.g., paddy, cropland, and horticulture; Figure 5). Therefore, cropland is the second most challenging LULC because of its negative impacts during the crop idle period. Among urban LULC categories, transportation projects substantially exacerbate the degradation.

In addition to LULCC and socioeconomic factors, precipitation and mean temperature consistently affect RSEI across the models (Figure 7, Section 3.3.2). However, its spatial homogeneity is relatively low compared to LULCC (Figure 7), which is even dominated by topographical patterns. The high terrain in southwest-northeast forms differences in climate patterns (Figure 1), and ultimately controls EEQ. The high terrain plays the role as a "natural wall" blocking southwest monsoon wind and leading to high precipitation along the coastal cities, while eastern forest and perennial plantations encounter water deficit. In contrast, it intensifies water stress during the dry season under northeast monsoon wind, which raises high temperature in the inland plantations. It means the EEC always confronts water stress due to its natural conditions.

4.3 | Policy implications

A combination of future prediction, spatial heterogeneity analysis using GWR, and conventional clustering (Figure 9) revealed future EEQ, dynamics, and obstacles of each subregion. This location-based information will be useful for regional planning, which may have to be tailored to each subregion. Specifically, the regional EEQ is predicted to be declined in quality and the deteriorated areas will expand forward inland areas in future contexts of LULCC and climate change (Section 3.4). The buffer zones between these two regions are "reformed land" under the Royal Decree, which greens deforestation areas to become agricultural lands. These areas would play a vital role in escalating the general EEQ. Hence, plant-orientated planning for these areas should weigh between cropland and perennial plants to promote ecological benefits against trade-offs.

Presently, the regional EEQ is relatively favorable, however, it is originated from forest offsets. Therefore, forest protection and restoration should be highly encouraged by integrated strategies, such as forest-dependent livelihood and community forest management (Kroeksakul et al., 2018). There is an enormous difference between two sides of the EEC. The regional master plan has a very limited land allocation for greening promotion along the west corridor, while this is the most populous region with numerous industry activities. Thus, there is a high demand of increasing green infrastructures in the west EEC. The most vulnerable districts (e.g., Phanom Sarakham, Bang Bueng, Siracha, and other districts in the same cluster) should be prioritized for greening interventions. While the western urban areas seem compact, the greening actions should be firstly deployed by potential entities such as community and government. Institutional land accounts for 10.9% of urban lands in the EEC, considerable higher than in other regions. Yet, their land use is often low efficiency with high unused rate. Advocating for greening campaigns on unused land is a potential solution to increase green spaces in dense urban areas.

Furthermore, the EEC will have more extensive transportation projects to support logistics and regional connection. Yet, this is the LULC with the highest impact on EEQ (Figures 7, 8c,e, and 10b). Integrated assessment and scenarios should be insightfully considered to limit negative impacts on EEQ, especially in eastern Chachoengsao.

The most concerned issue in the EEC is water supply and management, reflected by correlation with distance to river and climate elements. Mountainous terrain, sandy loam soil, and water demand for production jointly intensify the regional water deficit, especially in paddy and cropland in middle north Chachoengsao. In the future, it will be more severe for the east agricultural zones when it will confront higher temperature and low precipitation. Water stress was gradually released in Rayong by the irrigation projects, which is a valuable lesson for both Chonburi and Chachoengsao. Plant structure should also be considered to reduce water demand and efficiency with appropriate water regimes (e.g., Alternate Wet and Dry Irrigation). The seasonal bare land is a hindrance for local climate and EEQ (Nguyen et al., 2021). It frequently distributes in Chachoengsao, which should be covered by suitable vegetation, while construction solutions for irrigation should be parallelly conducted in these areas to reduce exposure during dry season and to improve the EEQ.

Although this study attempted to take numerous factors reflecting different aspects into account for controlling factors assessment and future prediction of EEQ, non-availability of some socioeconomic indicators in this region may lead to an inadequate assessment. As a dynamic hub of industrial production, the influences of economic scale and industrial structure can be more significant than elsewhere. Therefore, specific economic and industrial development indicators should be collected and considered in future research for more accurate and comprehensive assessments.

5 | CONCLUSION

This study adopts the concept of remote sensing-based ecological index (RSEI) to monitor and assess the dynamics of EEQ in the EEC under rapid resurgence of this special economic zone. The regional EEQ is apparently differentiated from east to west and coast to inland. The EEQ of coastal areas is lower than others due to high concentration of population, city chains, numerous infrastructures, and industrial estates. Conversely, the western forest plays a crucial function to make up the environmental degradation in the east, which even reveals improvement signs due to perennial plantations on "reformed land" under the Royal Decree.

Within a short period of time, the region has experienced considerable changes in EEQ, which has strongly deteriorated along the coast, its adjacent regions, and agricultural zones in central Chachoengsao. The changes in EEQ are mainly controlled by proportion of built-up, LULCC, distance to roads and rivers, precipitation, temperature, slope, and NTL. Particularly, LULCC is the most important contributor, which consistently influences EEQ changes the entire region. Meanwhile, the impacts of other elements are frequently heterogeneous in terms of spatial patterns, where the spatial distribution is differentiated by northeast-southwest and northwest-southeast axes.

This study also attempted to include future LULCC scenario and more predictors in future EEQ simulation. Under the future scenario of local development, LULCC will be seamlessly changed. It along with future climate change will considerably affect the regional EEQ over one-fourth of the total area. Ultimately, 24.1% of the total area will be degraded in 2029. The districts were sorted into four clusters, with the worthiest concern should belong to unstable and degraded districts. These districts will have a high degree of degraded environment, the local authorities therefore should have appropriate interventions to deal with this deterioration.

Nevertheless, policymakers and authorities should thoroughly consider both potential opportunities and challenges to weigh and propose a vision that is appropriate to the regional natural, infrastructural, and social characteristics of this region. The LULCC due to rapid development and influences of topographic characteristics, causing different climate patterns and water deficit, which should be involved in future plans, including suitable crop structures, efficient water management, forest conservation and restoration, and green infrastructures. The uncertainties of legal foundations and scientific evidence should be gradually dimmed to promote environmental responsibility of relevant organizations and businesses toward sustainable development of the EEC under different challenges.

AUTHOR CONTRIBUTIONS

Can Trong Nguyen (CTN): conceptualization, methodology, formal analysis, visualization, data curation, writing—original draft, review and editing; Rungnapa Kaewthongrach (RK): conceptualization, supervision, writing—review and editing; Sittiporn Channumsin (SC): writing—review and editing; Mitchai Chongcheawchamnan (MC): writing—review and editing; Thanh-Noi Phan (TNP): writing—review and editing; Damrongrit Niammuad (DN): conceptualization, supervision, writing—review and editing. All authors have read and approved the published work.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Can Trong Nguyen https://orcid.org/0000-0003-0471-4062
Rungnapa Kaewthongrach https://orcid.org/0000-0003-4142-5411
Sittiporn Channumsin https://orcid.org/0000-0003-2344-7676
Thanh-Noi Phan https://orcid.org/0000-0002-2747-5028

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