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Assessing socioeconomic and climate driven road maintenance priorities in Southeast Asia using remote sensing approach

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A R T I C L E I N F O

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A B S T R A C T

Road infrastructure plays a vital role in national and regional development, particularly in Southeast Asia, where rapid economic growth is increasing pressure on transport systems. However, uneven investment, environmental stressors, and limited data-driven tools continue to hinder effective road maintenance planning. Previous studies have utilized remote sensing and statistical models for infrastructure analysis, but the integration of long-term environmental indicators with spatial prioritization methods remains limited. This study addresses this gap by developing a Road Maintenance Priority Index (RMPI) using ten parameters, including nighttime lights, population density, industrial zones, land surface temperature, precipitation, and wind speed. These variables were analyzed through machine learning regression and multi-criteria decision analysis to classify road segments into priority levels. Results show that 45.08 percent of roads fall into the low-priority category, followed by moderate (39.69 percent), high (9.06 percent), and very high (0.88 percent). Countries such as Singapore, Brunei, and Malaysia exhibited the highest RMPI scores, reflecting urgent maintenance needs, while Timor-Leste, Myanmar, and Laos scored lowest. The findings offer a transferable and scalable framework to support evidence-based infrastructure planning in economically and environmentally diverse regions.

1. Introduction

An essential dynamic of enhancing a nation's economic efficiency is to improve its road network infrastructure, which increases the quality of life and incomes of the population by providing accessibility to education, healthcare, and other social services (Kockelman, 2001). Government investments in the development of road network infrastructure can generate spillover effects across various sectors and offer long-term economic benefits (Haldea, 2013; Sangare & Maisonnave, 2018). Enhancing the quality of road infrastructure can reduce costs, increase trade volume, and facilitate labor and capital mobility, thereby boosting interregional trade in both the short and long term (Akpan, 2014; Shepherd et al., 2006). Road network infrastructure is improved by either expanding existing road networks or repairing and maintaining the quality of the current infrastructure to prevent damage. Damage to road infrastructure can have detrimental effects on the economy. For example, in the agricultural sector, road damage can increase the longer time required for farmers to transport their goods to the market, damage vehicles, and limit production potential and income, thereby reducing productivity (Tunde & Adeniyi, 2012).

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Several factors can damage road network infrastructure. The first is increased road usage for community activities, leading to higher traffic volumes and ultimately deteriorating infrastructure, such as potholes, edge failures, cracking, and rutting (Zumrawi, 2021). The second factor is climate, which can disrupt socioeconomic activities, impact the environment, and cause physical damage, particularly to road infrastructure (Ede & Oshiga, 2014). Climate change, including increases in CO_2 concentrations, temperatures, and humidity, can lead to road damage and economic consequences in the form of increased maintenance and repair costs (Shao et al., 2017; Wang et al., 2012). Higher rainfall under various climate change scenarios leads to floods, which is projected to become a major cause of road infrastructure damage and significant economic losses, especially after 2030 (Arndt et al., 2012). Solar radiation also contributes to oxidation, cracking, and asphalt brittleness, necessitating regular maintenance efforts and expenditures from relevant institutions (Shao et al., 2017). Additionally, annual temperature variations and poor rainwater drainage systems further contribute to road damage and shorten road lifespans (Zumrawi, 2021).

To improve road infrastructure quality, it is essential to consider the relationships between gross domestic product (GDP) and government investment in road infrastructure. Moreover, GDP and government investments negatively correlate with traffic accidents because they are closely related to road infrastructure quality (Sun et al., 2019). Southeast Asia experienced an average GDP growth of 5.5 % between 1970 and 2013 (Bong & Premaratne, 2018). However, government investments in road network infrastructure in Southeast Asia remain relatively low. For example, Indonesia allocates less than 5 % of GDP to road infrastructure investment, whereas the Philippines allocates only 0.6 % of GDP (Asian Development Bank, 2012b, 2012a). Economic activities and societal productivity are expected to increase along with higher investments in road infrastructure for public use (Álvarez & Blázquez, 2014). Given the limited investment in transportation infrastructure, efficiency and effectiveness must be enhanced to boost productivity, particularly in the economic sector (Álvarez & Blázquez, 2014). Therefore, decisions regarding road network infrastructure investment and maintenance must be based on scientific assessments to ensure that the impact is maximized and effort is minimized in a responsible manner.

Geographic information systems (GIS) have played a vital role in supporting the evaluation and maintenance of road network infrastructure. Several prior studies have demonstrated the application of spatial analysis tools in this domain. For example, Pantha et al. (2010) conducted a GIS-based road maintenance prioritization study to assist policy formulation in developing contexts. Pellegrini and Grigolato (2013) applied a combination of GIS and Analytic Hierarchy Process (AHP) to identify critical areas for maintenance in mountainous regions. Koks et al. (2019) assessed the vulnerability of global road and railway networks to multi-hazard risks using intersecting exposure and economic loss estimation methods, offering a significant contribution to disaster-resilient infrastructure planning. Song et al. (2021) employed fuzzy logic within a multicriteria decision-making framework to evaluate infrastructure performance. Additionally, Das and Nakano (2023) incorporated socio-technical factors into a decision-support model for prioritizing transportation bridge maintenance.

Building upon these foundational works, subsequent research has introduced more comprehensive and sustainability-oriented approaches. Jiang et al. (2021) explored optimal pavement maintenance strategies under sustainability constraints. Huang et al. (2024) proposed an integrated system for managing maintenance strategies using performance indicators. Alizadeh and Dodge (2024) applied data-driven methods to assess disaster vulnerability within road networks through network topology and movement activity analysis. Tu et al. (2025) highlighted disparities in infrastructure access and their association with health inequalities, while Karlsson et al. (2017) developed a spatial multicriteria model to assess natural hazard susceptibility in road planning. A machine-learning regression analysis segment-based approaches for ranking road network importance, such as the local–transit percolation and clustering-based method developed by Lyu et al. (2025), which enhances maintenance planning by identifying critical highway segments. Additionally, Hassan and Islam (2025) demonstrated the integration of GIS and remote sensing for sustainable road construction planning using environmental and geotechnical criteria.

Despite these advancements, a critical methodological gap remains. Existing studies typically focus on physical road condition indices, hazard vulnerability, or socio-technical prioritization as isolated components. However, very few have integrated remote sensing data, long-term environmental trends, and multi-criteria decision analysis within a single, spatially explicit framework. This integration is particularly lacking in the context of developing regions with diverse climatic and infrastructural challenges.

To address this gap, the present study aims to develop a Road Maintenance Priority Index (RMPI) that combines remote sensing data, environmental and socioeconomic indicators, and multicriteria spatial decision-making techniques. The objective is to support infrastructure maintenance planning across Southeast Asia by identifying priority areas for intervention based on a comprehensive geospatial assessment.

The novelty of this study lies in the use of long-term satellite data to model the environmental conditions of road infrastructure and multiple parameters to determine the levels of priority for road maintenance. This research is strategically important because implementing spatial analysis-based techniques for road maintenance management faces several challenges, such as a lack of funding, expertise, administration, and research and development, making sustainable road maintenance challenging to achieve (Zhang et al., 2021). Therefore, this study seeks to address these challenges by developing a geospatial intelligence-based approach for identifying road maintenance priorities in Southeast Asia. The findings of this study are expected to assist policymakers in identifying priority locations for road infrastructure maintenance.

2. Materials and methods

2.1. Road network dataset

The Southeast Asian countries included in this study were Brunei Darussalam, the Philippines, Indonesia, Cambodia, Laos, Malaysia, Myanmar, Singapore, Thailand, Timor Leste, and Vietnam. The administrative data utilized in this study consisted of polygon data representing the Southeast Asian region sourced from the Global Administrative Dataset (GADM). The GADM provides spatial datasets from various sources, including government agencies, non-governmental organizations (NGOs), and publicly available data curated by Robert J. Hijmans from the University of California, Davis (GADM, 2022). The road network data were obtained from the Global Roads Inventory Project (GRIP). GRIP was established to collect, harmonize, and integrate publicly accessible geospatial road data into a consistent global dataset (Meijer et al., 2018). The dataset consists of road data from 222 countries and covers over 21 million kilometers of roads. Data recorded after 1997 were gathered from credible institutions, such as the United Nations (UN), government agencies, and NGOs, and they have a positional accuracy of up to 500 m. When multiple road data sources were available for a country, the data were compared and merged to obtain the best results (Meijer et al., 2018). GRIP also provides road metadata, including road types, surface types, and countries of origin. The road types were classified into five categories based on the OpenStreetMap (OSM) classification (OSM, 2020): a. highways: these are the most important roads in a country, and they are designed for high-speed, uninterrupted traffic; b. primary roads: these roads typically feature one lane in each direction, have lower speed limits, and connect major cities; c. secondary roads: these roads are similar to primary roads but with lower speed limits and more intersections and connect smaller towns; d. tertiary road: these roads are comparable to secondary roads but serve more localized traffic and connect small towns and villages with more intersections than secondary roads; and e. local roads: these roads have the lowest importance and typically connect residential or rural areas to local destinations.

2.2. Longterm climate and environmental datasets

Climate environmental parameters including wind speed, precipitation, land surface temperature (LST), and aerosol optical depth (AOD) were analyzed using long-term satellite-derived time series covering a 22-year period from 2000 to 2022 to capture their temporal evolution and influence on road degradation. Each dataset was processed as a continuous multi-year series, and no temporal aggregation was applied prior to trend analysis. To ensure consistency across datasets, all time-series data were harmonized to a common annual timestep. The regression analysis was then applied pixel-wise to quantify temporal trends across the study area. The temporal and spatial characteristics of the datasets used are summarized in Table 1.

Wind is an environmental factor that can threaten the road network infrastructure. Damage caused by wind usually results from objects falling onto roads, necessitating road maintenance efforts, such as clearing debris and repairing road damage (Koks et al., 2019). In this study, wind data was sourced from the TerraClimate dataset using data from 2021. The wind speed data provided by TerraClimate were based on the average wind speed at a height of 10 m, and the spatial resolution was 4,638.3 m. TerraClimate is based on WorldClim v.2, a high-resolution (~4 km) global climate dataset that provides monthly data. Wind speed is a critical variable in road infrastructure development because it can impede construction efforts, as observed in cases where high wind speeds cause trees to fall (Virot et al., 2016). Therefore, the wind data used in this study were filtered to include only wind speeds at or above this threshold.

Precipitation in Southeast Asia is characterized by a tropical climate, predominantly occurs as rainfall, which can cause the erosion of road network infrastructure, leading to damage (Yang et al., 2019). This study utilized precipitation data from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS), which integrates satellite, observation station, and climatology data to monitor drought and environmental changes with high resolution and accuracy, low latency, and long-term availability (Funk et al., 2015). The CHIRPS data were processed using high-resolution climatological precipitation data from CHPclim, satellite estimates based on cold cloud duration from CHIRP, and a merging procedure for both datasets. The CHIRPS data, along with independent precipitation data from various regions and seasons, demonstrated low bias, high correlations, and low average absolute errors compared with the other products.

Land Surface Temperature (LST) is usually obtained through remote sensing. Variations in LST of road network infrastructure can lead to thermal expansion and subsequent road damage (Shao et al., 2017). High temperatures reduce the viscosity of the asphalt and increase the likelihood of deformation and cracking. LST data were derived from the Moderate Resolution Imaging Spectroradiometer (MODIS), which employs the MODIS LST algorithm to generate LST and emissivity values from instruments onboard the EOS satellite. The algorithm was constructed based on a review of physical and mathematical models used to calculate LST values. The physical model was based on radiation transfer equations, Planck's function, Kirchhoff's law, and the bidirectional reflectance distribution function (BRDF). The mathematical model describes the methods for calculating.

The aerosol optical depth (AOD) refers to solid particles present in the atmosphere that frequently result from human activities. A strong correlation has been found between AOD and both public and private vehicles, with R^2 values of 0.732 and 0.735, respectively (Li & Wang, 2014). AOD data were sourced from MODIS satellite observations using the Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm. This algorithm utilizes concurrent time series of aerosol optical thickness (AOT) measurements and bidirectional surface reflectance factors (Lyapustin et al., 2018).

2.3. Spatial socioeconomic dataset

The socioeconomic datasets used in this study represent human activity, demographic concentration, and economic infrastructure that collectively influence road usage intensity and maintenance demand. These variables were selected to capture both direct and indirect socioeconomic pressures on road networks at a regional scale. The selected indicators include nighttime light (NTL), population density, and the spatial distribution of major economic facilities such as power plants, mining areas, industrial zones, and palm oil plantations. Each dataset provides complementary information that reflects different dimensions of human influence on transportation systems, from population mobility to freight movement and industrial connectivity. The general characteristics of the socioeconomic data used in this study are presented in Table 2.

Nighttime light (NTL) data were used to quantitatively observe nocturnal light emissions captured during remote sensing processes. NTL is positively associated with airport performance, including passenger traffic and aircraft movement (Ma et al., 2014), and strongly correlates with population, GDP, electricity consumption, and road network extent, reflecting human activity at night. This study assumes that higher NTL values indicate greater traffic volume on road networks. NTL data were obtained from the Visible Infrared Imaging Radiometer Suite (VIIRS) Stray Light Corrected Day/Night Band (DNB), which

Table 2
Socioeconomic and supporting datasets used in this study.

Data	Product	Year	Resolution	Reference
Nighttime Light (NTL)	VIIRS Day/Night	2022	Raster-463.83 m	Elvidge et al. (2021)
Population Density	World Pop Dataset	2020	Raster-92.77 m	Tatem (2017)
Power Plant	World Resources Institute (WRI)	2018	Vector	Byers et al. (2018)
Mining Area	OpenStreetMap (OSM), Global mining	2020	Vector	Maus et al. (2020); OSM (2020)
Industry Area	OpenStreetMap (OSM)	2020	Vector	OSM (2020)
Palm Oil Plantation	Global Palm Oil Plantations Dataset	2022	Raster-10 m	Adrià et al. (2021)
Landslide Event	BNPB, NASA Landslide Global Catalog	2010–2020	Vector	BNPB (2022); Nasa (2022)
Gridded GDP	Global Gridded GDP –Aalto University	2015	Vector	Kummu et al. (2018)

Table 1
Temporal and spatial characteristics of environmental datasets.

Parameter	Product	Temporal Coverage	Temporal Resolution	Spatial Resolution	Reference
Wind Speed	TerraClimate	2000–2022	Monthly	Raster-4.63 km	(Abatzoglou et al., 2018)
Precipitation	CHIRPS	2000–2022	Monthly	Raster-5.56 km	(Funk et al., 2015)
Land Surface Temperature (LST)	MODIS MOD11A2 / MYD11A2	2000–2022	8-day composite	Raster-1,000 m	(Wan, 2014)
Aerosol Optical Depth (AOD)	MODIS MAIAC	2000–2022	Daily	Raster-1,000 m	(Lyapustin et al., 2018)

collects low-light imagery of Earth at night (Elvidge et al., 2021). The data were filtered to remove noise and contamination from sunlight, moonlight, stray light, lightning, high-energy particles, biomass burning, auroras, flare gas, volcanic activity, and background noise.

Population density reflects the concentration of people within a given area. Population density is strongly related to traffic density (Callender & Rice, 2000). The population dataset used in this study was sourced from WorldPop, a publicly accessible, high-resolution spatial dataset on the distribution of human populations and associated changes over time (Tatem, 2017). WorldPop employs a machine learning approach to disaggregate census data from administrative units to derive pixel-level estimates based on various geospatial parameters, including elevation, land slope, land cover, infrastructure, and climate. A multitemporal procedure was also used to obtain data on changes in population density over time.

To estimate the socioeconomic role of road infrastructure in Southeast Asia, we focused on infrastructure that significantly impacts society, including power plants, mining areas, industrial zones, and palm oil plantations. The development of power plants can enhance community income and stimulate economic growth in sectors that rely primarily on electricity as a resource (Isgiyarta et al., 2022). The mining industry, operating in designated mining areas, contributes socioeconomic benefits to communities as part of its legal responsibilities by government regulations as well as to Social Development Management Programs (SDMPs) that invest in various projects and services in education, health, infrastructure, and social welfare (Cuartero-Enteria, 2018). Industrial growth fosters economic expansion by enhancing investment, innovation, and productivity (Usman & Adejare, 2014). Expansion of the palm oil industry can contribute significantly to economic development and social welfare, especially with effective governance (Sayer et al., 2012). The mobility provided by road infrastructure is significantly correlated with the socioeconomic development of communities (Shi et al., 2019). Therefore, the regions surrounding power plants, mining areas, industrial zones, and palm oil plantations require well-developed road infrastructure. The socioeconomic value of road infrastructure was estimated based on its proximity to each type of infrastructure, namely, power plants, mining areas, industrial zones, and palm oil plantations. Table 3 summarizes the socioeconomic indicators used in this study, along with their data sources, underlying rationale, and the expected relationship between each parameter and road maintenance priority.

Table 3
Summary of socioeconomic parameters and their rationales.

Parameter	Data source	Rationale for inclusion	Expected relationship to maintenance priority
Nighttime Light (NTL)	VIIRS DNB	Serves as a proxy for human activity, traffic intensity, and economic development.	Higher NTL values indicate greater road usage and therefore higher maintenance priority.
Population Density (PD)	WorldPop	Reflects population pressure and mobility demand affecting road usage.	Higher population density corresponds to more frequent road use and higher maintenance requirements.
Industrial Areas (IA)	OSM	Represents zones of freight transport and industrial logistics activities.	Roads located closer to industrial areas experience heavier loads and consequently greater maintenance needs.
Power Plants (PP)	WRI	Denotes critical energy infrastructure that depends on reliable road accessibility.	Roads in proximity to power plants are of higher strategic importance for maintenance prioritization
Mining Areas (MA)	Global Mining Dataset, OSM	Reflects areas of intensive heavy-vehicle operations that accelerate pavement deterioration.	Roads near mining areas are more prone to structural degradation and thus require higher maintenance priority.
Palm Oil Plantations (POP)	Global Palm Oil Plantations	Represents agricultural zones contributing significantly to regional trade and transport flow.	Roads adjacent to palm oil plantations are vital for commodity transport and warrant higher maintenance priority.

2.4. Spatial data processing

The methodology for assessing road infrastructure maintenance in Southeast Asia begins with the collection of three key datasets: road socioeconomic dataset, which includes factors such as population density and industrial areas; administrative and road dataset, which provides geographical and administrative boundaries; and road hazard dataset, which captures environmental pressures such as precipitation and LST. Data processing techniques such as Euclidean distance calculations and reclassification were employed to prepare the data for analysis. Machine learning regression and MCDA methods integrated these datasets to evaluate the collective impacts on road infrastructure. This analysis determined the road infrastructure value, and trend and bivariate analyses revealed the relationships between variables. The final outcomes assessed the socioeconomic value and environmental pressure on roads, culminating in the creation of the Road Maintenance Priority Index (RMPI), which prioritizes road segments for maintenance based on their socioeconomic and environmental contexts. Fig. 1 illustrates the overall scheme of the methodology used in this study. In developing the RMPI, this study considers three main aspects that can be seen in Table 4.

Although previous studies have developed road-related indices using GIS and MCDA, this study introduces a geospatial intelligence framework that advances current methods in several key aspects. First, it integrates multi-temporal remote sensing variables (e.g., NTL, LST, AOD, precipitation) with socioeconomic and infrastructural drivers (e.g., industrial zones, plantations, power plants) to produce a harmonized regional model. Second, instead of applying static expert-assigned weights, this study employs machine-learning regression–based sensitivity calibration to dynamically adjust the influence of each parameter based on empirical relationships between socioeconomic intensity and environmental stress. Third, the proposed Road Maintenance Priority Index (RMPI) combines socioeconomic value (SV) and environmental pressure (EP) through a bivariate integration scheme, enabling the simultaneous visualization of infrastructural importance and degradation risk. Finally, the framework is designed for regional-scale prioritization across 11 Southeast Asian countries, demonstrating cross-national comparability and transferability of the approach.

To maintain consistency among multi-source datasets, all spatial layers were resampled to a common 1 km grid, corresponding to the coarsest input datasets (MODIS LST and AOD). This harmonization ensures compatibility for regional-scale analysis across Southeast Asia but may reduce the ability to detect highly localized variations in environmental stress around individual road segments. The approach was therefore designed to support *strategic, regional prioritization* rather than micro-scale pavement diagnostics.

2.5. Method terminologies

This study employs three main analytical methods: Geographic Information Systems (GIS), Multi-Criteria Decision Analysis (MCDA), and Machine Learning Regression (MLR). GIS is a computer-based system used to collect, store, analyze, and present geographic or spatial data. Its structure consists of Data Storage and Management, Data Input, Data Manipulation and Analysis, Data Output, and User Interfaces

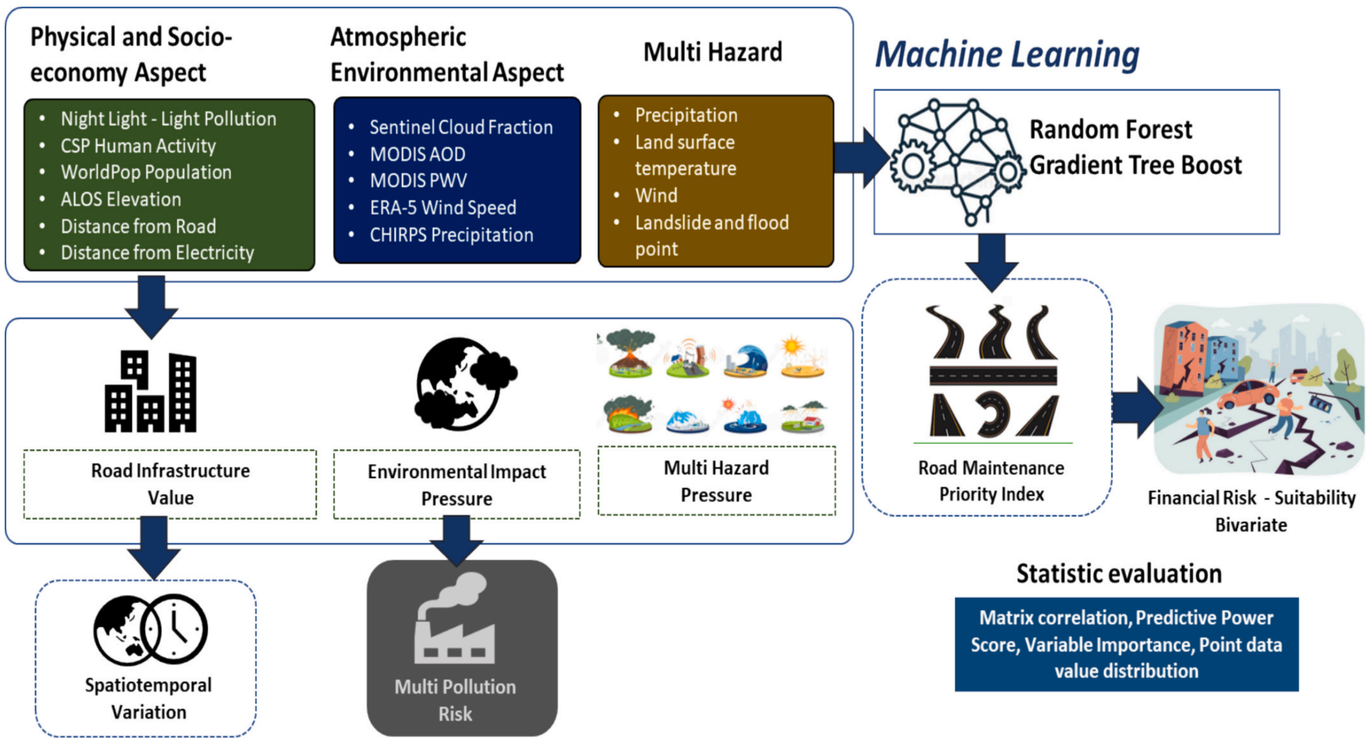

Fig. 1. The overall scheme of the methodology used in this study.

Table 4
Value aspects used in this study.

No	Aspect	Explanation
1	Road Network Infrastructure Value	The Road Network Infrastructure evaluates roads based on their functional class types because each road has a different class depending on its specific function. The road class also influences the volume of vehicles that will pass through it. This category will support the prioritization of road maintenance classes.
2	Socio-Economic Value	The socio-economic value considers the aspect of human pressure on the road (population and nightlight data). The higher the level of human pressure, the higher the priority for maintenance, as such roads are likely to experience higher traffic volumes.
3	Climate Environmental Pressure	Climate environmental pressure refers to stress on roads from climate and environmental factors, either directly or indirectly. Direct factors include temperature, rainfall, and wind speed. Indirect factors are assessed through AOD (Aerosol Optical Depth) as a parameter for air pollution, indicating that higher AOD levels correlate with increased vehicle traffic on the road.

(Malczewski, 2006). On the other hand, MCDA is a decision-making process or method that considers multiple criteria or "key factors" using mathematical programming (Malczewski, 2006). Generally, the concept of MCDA involves weighting to derive scores/rankings for each decision alternative. The criteria used are standards/measures that form the basis for evaluation in decision-making. This study integrates GIS and MCDA, often referred to as the Weight Overlay method. GIS-MCDA generally refers to the decision-making process using MCDA techniques based on GIS for spatial/geographic data. The GIS-MCDA process transforms and combines geographic data with value judgments from policymakers to derive information for policy determination (Malczewski, 2006). In this study, GIS-MCDA is used to integrate all spatial data based on predetermined weighting scores. Another method used in this study is Machine Learning Regression, specifically trend analysis using regression models. Regression models aim to identify the best-fitting line that represents the relationship between observed variables (Sakti et al., 2024). The MLR method is specifically applied in subsection 2.6 for modeling socioeconomic pressure on road infrastructure.

2.6. Road network infrastructure value

An exploration of vector data for road infrastructure from the GRIP was conducted to analyze road statistics in Southeast Asia. This data exploration utilized metadata associated with road data, including information on the location, type, source, and year. Additionally, the geodesic length of each road vector object in the study area was calculated within the geographic coordinate reference system using the WGS 1984 datum, which is measured in kilometers. The geodesic length calculation method was selected over the planar length to avoid distortion from the 2D plane projection. This study classified the value of road infrastructure into three categories: high, moderate, and low. This classification aims to simplify the statistical calculations for Southeast Asian roads based on the five existing road types: highways, primary roads, secondary roads, tertiary roads, and local roads. Three classes were established according to the definitions of each road type and reclassification scheme as follows: local roads and tertiary roads were assigned a low value for infrastructure, secondary roads were assigned a moderate value, and primary roads and highways were assigned a high value for infrastructure. Subsequently, the geodesic lengths of each class and road type were calculated to determine the statistical value of the road data in Southeast Asia.

2.7. Road network infrastructure socioeconomic value

The socioeconomic value (SV) of roads was estimated based on their proximity to and interaction with strategic socioeconomic features, reflecting the role of transport accessibility in supporting regional economic development (Ng et al., 2019). Roads located near areas of high socioeconomic activity are more frequently used and thus possess higher maintenance importance. This study employed six key socioeconomic parameters: Nighttime Light (NTL), Population Density (PD), proximity to Industrial Areas (IA), Power Plants (PP), Palm Oil Plantations (POP), and Mining Areas (MA). The integration of these parameters followed a weighted normalization scheme within a multi-criteria decision analysis (MCDA) framework. Each socioeconomic factor X_i was first normalized to a 0–1 scale using min–max normalization to ensure comparability across datasets with different units and ranges, as expressed in Equation (1), where X_i is the original value, and $X_{i,min}$ and $X_{i,max}$ are the minimum and maximum observed values of the parameter across the study area.

$$X_{i,norm} = \frac{X_i - X_{i,min}}{X_{i,max} - X_{i,min}} \tag{1}$$

For distance-based variables (IA, PP, POP, and MA), the Euclidean distance from each road segment to the nearest feature was computed using Eq. (2). Since shorter distances imply higher socioeconomic importance, an inverse distance transformation was applied to derive the influence factor $D_{i,norm}$ (Eq. (3)). To account for the varying contributions of each parameter, a weighting vector W_i was derived through a hybrid approach combining the natural breaks classification and machine-learning regression-based sensitivity analysis. The regression model quantified each variable's relative contribution to the socioeconomic intensity (using NTL and PD as dependent variables), producing empirically derived weights normalized to sum to 1. The composite socioeconomic value for each road segment was then calculated as Eq. (4), where $n = 6$ corresponds to the total number of socioeconomic parameters.

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{2}$$

$$D_{i,norm} = 1 - \frac{d_{ij} - d_{min}}{d_{max} - d_{min}} \tag{3}$$

$$SV = \sum_{i=1}^{n} W_i \times X_{i,norm} \tag{4}$$

A machine-learning linear regression analysis was then performed to capture the temporal evolution of the two dynamic socioeconomic indicators, NTL and PD. The regression was implemented as a pixel-wise linear trend estimation using the ordinary least squares (OLS) algorithm. The regression model for each pixel follows the standard linear form (Eq. (5)), where y_t represents the value of the variable (NTL or PD) at time t, β_0 is the intercept, β_1 is the slope or trend coefficient representing the direction and magnitude of temporal change, and ε_t is the residual error term. The trend coefficient β_1 was estimated using the OLS method as Eq. (6), where $\bar{t}$ and $\bar{y}$ are the mean values of time and the observed variable, and n is the total number of temporal observations. The resulting slope (β_1) quantifies the rate of change per unit time and serves as an indicator of long-term socioeconomic dynamics. To enhance comparability across variables with different scales, the slope values were normalized using Eq. (7), where σ_y denotes the standard deviation of the observed variable y_t over time. The normalized coefficient (β_{norm}) was subsequently integrated into the socioeconomic value model.

$$y_t = \beta_0 + \beta_1 t + \varepsilon_t \tag{5}$$

$$\beta_1 = \frac{\sum_{t=1}^{n}(t - \bar{t})(y_t - \bar{y})}{\sum_{t=1}^{n}(t - \bar{t})^2} \tag{6}$$

$$\beta_{norm} = \frac{\beta_1}{\sigma_y} \tag{7}$$

The weight of each parameter was determined based on natural breaks and quantile classification. The natural-breaks method was used to determine the weights for the NTL and PD data because both contain significant outliers, thus allowing for classification results that minimize variation within a class and maximize differences between classes. The quantile method was used for the other variables because it has a uniform data distribution, enabling an equal number of data points in each class without adversely affecting the overall distribution. Each parameter was divided into three classes low, moderate, and high, which indicate the extent of influence each parameter has on the estimation of the socioeconomic value of the road.

2.8. Road network infrastructure climate-environmental value

The diverse geographical conditions of Southeast Asia pose varying degradation threats to road network infrastructure. This has affected government efforts to maintain and repair these roads. To estimate the environmental burden value (EP) of roads, we utilized four parameters: precipitation, LST, wind speed, and AOD. This study employed the GIS-MCDA method by overlaying each dataset, classified into three classes, to identify the road infrastructure facing the highest threats according to Eq. (8). Trend change analysis was also conducted on the four datasets to observe spatiotemporal changes across Southeast Asia for further analysis. Subsequently, a reclassification process was undertaken using the natural break method to categorize each parameter into low, moderate, and high classes, indicating the extent of influence each parameter has on calculating the environmental burden. where P represents precipitation, LST represents land surface temperature, W represents wind speed, and AOD represents aerosol optical depth.

$$\sum_{i=0}^{m} P_i + LST_i + W_i + AOD_i \tag{8}$$

2.9. Road maintenance priority index (RMPI)

The Road Maintenance Priority Index (RMPI) was developed to identify spatial variations in road maintenance needs across Southeast Asia by integrating socioeconomic value (SV) and environmental pressure (EP) within a unified geospatial framework. The environmental pressure component represents degradation risk caused by climatic and environmental stressors, while the socioeconomic value component captures the functional and social importance of roads in supporting regional mobility and economic activity (Koks et al., 2019). Both SV and EP were normalized to a common scale before integration. A weighted overlay approach was applied to combine these components, as expressed in Equation (9):

$$RMPI = W_{SV}XSV + W_{EP}XEP \tag{9}$$

In this study, an equal weighting scheme was adopted ($W_{SV} = W_{EP} = 0.5$) because both dimensions represent complementary but independent factors influencing road maintenance demand. One reflects functional significance, and the other represents exposure to degradation. The equal-weight approach also minimizes subjective bias that may occur in expert-driven weighting and ensures comparability among the 11 Southeast Asian countries analyzed. To evaluate the robustness of this assumption, a sensitivity test was performed by varying each weighting coefficient within ±20 percent of its baseline value. The resulting RMPI classifications showed a spatial consistency exceeding 92 percent, indicating that moderate changes in parameter weights do not substantially alter the overall prioritization pattern. This result supports the suitability of the equal-weight framework for regional-scale applications where uniform interpretability is important for cross-country comparison.

Model validation was carried out by comparing the spatial distribution of RMPI scores with independent landslide event data obtained from the Indonesian National Disaster Management Agency (BNPB) and NASA's Global Landslide Catalog. This validation served as an indirect method to assess the RMPI's capacity to reflect real-world road vulnerability, assuming that higher RMPI values correspond to areas more prone to environmental stress and maintenance needs. The spatial intersection between recorded landslide events and RMPI classes was calculated to quantify consistency between model predictions and observed hazard occurrences. The resulting RMPI outputs provide a spatially explicit prioritization framework that can assist governments and infrastructure agencies in allocating maintenance resources more effectively and proactively across Southeast Asia.

3. Results

3.1. Road network infrastructure value

Road network infrastructure data for Southeast Asia were obtained from the GRIP dataset. These data include classifications of road network infrastructure across various categories, such as road type, surface type, year of data acquisition, and data source. These categories were then used to analyze the socioeconomic value, environmental burden, and road maintenance priorities. The geodesic length of each road vector was calculated using the WGS 1984 Coordinate Reference System (EPSG4326). The road network infrastructure in Southeast Asia is predominantly characterized by low infrastructure values, specifically tertiary and local roads. Fig. 2 illustrates the road infrastructure values for Southeast Asia. Fig. 2(a) displays the spatial distribution of the road infrastructure value and Fig. 2(b) presents the statistical distribution of the road infrastructure value for each country. Overall, Fig. 2 indicates that a majority of the road network infrastructure in Southeast Asia has a low value, accounting for 80.30 % (~881,347.4 km), followed by a moderate value at 13.94 % (~152,993.5 km) and a high value at 5.76 % (~63,239.7 km). The highest percentage of low-value road infrastructure in Southeast Asia was found in Timor-Leste at 95.42 % (~14,188.39 km), Indonesia at 94.17 % (~377,325.6 km), and Vietnam at 88.11 % (~156,164 km). On the other hand, the highest percentage of high-value infrastructure was found in Thailand at 16.33 % (~37,995.36 km), Malaysia at 12.78 % (~35,788.55 km), and Laos at 10.48 % (~2,582.636 km).

3.2. Socioeconomic value of road network infrastructure

The socioeconomic value of the road network infrastructure in Southeast Asia was calculated to explain the social and economic weights that this infrastructure provides to communities. This value is estimated using six parameters: NTL, PD, POPs, IAs, MAs, and PPs. These data were integrated through spatial analysis to obtain the socioeconomic value of road network infrastructure in Southeast Asia. The NTL and PD data utilized trend change analysis to observe trends in PD and NTL values at specific locations over a defined period. The results of the trend change calculations for the socioeconomic data are shown in Fig. 3, where Fig. 3(a) presents the PD data and Fig. 3(b) displays the NTL data. Based on Fig. 3, both the PD and NTL data exhibited a positive trend, indicating a significant increase across Southeast Asia.

The parameters represented as vector data, such as POPs, IAs, Mas, and PPs, were processed using the Euclidean distance of each pixel from these point locations. The closer the Euclidean distance of these parameters to the road infrastructure, the greater the socioeconomic value of the road. Fig. 4 illustrates the socioeconomic value of road infrastructure in Southeast Asia. Fig. 4(a) shows the spatial distribution, and

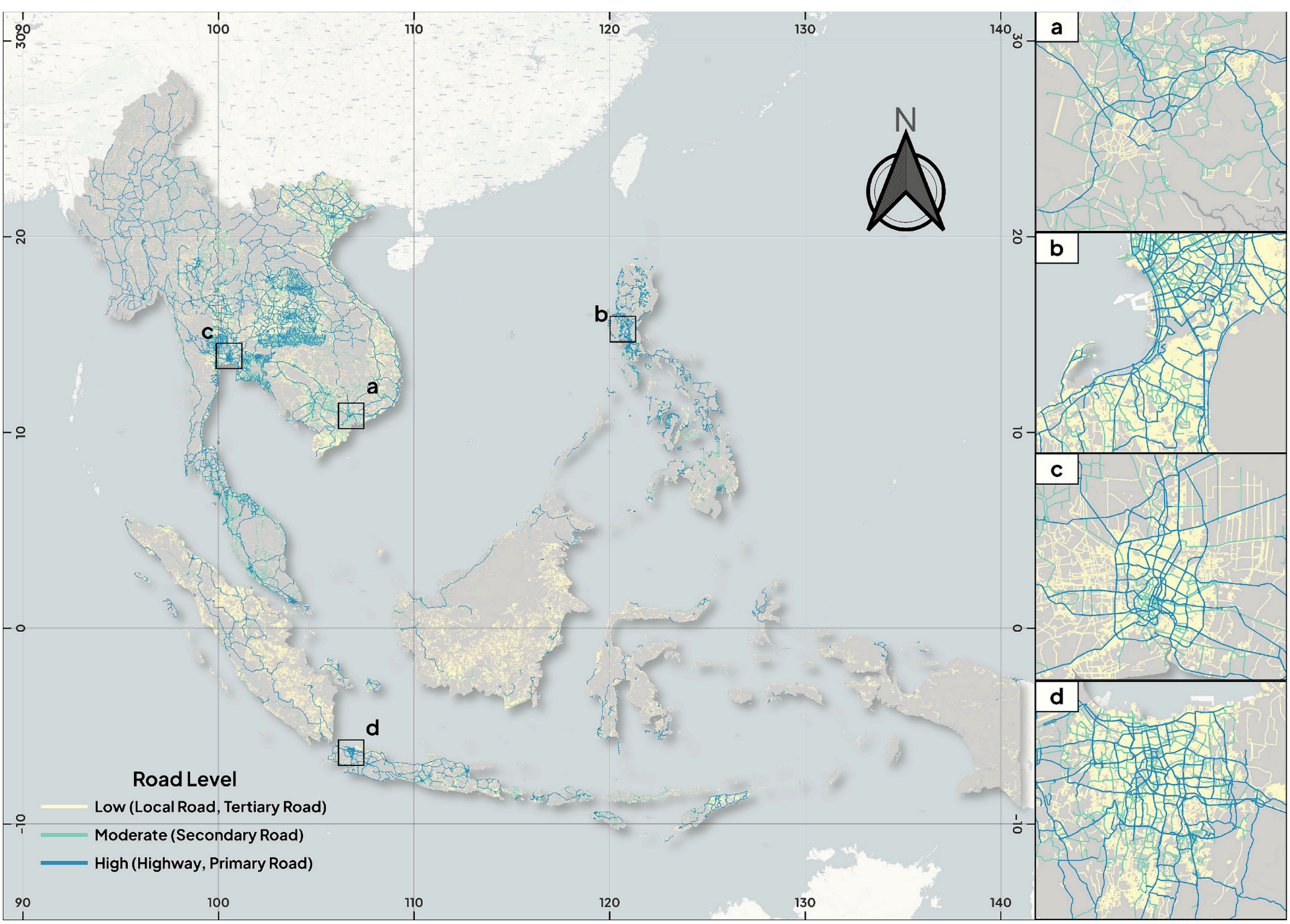

Fig. 2. Spatial distribution of Road network infrastructure value.

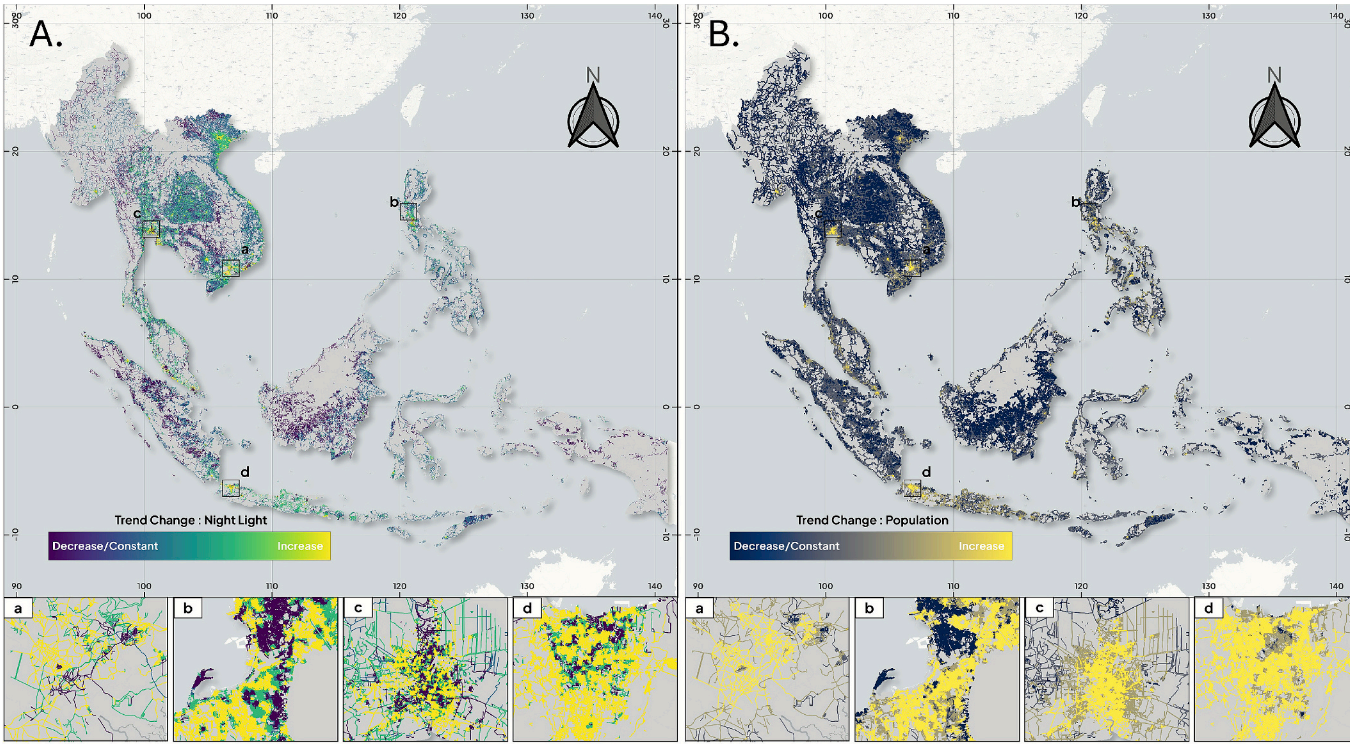

Fig. 3. Relative trends change analysis of the (A) population and (B) nighttime light.

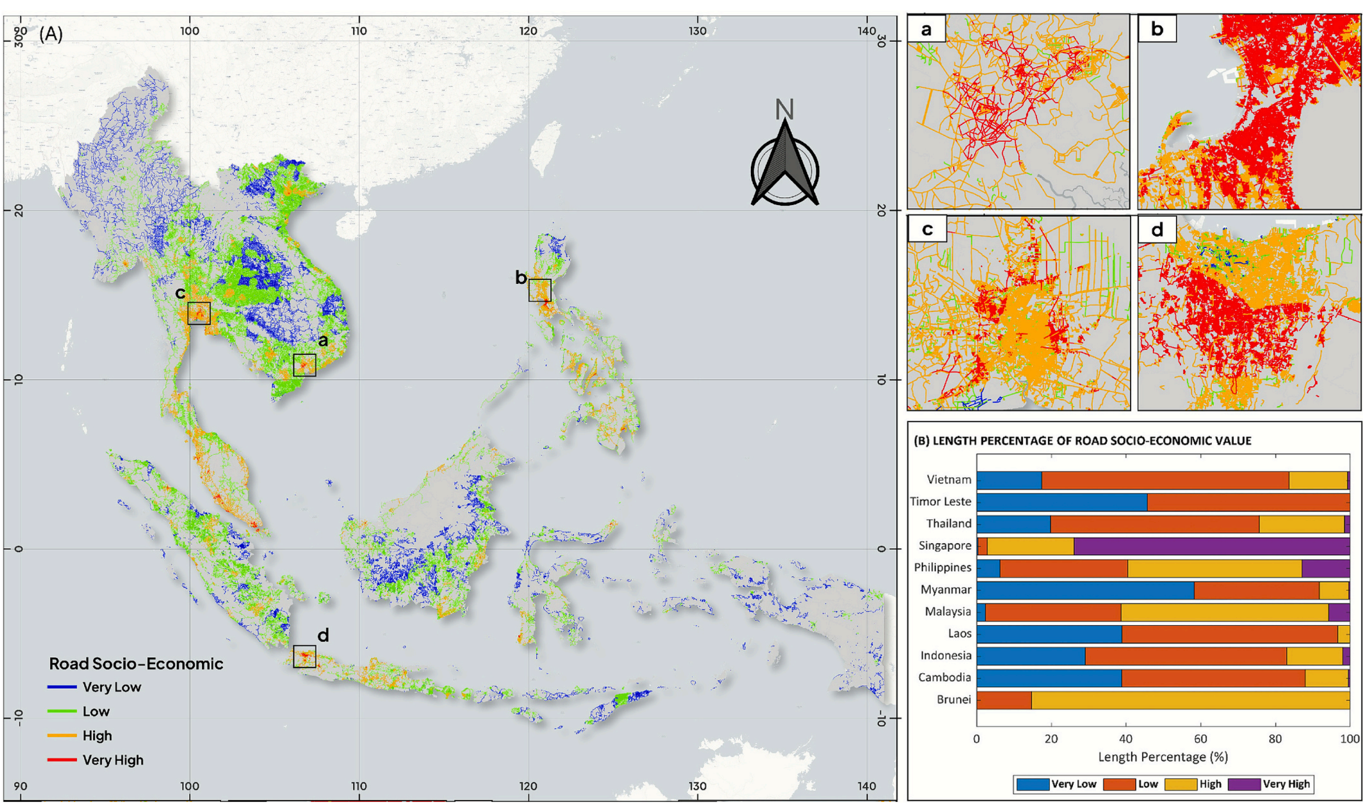

Fig. 4. Road socioeconomic value: (A) spatial distribution and (B) length percentage in each country.

Fig. 4(b) presents the statistical values of the percentage of road length in each class for each country. Overall, the road infrastructure in Southeast Asia is predominantly classified as low at 52.69 % (~577,927.8 km), followed by very low at 25.09 % (~275,160.8 km), high at 19.65 % (~215,545.9 km, and very high at 2.56 % (~28,118.11 km). Countries with the highest proportions of socioeconomic values in the very high and high classes were Singapore at 97.17 % (~1,929.78 km, Brunei at 85.28 % (~563.00 km), and Malaysia at 61.33 %

(∼21,950.18 km). Conversely, countries with the largest proportions of socioeconomic values in the very low and low classes were Timor-Leste at 99.94 % (∼14,797.35 km), Laos at 96.69 % (∼23,778.03 km), and Myanmar at 91.73 % (∼61,095.98 km). As shown in Fig. 4(a1), 4(a2), and 4(a3), the urban centers of cities such as Ho Chi Minh, Singapore, and Jakarta exhibit very high socioeconomic values, which gradually decrease with distance from the city center.

3.3. Environmental pressure value of road network infrastructure

The environmental load value of road network infrastructure in Southeast Asia was calculated to determine the environmental pressures that threaten and damage the road network infrastructure. The environmental load was estimated based on four parameters: LST, precipitation, wind speed, and AOD. Calculating this environmental load utilized a trend change analysis for each environmental parameter. A higher trend change value indicated a greater impact on the environmental load value, while a lower value signified a lower impact. The results of the trend change calculations are shown in Fig. 5, with Fig. 5 (a)–(d) sequentially displaying the AOD, LST, precipitation, and wind speed parameters.

Fig. 5 shows that some areas in Southeast Asia experienced an increase in the environmental parameters, whereas others showed a decrease. Fig. 5 (a)–(b) indicate that the central areas of Ho Chi Minh City and Singapore experienced an increase in AOD and LST, with values decreasing with distance from the city center. In contrast, the city center in Jakarta showed a decrease in AOD and LST, whereas the surrounding areas exhibited an increase in both parameters. The precipitation

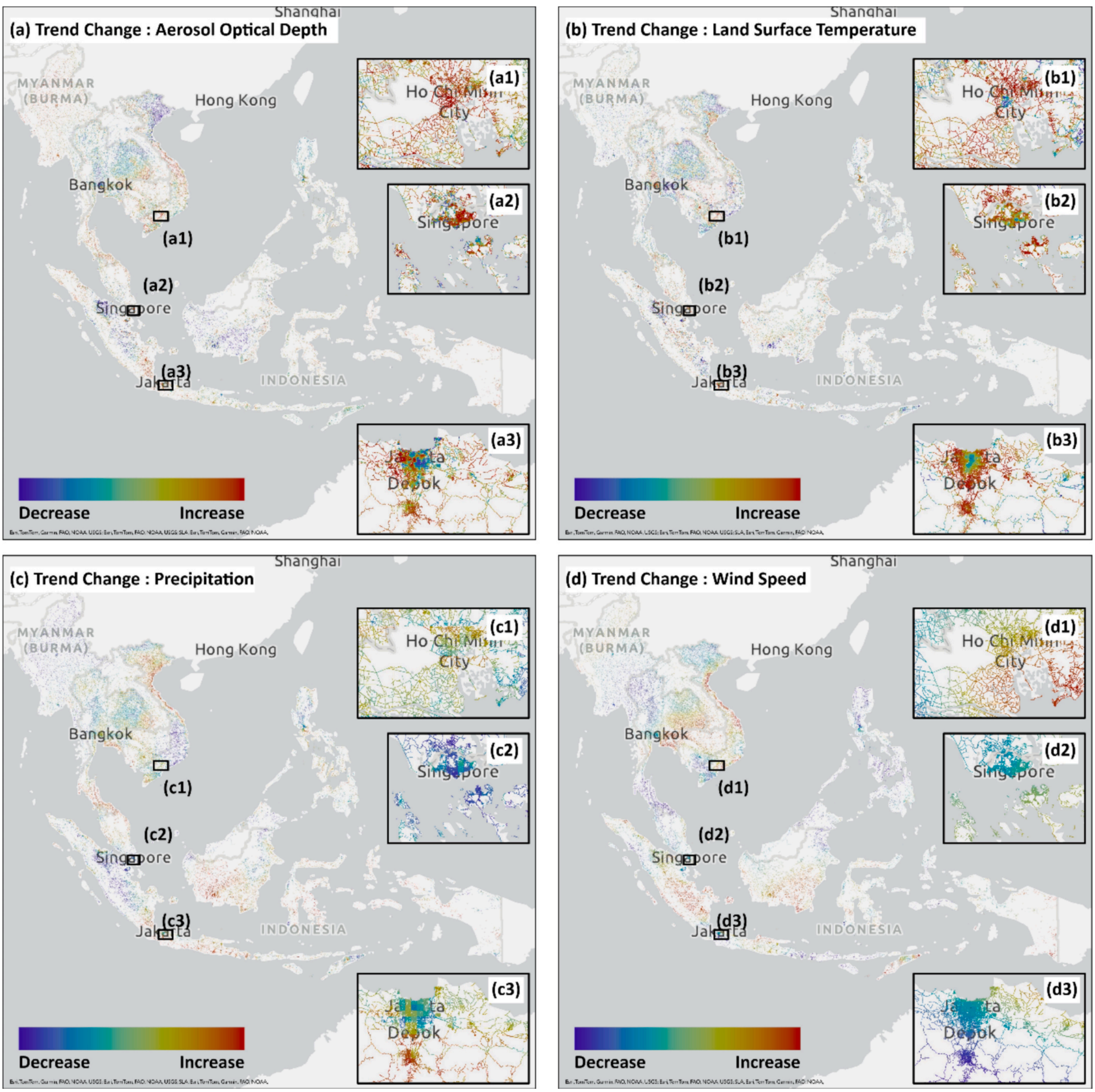

Fig. 5. Trend changes in (a) aerosol optical depth, (b) land surface temperature, (c) precipitation, and (d) wind speed.

parameter in Fig. 5(c) indicates that Ho Chi Minh City has a positive trend in the city center extending westward but a negative trend in the eastern part of the city. Moreover, Singapore showed a negative trend in precipitation throughout the area [Fig. 5(c)], and Jakarta exhibited a negative-positive precipitation trend in the city center and a positive trend in the surrounding areas, particularly in the southern parts of the city. The wind speed trends shown in Fig. 5(d), the city center and southern parts of Ho Chi Minh City were predominantly positive, whereas the western area showed a negative trend. Overall, Singapore exhibited a negative trend for wind speed, with the southeastern part showing relatively positive values. In contrast, Jakarta showed a negative trend across the entire city, with a positive trend observed in the northeastern region.

Fig. 6 displays the cliate-environmental value of road infrastructure in Southeast Asia. Fig. 6(a) shows the spatial distribution, whereas Fig. 6 (b) presents the statistical percentages of road lengths in each class across the countries. Overall, the road infrastructure in Southeast Asia is dominated by the high class at 46.79 % (~512,346.81 km), followed closely by the low class, at 46.22 % (~506,128.30 km). The very high class accounted for 3.53 % (~38,688.70 km), while the very low class accounted for 3.44 % (~37,737 km). The countries with the largest proportions of very high and high environmental classes were Singapore at 100 % (~1,964.99 km), Brunei at 100 % (~660.15 km), and Cambodia at 71.77 % (~38,445.41 km). Conversely, the countries with the largest proportion of very low and low classes were Myanmar at 79.12 % (~52,750.66 km), Timor-Leste at 69.35 % (~10,299.02 km), and Indonesia at 61.55 % (~245,603.28 km). Fig. 6 (a1)-(a3) demonstrate that the city centers such as Ho Chi Minh City, Singapore, and Jakarta, are dominated by high and very high environmental values.

3.4. Road maintenance priority index development

The Road maintenance priority index (RMPI) value indicates the maintenance priorities for road infrastructure in Southeast Asia (Fig. 7). It is calculated based on socioeconomic and environmental load values using a weighted overlay, assuming that both parameters have an equal influence on road damage according to their respective classes. Fig. 8(a) shows the spatial distribution of the RMPI values, whereas Fig. 8(b) illustrates the statistical distribution of RMPI values. In general, the RMPI values in Southeast Asia are mostly dominated by the low class, accounting for 45.08 % (~493,418.39 km), followed by the moderate class at 39.69 % (~434,478.17 km), high class at 9.06 % (~99,170.58 km), very low class at 5.28 % (~57,825.96 km), and very high class at 0.88 % (~9,640.51 km). The countries with the highest RMPI values were Singapore at 99.98 % (~1,964.69 km), Brunei at 48.20 % (~318.213 km), and Malaysia at 36.59 % (~13,052.02 km). Conversely, the countries with the lowest RMPI values were Timor-Leste at 92.29 % (~13,667.96 km), Myanmar at 81.80 % (~54,530.73 km), and Laos at 66.99 % (~16,483.89 km). Fig. 8 (a1)–(a3) also show that major cities such as Ho Chi Minh City, Singapore, and Jakarta, predominantly exhibit high RMPI values.

4. Discussion

4.1. Data model comparison with disasters

A comparative analysis was conducted between landslide event data from 2010 to 2020 and the RMPI generated in this study to evaluate the spatial correspondence between hazard occurrences and maintenance priorities. The spatial relationship between landslide hazards and the RMPI results was examined to assess how well the index reflects areas affected by terrain-related disruptions. Landslides can significantly influence road hazard levels (Fig. 9a). The orange color represents landslide magnitudes occurring outside the RMPI areas. However, certain landslide events with low, medium, and high magnitudes occurred within RMPI areas classified as low, medium, and high, as indicated by the blue to purple points. Based on the statistics shown in Fig. 8(b), 14.93 % of the landslide events from 2010 to 2020 occurred in RMPI

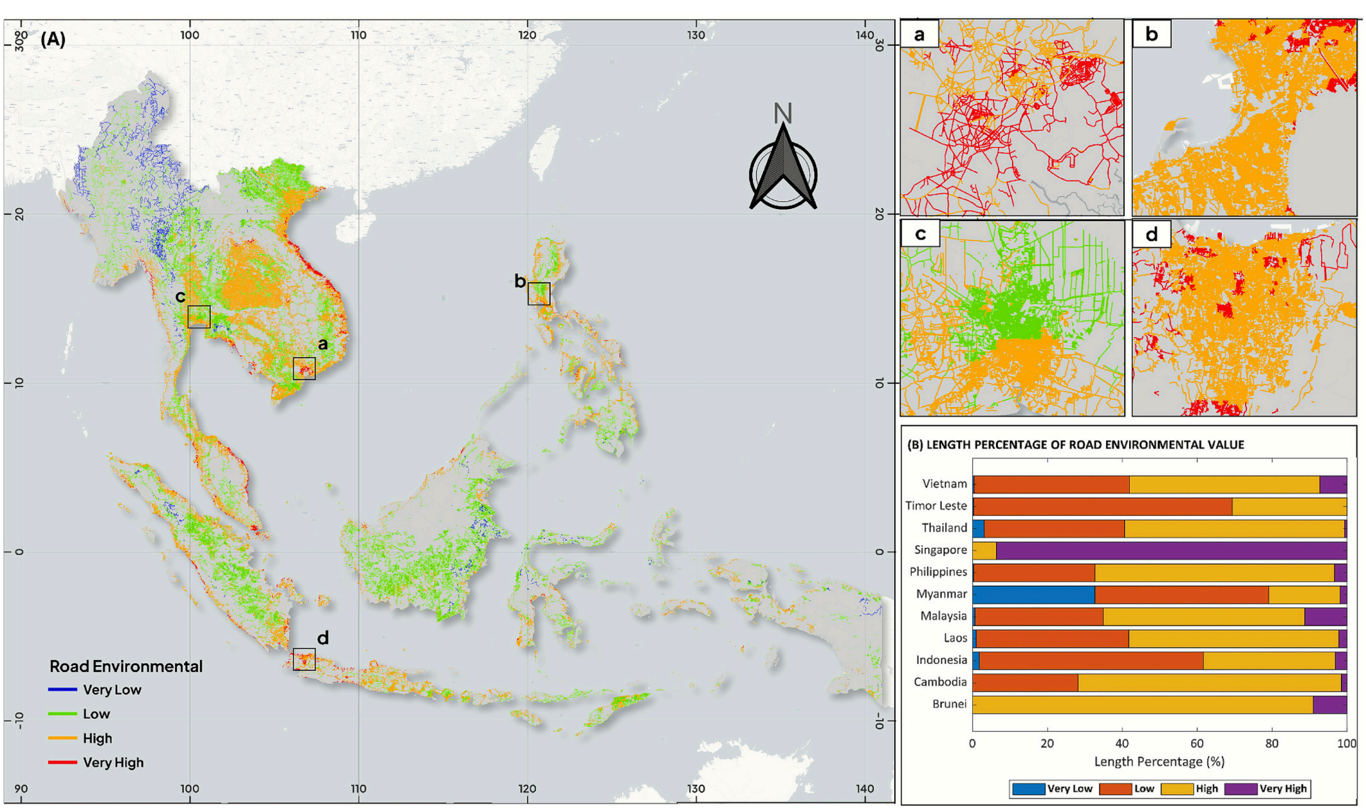

Fig. 6. Road climate-environmental value: (A) spatial distribution and (B) length percentage in each country.

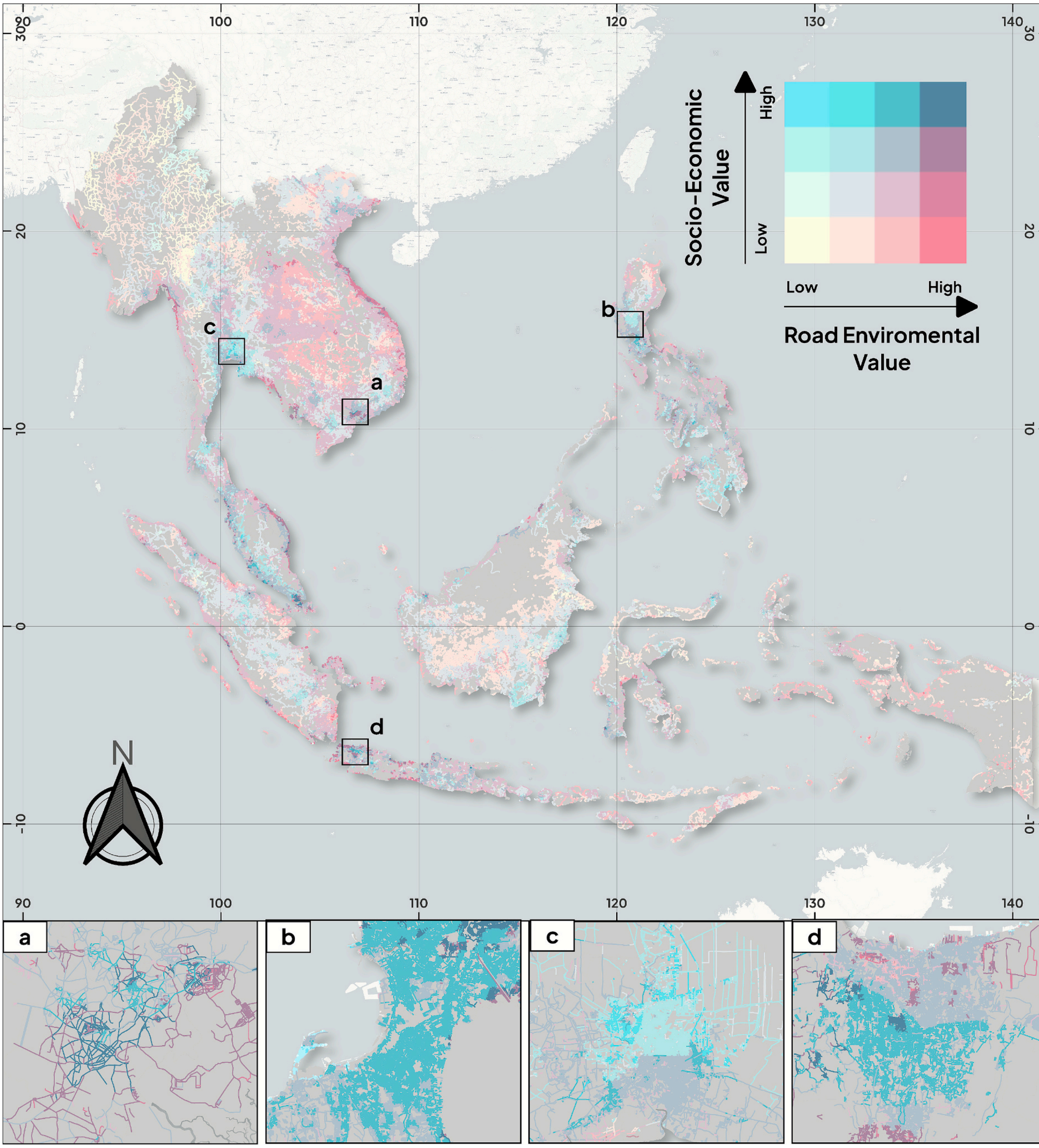

Fig. 7. Road maintenance priority index (RMPI) development based on bivariate analysis between socioeconomic value and environmental pressure.

areas while approximately 85.17 % occurred in non-RMPI areas. The results indicated that 9.18 % of these events had high RMPI values and medium landslide magnitudes. The next most dominant class was the medium class for both landslide events and the RMPI, accounting for 2.54 %. The third dominant class included low-class landslide events with high RMPI values (1.41 %). This suggests that the higher the RMPI value and the greater the magnitude of past landslides, the higher the RMPI priority for immediate intervention, which is evident for Java Island, Indonesia, and the Philippines. Java is the most densely populated island in Indonesia and has experienced massive residential development. Consequently, significant land clearing and illegal logging have increased the risk of landslides in the region. In addition, the high population density of Java contributes to a high RMPI. Therefore, from the perspective of landslide disasters and RMPI in Indonesia, Java Island requires prioritization.

The comparison with landslide events provides an indirect yet meaningful form of validation. Although detailed pavement-condition or maintenance-record data were not uniformly available for Southeast Asian countries, the strong spatial overlap between high-RMPI zones and historical landslide occurrences supports the model's capability to capture areas exposed to environmental and structural stress. This proxy validation suggests that the RMPI reliably identifies regions requiring maintenance attention at the regional scale.

4.2. Model data comparison with economic analysis

Fig. 10 shows a comparison between the GDP values and RMPI across cities/provinces in Southeast Asia. Fig. 10(a) provides a spatial visualization of the comparison between the GDP and RMPI, while Fig. 10(b) shows the statistical distribution. Statistically, the results indicate that

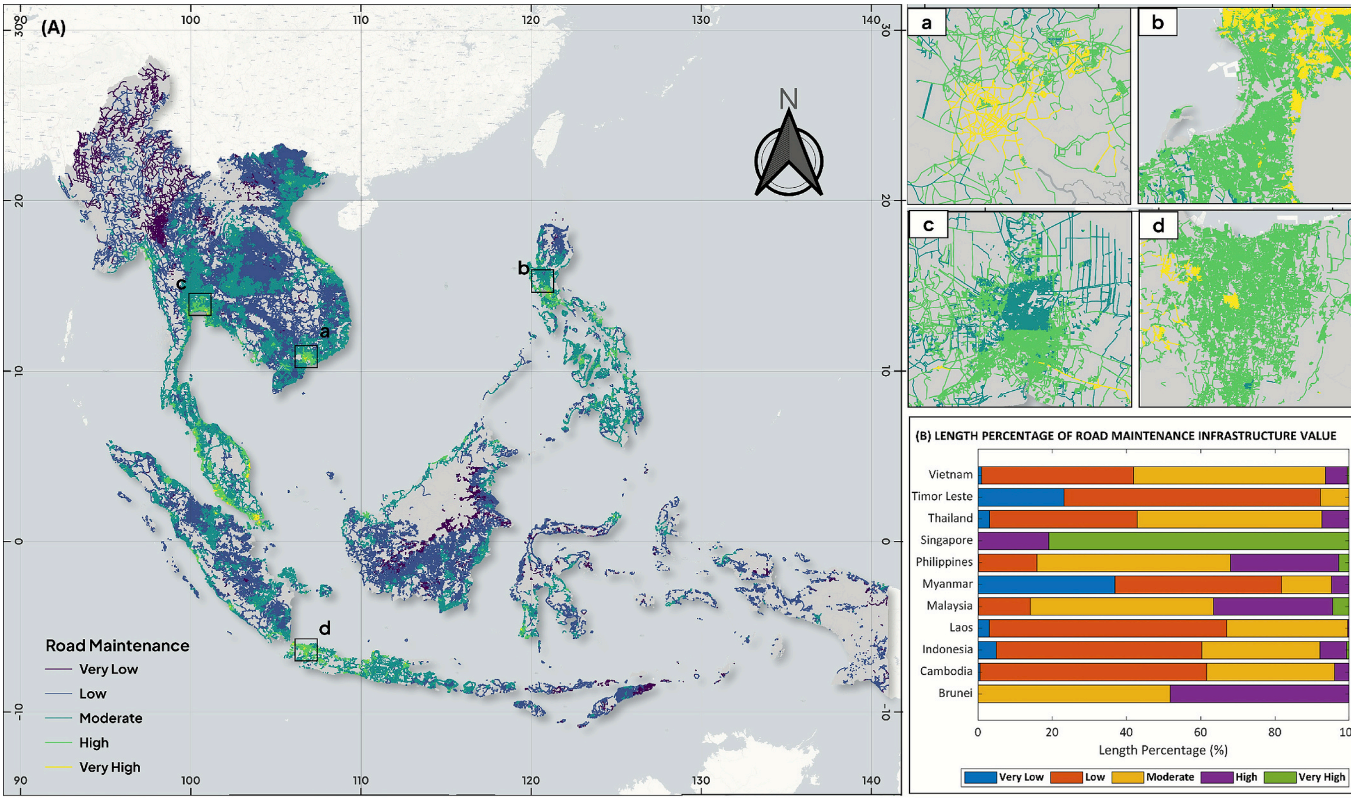

Fig. 8. Road maintenance priority index (RMPI): (A) spatial distribution and (B) length percentage in each country.

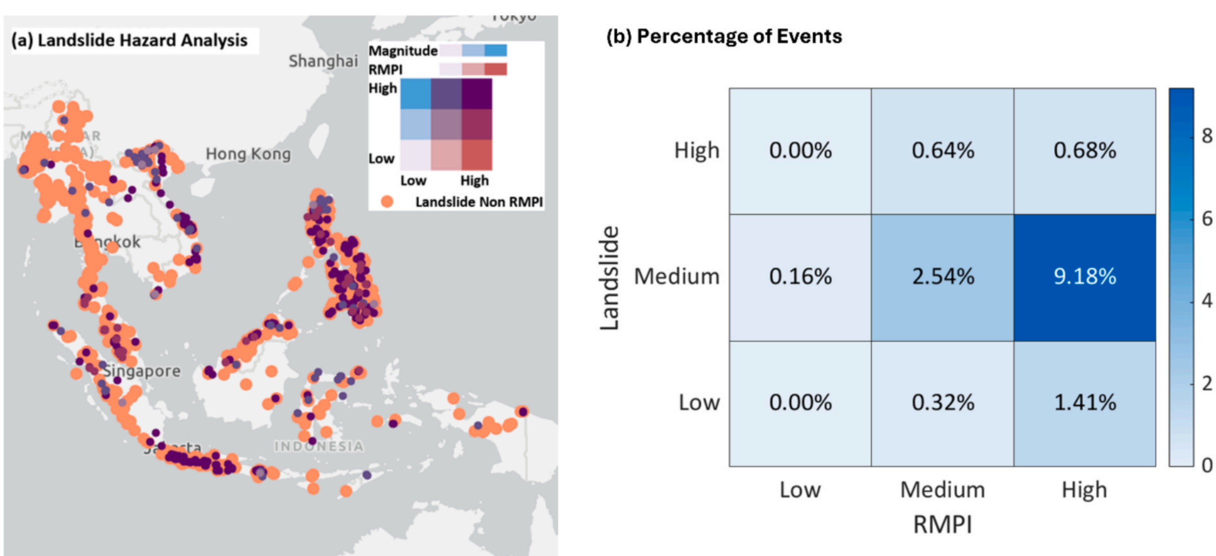

Fig. 9. RMPI and landslide disaster comparison: (a) spatial and (b) statistical comparisons.

Southeast Asia is dominated by RMPI low–GDP high, RMPI high–GDP low, and RMPI medium–GDP medium, accounting for 23.77 %, 21.47 %, and 16.32 %, respectively. This implies that if the RMPI is high and GDP is low, local governments can request funding from the central government for infrastructure maintenance. Conversely, if both the RMPI and GDP are high, local governments can independently maintain their existing infrastructure. Fig. 10(c) shows a statistical comparison of the GDP and RMPI for each country in Southeast Asia. According to Fig. 9 (c), Laos, Indonesia, Malaysia, and Singapore are predominantly classified as RMPI high and GDP high, with values of 50 %, 27.97 %, 31.48 %, and 100 %, respectively. This implies that most areas in these four countries can maximize their potential to maintain infrastructure networks effectively. Conversely, Laos exhibits a balanced proportion of 50 % for both GDP low and RMPI high, indicating that some regions in Laos require support from the central government to aid in road infrastructure maintenance.

4.3. Limitations and future research direction

This study introduced a data-driven geospatial intelligence

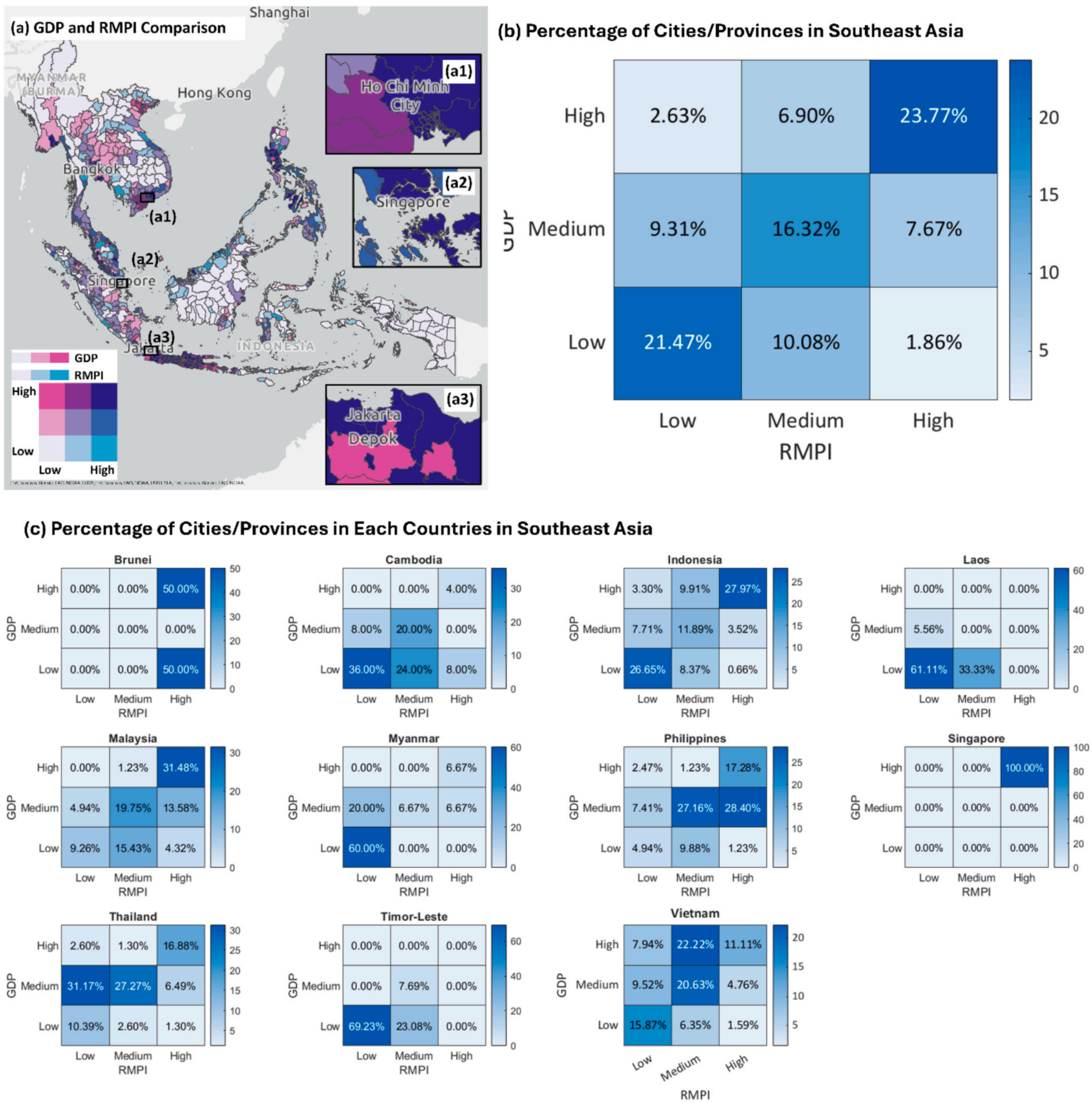

Fig. 10. GDP and RMPI comparison: (a) spatial distribution, (b) overall statistics in Southeast Asia, (c) statistically in each Southeast Asian country.

framework for road maintenance prioritization that integrates socio-economic and environmental variables. Despite its comprehensive design, several methodological limitations remain. The weights assigned to each parameter were assumed to have equal contributions to minimize subjectivity and ensure consistency across multiple countries with different data quality and infrastructure contexts. However, each parameter undoubtedly contributes differently to determining the priority level of road infrastructure maintenance. Future studies could incorporate expert-based weighting approaches, such as the Analytic Hierarchy Process (AHP) or entropy weighting, to enhance precision and policy relevance, particularly for national- or subnational-scale applications where contextual expertise is available.

Another limitation concerns the spatial resolution of input datasets. Certain environmental variables, such as aerosol optical depth (AOD) and land surface temperature (LST), were derived from MODIS imagery at a 1 km spatial resolution. While this level of detail is adequate for regional-scale assessments, it can obscure localized variations in road conditions and microclimate that are relevant to maintenance operations. Aggregating finer-resolution layers (e.g., VIIRS nighttime lights at 463 m and WorldPop population data at 100 m) to the 1 km scale minimized inconsistencies and enhanced cross-country comparability. However, future research should integrate higher-resolution satellite products, such as Sentinel-2 (10–20 m), PlanetScope (3 m), or unmanned aerial vehicle (UAV) observations, to capture fine-scale spatial heterogeneity and improve the accuracy of the RMPI at the city or corridor level.

Future studies could also incorporate additional parameters, including climate hazards and infrastructure-specific attributes, to better align the RMPI with real-world maintenance priorities. Another important limitation lies in the absence of direct validation using road-condition surveys or official maintenance records, which remain inconsistent across Southeast Asia. As a result, the RMPI was validated indirectly through its spatial relationship with historical landslide events and GDP-related infrastructure statistics. While this approach provides a meaningful proxy for assessing model reliability, further integration of empirical road-condition data, maintenance expenditure records, and high-resolution remote sensing observations would significantly improve validation robustness. Strengthening this empirical linkage would enhance the operational applicability of the RMPI and support its adoption as a decision-support tool for data-driven and climate-resilient infrastructure management.

5. Conclusions

This study aimed to identify priority locations for road infrastructure maintenance in Southeast Asia using an integrated approach of GIS technology, remote sensing data, long-term trend analysis, and MCDA. The results indicate that the infrastructure value of the road network in Southeast Asia is predominantly classified as low, accounting for 80.30 % of the road network (~881,347.4 km), followed by the moderate category at 13.94 % (~152,993.5 km), and high category at 5.76 % (~63,239.7 km). In terms of socioeconomic value, the road network in Southeast Asia is dominated by the low class, accounting for 52.69 % (~577,927.8 km), followed by the very low class at 25.09 % (approximately 275,160.8 km), the high class at 19.65 % (~215,545.9 km), and very high class at 2.56 % (~28,118.11 km). The environmental load value of road infrastructure is predominantly high, accounting for 46.79 % (~512,346.81 km), followed closely by the low class at 46.22 % (~506,128.30 km), very high class at 3.53 % (~38,688.70 km), and very low class at 3.44 % (~37,737 km). Finally, the RMPI value for road infrastructure was mainly low at 45.08 % (~493,418.39 km), followed by the moderate class at 39.69 % (~434,478.17 km), high class at 9.06 % (~99,170.58 km), very low class at 5.28 % (~57,825.96 km), and very high class at 0.88 % (~9,640.51 km). Future research could also consider and add additional parameters such as disaster parameters and another challenge is improving the spatial resolution of modeling. The proposed method and index developed in this study are expected to assist policymakers in determining priority locations for road infrastructure maintenance. This study assumes equal weight for all parameters, which may not accurately reflect their contributions. Future research should incorporate methods like AHP for better weighting and include additional parameters such as disaster risk. Additionally, improving the spatial resolution of modeling using remote sensing data could enhance the accuracy of the findings.

CRediT authorship contribution statement

Anjar Dimara Sakti: Methodology, Investigation, Formal analysis, Writing – original draft. **Muhammad Asa:** Formal analysis, Resources. **Agung Budi Harto:** Conceptualization. **Tania Septi Anggraini:** Writing – review & editing, Visualization. **Cokro Santoso:** Writing – review & editing, Investigation. **Albertus Deliar:** Methodology. **Riantini Virtriana:** Conceptualization. **Akhmad Riqqi:** Writing – review & editing. **Budhy Soeksmantono:** Supervision. **Dudy Darmawan Wijaya:** Writing – review & editing, Resources. **Can Trong Nguyen:** Resources, Methodology. **Khairul Nizam Abdul Maulud:** Resources, Methodology. **Maya Safira:** Writing – review & editing, Resources, Methodology. **Ketut Wikantika:** Supervision, Conceptualization.

Declaration of competing interest

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.

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Data availability

The spatial data products used in the road maintenance prioritization model, along with additional datasets generated during this study, are available from the corresponding author (A.D.S., anjar@itb.ac.id) upon reasonable request.

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