Landscape Dynamics and Environmental Fragility Zoning in Hinh River Basin: Insights for protecting natural ecosystems

Quoc Khanh Nguyen[‡], Hanh T. Tong[§], Liem D. Nguyen[|], Thu Nga T. Nguyen[§], Trung Dung Ngo[‡], Nguyen Hong Quang[¶], Anh Tu V. Dinh[‡], Mai-Phuong Pham[‡]

‡ Joint Vietnam - Russia Tropical Science and Technology Research Center, Ha Noi, Vietnam
§ Le Quy Don University, Ha Noi, Vietnam
| Nong Lam University, Ho Chi Minh, Vietnam
¶ Vietnam National Space Center (VNSC), Vietnam Academy of Science and Technology (VAST), Ha Noi, Vietnam

Corresponding author: Mai-Phuong Pham (maiphuong.vrtc@gmail.com)

Academic editor: Jan Staes

Abstract

The landscapes in the Hinh River Basin are crucial and highly sensitive to climate change for the coastal province of Phu Yen and the entire south-central coastal region of Vietnam, offering vital environmental services to its downstream areas. Hinh River Basin has a rich system of rivers and streams and abundant surface water resources. However, it remains one of the region's top localities at risk and a very vulnerable region. This study aims to evaluate the changes in landscape (LC) over 10 years (2010-2023) and predict LC over the next six years using machine-learning (ML) algorithms on Google Earth Engine. To achieve these study goals, we establish: (i) potential environmental fragility (PEF) levels based on: terrain slope; geological domains; river hierarchy; percentage of sand in soil; annual mean precipitations; and (ii) emergent environmental fragility (EEF) levels through the addition of LC parameter to model. The methodology includes integrating the Analytic Hierarchy Process (AHP) into a Geographic Information System (GIS). Results show that three LC types (water, annual industrial crop, forest) are related to extremely high EEF. The predictive model suggests that, by 2030, the forest and annual industrial crop LCs in the study area will increase by around 20%. The analysis results show that there has been an increase in the area of planted forests, which can confirm the futher effectiveness of agricultural, forestry, afforestation and forest protection programmes in the study area (Plan for the implementation of forestry development strategy for the period 2021-2030, with a vision to 2050, Phu Yen Province, N° 126/KH-UBND 13/7/2021; and Decision on the approval of the project for planting 15 million trees in Phu Yen Province for the period 2021-2025, N° 1646/QĐ-UBND 16/11/2021).

Keywords

landscape, dynamic, environmental fragility, Google Earth Engine, MCA

Introduction

Managing land cover and landscape (LC) in the Basin is becoming an urgent issue, particularly in ensuring fair uses without harming the external environment (Liu et al. 2008). Hinh River's landscape is an important part not only of the central regions of Vietnam, but also of the entire landscape of Phu Yen Province. This area provides many essential environmental services and offers greater benefits than direct resource exploitation, such as hydropower and climate regulation. Besides the environmental services provided by the Hinh River landscape, the forested areas help absorb carbon, contributing to the fight against global warming.

One of the main causes of climate change is the expansion of human activities. The Hinh River landscape has been facing this issue, largely related to drought and food imbalance (due to crop failure) (Pham et al. 2022, Nga et al. 2023). Additionally, the growing focus on agricultural development, coupled with increased urbanisation and rising population pressures, along with the diminishing availability of arable land, has created substantial challenges. These factors have collectively contributed to significant and rapid alterations in the regional landscape. The expansion of agricultural activities and urban areas has transformed natural environments, leading to noticeable changes in land-use patterns and ecosystem dynamics. The combination of these pressures highlights the urgent need for sustainable land-management practices to address the environmental impacts and ensure balanced development in the region (Phan et al. 2021, Pham et al. 2021).

In recent years, especially since 2010, the rate of deforestation in the Hinh River area has tended to decrease and, therefore, LC changes need to be studied to detect trends in land-use changes up to 2030 and beyond. Nowadays, multistrata farming has become one of the main economic activities in Hinh River Basin (Chuong et al. 2015). These activities assist residents in stabilising cultivation, limiting forest encroachment and reducing forest burning and destruction. However, the increase in agricultural land area raises concerns about potential environmental fragility (PEF), which is determined through environmental factors such as terrain slope; geological domains; river hierarchy; percentage of sand in soil; and annual mean precipitations. Assessing LC changes using high-resolution satellite images such as Landsat, Sentinel and analytical tools on the Google Earth Engine (GEE) platform has become common. The LC map and PEF results were integrated into the evaluation model of the emergent environmental fragility (EEF) (França et al. 2022).

Many studies provide useful solutions for large-scale monitoring of land-use status in the area, especially forest and water LC (Floreano and de Moraes 2021). Through research on environmental fragility (EF), zoning for potential environmental fragility (PEF) supports local managers in planning development policies for each area within the territory. Studies also reflect the vulnerability of artificial LC (Amorim et al. 2021). These results can provide a crucial basis for proposing solutions to mitigate impacts on protected water and forest LC supported by Junior and Röhm (2014). Ecological regions are distinct areas defined by ecological zone classifications, where anthropogenic components interact with environmental ones (Blasi et al. 2014). These classifications guide sustainable management (FAO 2000), provide a framework for conserving natural resources and evaluate the fragility zoning. They support biodiversity conservation, forest evaluations, climate change studies and protected area planning. Ecoregion fragility depends on ecological susceptibility and anthropogenic pressure, both of which are quantitatively measurable.

PEF depends on LC units and relates to susceptibility to soil erosion, land degradation, sediment deposition or geological activities leading to LC degradation (França et al. 2022). PEF allows for evaluating the natural dynamic balance of a geological system. It considers the natural attributes of LC (e.g. geological regions, soil, rainfall, slope, river systems), while emergent environmental fragility (EEF) results from applying potential fragility and land-use cover. The variables used assess both natural and human-induced hazards (Mastronardi et al. 2022). This model assigns weights to spatial data, ensuring higher consistency in the analysis process (Junior and Röhm 2014). AHP analysis allows experts to evaluate the weight of factors employed in constructing the PEF and EEF maps (França et al. 2022).

Based on previous literature reviews, this study presents a new dimension, which also represents a gap in current research that has yet to be addressed or thoroughly explored: LC dynamics prediction after some years of plan for the implementation of forestry development strategy in Phu Yen Province, N^{o} 126/KH-UBND 13/7/2021; and Decision on the approval of the project for planting 15 million trees in Phu Yen Province for the period 2021-2025, N^{o} 1646/QĐ-UBND 16/11/2021. The results of the assessments were used to map PEF and EEF zoning. This approach not only advances current methodologies, but also provides a robust framework for effective LC management, benefitting stakeholders involved in land conservation and resource allocation. The insights gained from this study will be instrumental in guiding policy development and strategic planning, ultimately contributing to sustainable land-use practices.

Material and methods

Study area

The Hinh River Basin is in a mountainous district in the southwest of Phu Yen Province of Vietnam. It features extensive land, majestic mountains and numerous stunning natural landscapes. The land is home to more than 20 ethnic groups occupying nearly half of the total population sharing the territory with the Kinh ethnicity (the majority ethnic group in Vietnam). Hinh River Basin has a diverse range of land covers (LC), including forest landscapes, agroforestry and waterbodies. Hinh River is a primary tributary of the Ba River, flowing through the Hinh River Basin in Phu Yen Province (Fig. 1).

The landscpae map

Landsat Image Collection

The images used in this study are surface reflectance images from Landsat 5-TM and 8-OLI satellites, with a spatial resolution of 30 m, creating a rich and reliable database for monitoring and studying environmental and geographical phenomena. Table 1 details the images used. The image classification process was conducted for four periods: 2010, 2015, 2018 and 2023, using separate scripts and datasets for each year.

Image Pre-processing

An open-source cloud computing platform was implemented to perform image collection, supervised classification and accuracy assessment by applying machine-learning and artificial intelligence algorithms (Tamiminia et al. 2020). The cloud computing system provides a flexible and powerful environment for processing and analysing large datasets from Landsat. Machine-learning algorithms are applied to improve the accuracy of image classification, ensuring that the results accurately reflect changes on the Earth's surface. Specifically, using open-source technology not only helps reduce costs, but also allows the scientific community to access, verify and improve the methods and algorithms used. We performed image pre-processing by applying a cloud mask to each dataset to create composite images with acceptable cloud-cover levels. This cloud filtering process uses the "pixel qa" band in the surface reflectance collections to remove clouds and cloud shadows, resulting in cloud-free RGB composites (Markert et al. 2018). To further analyse the study area, we used the boundary of Song Hinh District to clip the images, retaining only the portion within this area. This guarantees that the processed image data only focuses on the Song Hinh District and is unaffected by factors outside the study region.

LC Training, Classification and Accuracy Evaluation

The Landsat 5 and 8 images of the years; 2010, 2015, 2018 and 2023 were processed from the Google Earth archive by coding in JavaScript in the GEE platform. As the images are provided at level 2 by the provider, no atmospheric and geometric corrections were required for further processes. The remote sensing scenes were clipped for the region of interest (ROI) and filled for the images with a cloud percentage of less than 30%. Representative samples for LC classes such as annual industrial crop, forest and plantation forests, scattered trees, rice, crop/shrub/grass, urban/built-up and water were selected based on the maps of: (i) the 2010 land-use map (provided by the Phu Yen

People's Committee, scale 1:100,000); and (ii) a field survey. A total number of 978 training points were sampled. The collected points were photographed, described and geotagged. We used the Random Forest classification algorithm (Zhao et al. 2024), utilising 70% of the points to train the model and 30% to evaluate accuracy. The model's accuracy was evaluated using metrics, such as AUC (Huang J and Ling 2005) and Kappa (Cohen 1960). The model results were further processed in QGIS 3.22.1 to classify into LC maps for four different periods. Finally, an LC change graph was calculated for the period from 2010-2023 and projected to 2030 using the Markov algorithm.

Environmental Sensitivity Zoning

Selection Evaluation Criteria

The study identified Environmental Sensitivity Zoning (PEF) using methods recommended by França et al. (2022). The PEF map was built using five factors (F1-F5). Table 2 shows information of the factors used to create these maps. Elevation (DEM) downloaded from Worldclim 2.0 to interpolate slope factor (**F1**) using Spatial Analyst Tools in ArcGIS 10.8; Annual mean precipitation (**F2**) downloaded from Worldclim 2.0; Fluvial hierarchy (**F3**) extracted from DEM data and analysed using the Strahler method; Percentage of sand in soil at 5 cm depth (**F4**) downloaded from the SoilGrid database; Geological domains (**F5**) were used from the data of Vietnam Institute of Geosciences and Mineral Resources.

The EEF map was constructed using six factors (F1-F6). **F6** is the landscape (LC) type that was obtained from the result of this study. A group of six experts was invited to participate in a focus group discussion (FGD) to assign weight scores to each factor (Hennink 2013, Yulianti and Sulistyawati 2021). The weights were on a scale of 9 (9: extremely high; 7: high; 5: medium; 3: rather low and 1: low) to determine the level of EF related to the resilience of each sub-factor (Table 2). Each map was ranked according to sub-factors to facilitate expert evaluation by QGIS version 3.22.1 (Fig. 2).

Each sub-factor was scored from low to high (Fig. 2, Table 2) as follows:

- **F1**: Slope: 0-6%, 6-12%, 12-20%, 20-30%, above 30%.
- **F2**: Annual mean precipitation: 1,250–1,300 mm/year, 1,300–1,350 mm/year, 1,350–1,400 mm/year, 1,400–1,450 mm/year, 1,450–1,500 mm/year, 1,500–1,678 mm/year.
- **F3**: Fluvial hierarchy: from 1st order to 7th order.
- **F4**: Percentage of sand in soil: < 15%, 15-20%, 20-25%, 25-35%, > 35%.
- **F5**: Geological domains: Archean Gneisses and Migmatites, Cenozoic Detrital Lateritic Covers, Deformed Granitoids, Metasedimentary Rocks, Paragneisses Complex, River and Lake, Sedimentary Rocks, Undeformed Granitoids.
- **F6**: LC types: annual industrial crop, urban/built-up, water, crop/shrub/grass, rice, scattered trees, forest (natural and plantation forest).

Analytic Hierarchy Process (AHP)

We used the AHP method for multi-criteria decision-making and pairwise comparison of components, based on a scale (Saaty 2008). This scale ranges from 1 (equal importance) to 9 (extreme importance of one criterion over another). We checked the consistency ratio of the AHP evaluation by calculating the consistency index *CI* (Equation (1)), where *CI* = consistency index; *n* = number of criteria evaluated; λ_{Max} = eigenvector. The average of the eigenvector was then calculated.

$$CI = (\lambda_{max} - n)/(n-1) \quad (1)$$

The consistency ratio *(CR)* is the ratio of the consistency index *(CI)* to the random index *(RI)* as determined by Equation (2). *RI* is a fixed value that depends on the matrix size: the number of criteria evaluated *(n)*; the matrix is considered consistent if *CR* ≤ 0.1.

$$CR = \frac{CI}{RI} \quad (2)$$

The data collected consists of pairwise comparisons of all factors in the proposed hierarchical model. Six experts were invited to participate in the FGD meeting, where they were asked to complete a survey on the importance of the six criteria listed in Table 2.

Multi-Criteria Analysis

Each criterion was classified into different classes and each class was assigned a suitable score, based on the experts' opinions (Dean 2020). Finally, the maps (PEF and EEF) were created by establishing AHP weights and performing multi-criteria analysis (MCA) by considering weighted overlaps for the criteria (Ruiz et al. 2020). The output diagram for PEF with five identified fragility criteria is defined by Equation (3).

$$GVBI = 2NDVI^{\smile}NDBI$$

(3)

S = PEF value; wi = weight of the factor for the i-th criterion obtained through the AHP method; xi = normalised or standardised value of the cell for the i-th criterion. We used the Jenks method to reclassify the output map, identifying natural breaks in the datasets by grouping similar values.

Results and Discussion

Landscape Dynamic from 2010 to 2023

The four land-cover maps for the years 2010, 2015, 2018 and 2023 were produced by using the Random Forest (RF) algorithm to classify Landsat images from the corresponding years (Fig. 3). The accuracy assessment results showed a mean AUC value of 0.85 and a Kappa value of 0.8. The results indicate the area of 07 LC types (Annual industrial crop; Urban/built-up; Water; Crop/Shrub/Grass; Rice; Scattered trees; Forest (natural and plantation forests) over the years 2010, 2015, 2018 and 2023. The results in Fig. 3 showed that the area of forest and plantation forests and annual industrial crops are the two types of LC that increased in area from 2010 to 2023. Meanwhile, the other LC types (urban/built-up; water, crop/shrub/grass; rice) all decreased in area (Fig. 4). These results indicated a significant change and effectiveness in forest management policies, with an increase in forest area; in contrast, the bare land gradually decreased and the relevance of the RF approach for the accurate classification and analysis of land-cover changes over time, providing valuable insights into environmental and land-use dynamics over more than two decades.

Landscape Prediction for 2030

Overall, there are changes in landscape, with an increasing trend in forest and annual industrial crops, while the area of scrattered trees and urban and other types of cultivation gradually decreases. The forest area (both natural and plantation) has significantly increased from around 25,000 ha in 2010 to nearly 40,000 ha in 2030. This is a positive trend for the environment and ecosystems. The area of annual industrial crops has slightly risen from around 15,000 ha in 2010 to below 20,000 ha in 2030. The urban and built-up area has decreased from around 8,000 ha in 2010 to nearly 7,000 ha in 2030. The area of rice cultivation has remained quite stable, fluctuating around 10,000 ha throughout this period from 2010 to present (2023). The area of scattered trees has remained almost unchanged, staying stable at around 5,000 ha. The water area has also remained stable, with slight changes throughout this period. The area of crops, shrubs and grass has significantly decreased from around 26,000 ha in 2010 to 23,000 ha in 2023 and predicted below 20,000 in 2030. (Fig. 4).

The Markov method demonstrates robust analytical capabilities for predicting changes in land-use types up to 2030 by analysing probabilistic transition models from one state to another (Floreano and de Moraes 2021). From these analysis results, we observe significant changes in Forest and plantation forests and Scattered trees; while forests are expanding significantly, Scattered trees are declining. These areas not only hold crucial ecological value, but also harbour substantial potential for developing pure plantation forestry activities, enriching forests in the future. Protecting and restoring Scattered Tree areas not only contributes to environmental conservation, but also opens opportunities for integrated agroforestry projects to enhance LC sustainability (Vo and Hoang 2014).

Forest resource management has not been improving in many parts of Vietnam. The study, utilising census and geographic data from 1990, has clarified the distinction between natural forest regeneration and the increase in plantation forests and has found that policies allocating forest land, the scarcity of forest products and the demand for timber in remote areas have driven the increase in forest area. However, not all areas in Vietnam that are reforested receive equal attention. This means that, while reforestation efforts are taking place, some regions may not be given the same level of focus or resources (Meyfroidt and Lambin 2008). Thien and Phuong (2024) studied LC changes over 20 years in Ba Ria Vung Tau Province (Vietnam) using Landsat imagery, Normalised Difference Vegetation Index (NDVI) and Normalised Difference Water Index (NDWI), revealing a decline in forest area during this period. Different regions exhibit varying increases and decreases in forest and other LC types, which can serve as indicators for land-use management (Gupta and Sharma 2020). The integrated approach of LC modelling and remote sensing (multi-year phases) helps in assessment and analysis, providing a reliable method to recommend solutions to mitigate human-induced disruptions (Piao et al. 2021, Hishe et al. 2021, Delgado-Artés et al. 2022). Results from GEE can be developed into applications for free sharing amongst researchers, managers, ecologists, facilitating ongoing research, improving processes and monitoring LC changes (Hird et al. 2021).

PEF Map

The score of each factor and sub-factor in the AHP model was prioritised. The results from the FGD process helped identify the types of important sub-factors (Table 3). Results showed the LC is the most influential factor on PEF, with a weight of 40%, followed by slope (27.5%), precipitation (14%); fluvial hierarchy (11%); percentage of sand in soil (4.5%) and geological type (3%). The consistency index (CI) and consistency ratio (CR) were < 0.10. The MCA evaluation process resulted in the PEF Map, dividing the area into five different zoning of EF (Fig. 5). Generally, areas with low PEF are distributed in the northeast or southwest parts of the study area, characterised by extensive natural and plantation forests. Areas with very high PEF are located in the northwest or around large reservoirs. Specifically, dark-green-coded areas indicate environments with low fragility and high resilience to external impacts (covering approximately 19% of the total area). These are typically stable areas less affected by human or natural activities. Light-green-coded areas indicate moderately fragile environments (covering approximately 20% of the total area). These areas still exhibit good resilience, but are beginning to show susceptibility to damaging factors. Yellow-coded areas represent moderately fragile environments (covering approximately 27% of the total area). The environment here is less prone to damage from human and natural impacts. Orange-coded areas indicate highly fragile environments (covering approximately 17.7% of the total area). Environments in these areas are very susceptible to damage from human and natural impacts. Red-coded areas represent extremely high fragility (covering approximately 16.3% of the total area). These are the most sensitive areas, highly susceptible to severe damage from human and natural impacts. Priority should be given to protection and management measures to safeguard these areas.

EEF Map

The EEF was generated through integrated PEF and LC using the AHP-MCA analysis, offering a comprehensive view of the environmental impacts of human activities in the region (Fig. 6). Areas categorised as requiring extremely high protection (Extremely high EEF) are predominantly characterised by low-lying terrain, extensive river networks, lakes and scattered trees that have not yet matured into forests, covering 26% of the territorial area. Areas necessitating high protection (High EEF) are primarily located in high mountainous regions with extensive natural forests and well-established plantations, encompassing 29% of the territorial area, predominantly situated in the southern and eastern parts of the study area. Areas requiring moderate to low protection (Medium and Slightly low EEF) are associated with medium and low mountainous areas, featuring numerous small farms and annual industrial crop trees. These areas exhibit relatively stable environmental conditions and, thus, require less intensive protection. Areas classified as requiring low protection (Low EEF) are mainly found in low-lying areas with extensive rice paddies and flower fields.

The EEF map indicated the high sensitivity areas to EF, with Water LC (WT) being the most sensitive, followed by Annual industrial crop (AIC), Forest (FST), Scattered trees (SCT); Rice (RC), Crop/Shrub/Grass (CR) and Urban/Built-up (UB) (Fig. 7). Water LC often depends on multiple environmental factors to maintain ecological balance (França et al. 2022). Factors such as water quality, pollution levels and changes in these factors can significantly impact the ecological health and development of aquatic LCs. Water pollution, agricultural practices and industrial activities can degrade water quality, alter flow regimes and affect species distribution within aquatic LCs, leading to a decline in their quality (Gayathri et al. 2021). Aquatic areas are typically sensitive and vulnerable to changes from the surrounding environment, especially when fragmented or under pressure from human activities (Jumani et al. 2020). Small fragmented aquatic areas or those not connected to each other may become less sustainable and more vulnerable to external threats. Plant and animal species within aquatic environments are often sensitive to changes in their habitats (Mayeda and Boyd 2020). When environments are disrupted, these species may struggle to adapt or migrate to other areas, increasing the risk of extinction or population decline. These factors make Water LC more sensitive and prone to damage from environmental changes and human activities, resulting in a high EF index. The evaluation results accurately reflect that areas with high PEF indices are primarily Water LC. This recommendation could assist local authorities in enhancing solutions to protect river, lake, irrigation and canal ecosystems, optimising land resource use and improving the economic efficiency of local agriculture and forestry production. Forecasting changes in aquatic, forest and agricultural LC using a Markov-CA model in GEE cloud technology has proven highly useful in guiding the early detection of urban development trends linked with environmental protection.

Conclusions

Assessing LC dynamics in the Hinh River Basin, a tributary of the lower Ba River flowing through Phu Yen Province, Vietnam from 2010 to 2023 using a Markov-CA model in Google Earth Engine, also helps to forecast the landscape change trends from the present to 2030. The results of this study provide a potential environmental function (PEF) map and an emerging environmental vulnerability (EEF) map, all of which highlight areas that need to be protected in the future. Aquatic ecosystems (water LC) need the most protection amongst the types in the study area, followed by annual industrial crop LC, natural forest LC and plantation forests LC that need to be protected due to high EEF index occupy the majority of the area in the study area. Of these, the forest area is forecast to increase significantly from about 25,000 ha in 2010 to nearly 40,000 ha in 2030. This new finding has further clarified the positive trend in local forest restoration management and suggested the need to enhance the protection of highly sensitive surface water LC.

Acknowledgements

We thank *Joint Vietnam - Russia Tropical Science and Technology Research Center* for providing the research grant for the period of 2023-2025 (Research and propose solutions to manage and use water resources and protect the landscape and environment of the Hinh River Basin, Phu Yen Province). We are grateful to the committee members of Phu Yen Province and Song Hinh District for their permission to conduct the surveys.

Conflicts of interest

The authors have declared that no competing interests exist.

References

- Amorim AT, do Nascimento Lopes ER, de Sousa JAP, de Cassia Ferreira da Silva R, de Souza JC, Lourenço RW (2021) Geomorphometric environmental fragility of a watershed: a multicriteria spatial approach. Environmental Monitoring and Assessment 193 (12). https://doi.org/10.1007/s10661-021-09634-6
- Blasi C, Capotorti G, Copiz R, Guida D, Mollo B, Smiraglia D, Zavattero L (2014) Classification and mapping of the ecoregions of Italy. Plant Biosystems - An International Journal Dealing with all Aspects of Plant Biology 148 (6): 1255-1345. https://doi.org/10.1080/11263504.2014.985756
- Chuong HV, Phu NQ, Khoa NP (2015) Multi-criteria land suitability assessment for converting crop structure in Tay Hoa district, Phu Yen province. Hue University Journal of Science (HU JOS 103 (4). [In Vietnamese].
- Cohen J (1960) Kappa: Coefficient of concordance. Educ Psych Measurement 20 (37): 37-46.
- Dean M (2020) Multi-criteria analysis. Standard Transport Appraisal Methods165-224. https://doi.org/10.1016/bs.atpp.2020.07.001
- Delgado-Artés R, Garófano-Gómez V, Oliver-Villanueva J, Rojas-Briales E (2022) Land use/cover change analysis in the Mediterranean region: a regional case study of forest evolution in Castelló (Spain) over 50 years. Land Use Policy 114 https://doi.org/10.1016/j.landusepol.2021.105967
- FAO (2000) Global forest resources assessment. Main Report. FAO Forestry Paper 140 URL: http://www.fao.org/forestry/fra/86624/en/

- Floreano IX, de Moraes LAF (2021) Land use/land cover (LULC) analysis (2009–2019) with Google Earth Engine and 2030 prediction using Markov-CA in the Rondônia State, Brazil. Environmental Monitoring and Assessment 193 (4). https://doi.org/10.1007/s10661-021-09016-y
- França LCdJ, Lopes LF, Morais MSd, Lisboa GdS, Rocha SJSSd, Morais Junior VTMd, Santana RC, Mucida DP (2022) Environmental Fragility Zoning Using GIS and AHP Modeling: Perspectives for the Conservation of Natural Ecosystems in Brazil. Conservation 2 (2): 349-366. https://doi.org/10.3390/conservation2020024
- Gayathri S, Krishnan KA, Krishnakumar A, Maya TMV, Dev V, Antony S, Arun V (2021) Monitoring of heavy metal contamination in Netravati river basin: overview of pollution indices and risk assessment. Sustainable Water Resources Management 7 (2). https://doi.org/10.1007/s40899-021-00502-2
- Gupta R, Sharma LK (2020) Efficacy of Spatial Land Change Modeler as a forecasting indicator for anthropogenic change dynamics over five decades: A case study of Shoolpaneshwar Wildlife Sanctuary, Gujarat, India. Ecological Indicators 112 https://doi.org/10.1016/j.ecolind.2020.106171
- Hennink MM (2013) Focus group discussions. Oxford University Press
- Hird JN, Kariyeva J, McDermid GJ (2021) Satellite time series and Google Earth Engine democratize the process of forest-recovery monitoring over large areas. Remote Sensing 13 (23): 4745. https://doi.org/10.3390/rs13234745
- Hishe H, Giday K, Van Orshoven J, Muys B, Taheri F, Azadi H, Feng L, Zamani O, Mirzaei M, Witlox F (2021) Analysis of Land Use Land Cover Dynamics and Driving Factors in Desa'a Forest in Northern Ethiopia. Land Use Policy 101 https://doi.org/10.1016/j.landusepol.2020.105039
- Huang J, Ling CX (2005) Using AUC and accuracy in evaluating learning algorithms. IEEE Transactions on Knowledge and Data Engineering 17 (3): 299-310. https://doi.org/10.1109/tkde.2005.50
- Jumani S, Deitch MJ, Kaplan D, Anderson EP, Krishnaswamy J, Lecours V, Whiles MR (2020) River fragmentation and flow alteration metrics: a review of methods and directions for future research. Environmental Research Letters 15 (12). https://doi.org/10.1088/1748-9326/abcb37
- Junior AC, Röhm SA (2014) Analysis of environmental fragility using multi-criteria analysis (MCE) for integrated landscape assessment. Journal of Urban and Environmental Engineering 8 (1): 28-37. https://doi.org/10.4090/juee.2014.v8n1.028037
- Liu Y, Huang S, Chen J (2008) Study on the ecosystem-based management for the international river basin. Journal of Fisheries of China 32 (1): 125-130.
- Markert K, Schmidt C, Griffin R, Flores A, Poortinga A, Saah D, Muench R, Clinton N, Chishtie F, Kityuttachai K, Someth P, Anderson E, Aekakkararungroj A, Ganz D (2018) Historical and Operational Monitoring of Surface Sediments in the Lower Mekong Basin Using Landsat and Google Earth Engine Cloud Computing. Remote Sensing 10 (6). https://doi.org/10.3390/rs10060909
- Mastronardi L, Cavallo A, Romagnoli L (2022) A novel composite environmental fragility index to analyse Italian ecoregions' vulnerability. Land Use Policy 122: 106352. https://doi.org/10.1016/j.landusepol.2022.106352
- Mayeda AM, Boyd AD (2020) Factors influencing public perceptions of hydropower projects: A systematic literature review. Renewable and Sustainable Energy Reviews 121 https://doi.org/10.1016/j.rser.2020.109713

- Meyfroidt P, Lambin E (2008) The causes of the reforestation in Vietnam. Land Use Policy 25 (2): 182-197. https://doi.org/10.1016/j.landusepol.2007.06.001
- Nga NTT, Phuong PM, Khanh NQ, Hanh TT, Quoc PB, Lahori AH, Yeremenko S, Tyshchenko V, Murasov R (2023) Risk of Land Degradation: A Case Study of Phu Yen Province, Vietnam. Ecological Questions 35 (2): 1-21. https://doi.org/10.12775/eq.2024.019
- Pham MP, Nguyen K, Vu G, Nguyen NT, Tong H, Trinh LH, Le P (2022) Drought risk index for agricultural land based on a multi-criteria evaluation. Modeling Earth Systems and Environment 8 (4): 5535-5546. https://doi.org/10.1007/s40808-022-01376-9
- Pham TM, Nguyen T, Tham HN, Truong TK, Lam-Dao N, Nguyen-Huy T (2021) Specifying the relationship between land use/land cover change and dryness in central Vietnam from 2000 to 2019 using Google Earth Engine. Journal of Applied Remote Sensing 15 (02). https://doi.org/10.1117/1.jrs.15.024503
- Phan DC, Trung TH, Truong VT, Sasagawa T, Vu TP, Bui DT, Nasahara KN (2021) First comprehensive quantification of annual land use/cover from 1990 to 2020 across mainland Vietnam. Scientific reports 11 (1): 9979. https://doi.org/10.1038/s41598-021-89034-5
- Piao Y, Jeong S, Park S, Lee D (2021) Analysis of Land Use and Land Cover Change Using Time-Series Data and Random Forest in North Korea. Remote Sensing 13 (17). https://doi.org/10.3390/rs13173501
- Ruiz HS, Sunarso A, Ibrahim-Bathis K, Murti SA, Budiarto I (2020) GIS-AHP Multi Criteria Decision Analysis for the optimal location of solar energy plants at Indonesia. Energy Reports 6: 3249-3263. https://doi.org/10.1016/j.egyr.2020.11.198
- Saaty TL (2008) Decision making with the analytic hierarchy process. International journal of services sciences 1 (1): 83-98. https://doi.org/10.1504/IJSSCI.2008.017590
- Tamiminia H, Salehi B, Mahdianpari M, Quackenbush L, Adeli S, Brisco B (2020) Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. ISPRS Journal of Photogrammetry and Remote Sensing 164: 152-170. https://doi.org/10.1016/j.isprsjprs.2020.04.001
- Thien BB, Phuong VT (2024) Detection of Land Use and Land Cover Change Using Remote Sensing and GIS in Ba Ria-Vung Tau Province, Vietnam. Geography and Natural Resources 44 (4): 383-393. https://doi.org/10.1134/s1875372823040133
- Vo DH, Hoang PM (2014) Research on protection forest planting techniques in coastal hilly-mountainous areas, Phu Yen province. Forestry Science Magazine 1: 3119-31128. [In Vietnamese].
- Yulianti T, Sulistyawati A (2021) Enhancing public speaking ability through focus group discussion. JURNAL PAJAR (Pendidikan Dan Pengajaran 5 (2): 287-295.
- Zhao Z, Islam F, Waseem LA, Tariq A, Nawaz M, Islam IU, Bibi T, Rehman NU, Ahmad W, Aslam RW, Raza D, Hatamleh WA (2024) Comparison of Three Machine Learning Algorithms Using Google Earth Engine for Land Use Land Cover Classification. Rangeland Ecology & Management 92: 129-137. https://doi.org/10.1016/j.rama.2023.10.007

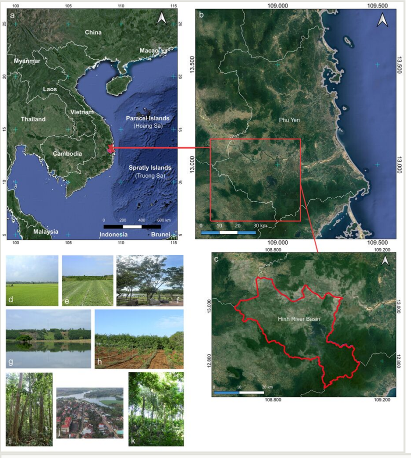

Figure 1.

Hinh River Basin, Phu Yen Province, Vietnam. The map of the study area in Vietnam (**a**); the map of Phu Yen Province (**b**); The map of Hinh River Basin, Song Hinh district (**c**). Landscape types: rice (**d**), crop (**e**), scattered trees (**f**), water (**g**), annual industrial crop (**h**), natural forest (**i**), urban/built-up (**j**), plantation forest (**k**).

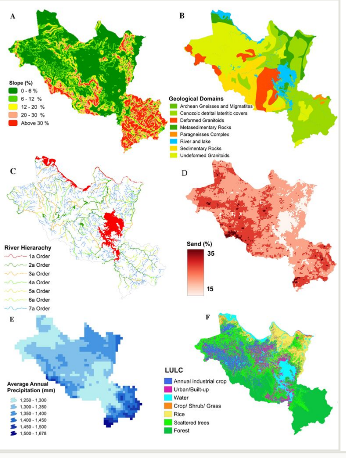

Figure 2.

The factors used for the evaluation of potential environmental fragility (PEF) and Emergent Environmental Changes (EEC) of Song Hinh. Terrain slope (**A**); Geological domains (**B**); River hierarchy (**C**); Percentage of Sand in soil (**D**); Annual mean precipitations (**E**); Land use-land cover (**F**).

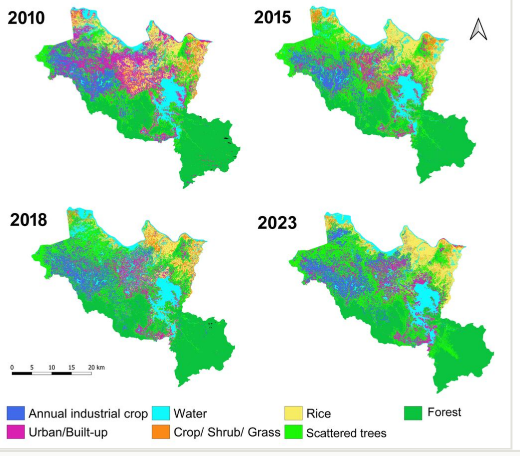

Figure 3.

Map of LC from 2010 to 2023.

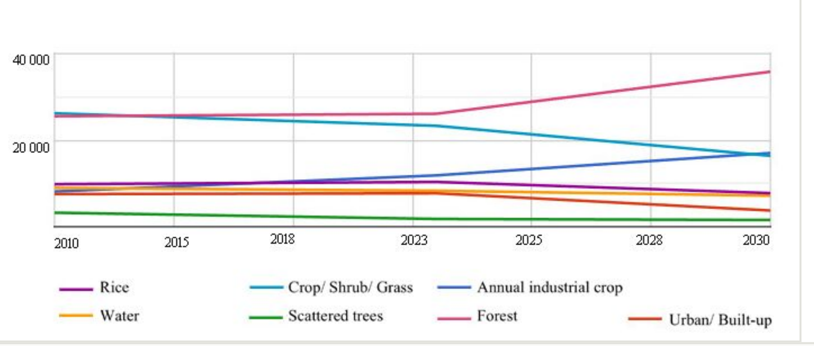

Figure 4.

LC dynamics over from 2010 to 2023 and prediction for 2030.

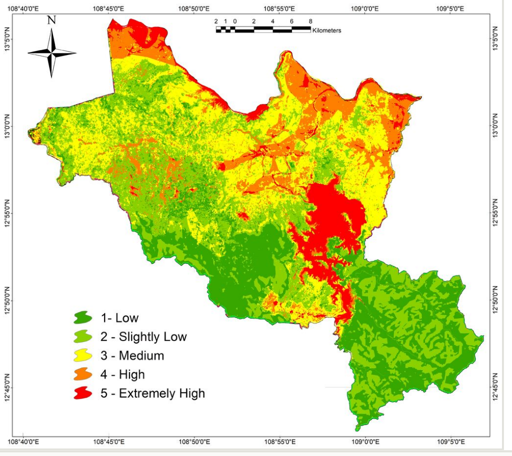

Figure 5.

Map of potential environmental fragility (PEF).

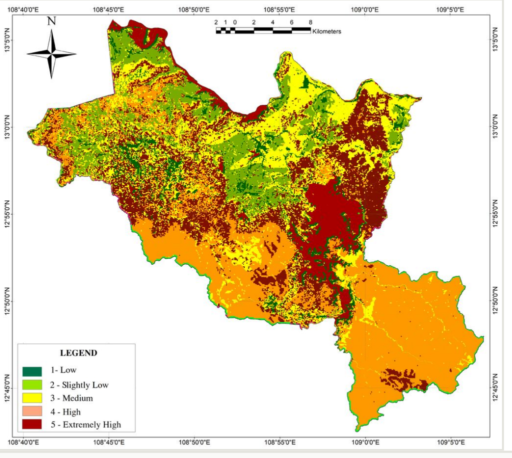

Figure 6.

Zoning of Emergent Environmental Fragility (EEF).

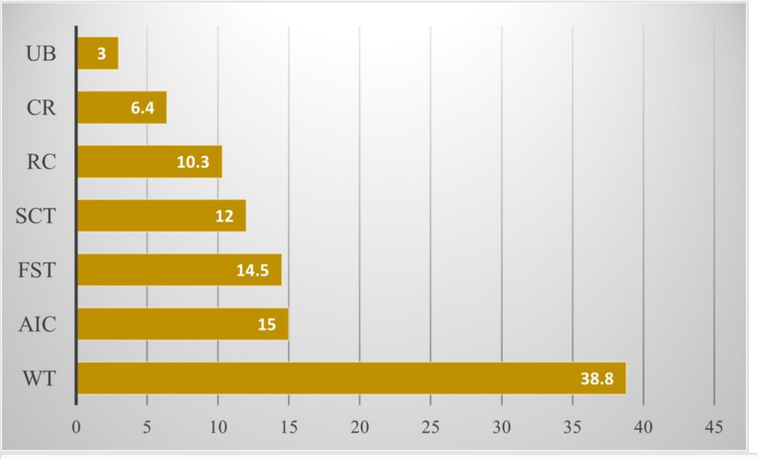

Figure 7.

The percentage of LC in total area of extremely high EEF. **UB**: urban/built-up LC; **CR**: Crop/shrub/grass LC; **RC**: Rice LC; **SCT**: Scattered tree LC; **FST:** Forest LC (natural and plantation forests); **AIC**: annual industrial crop LC; **WT**: water LC.

Table 1.

Satellite imagery information used.

Period	Name of Satellite images	Acquisition time
2010	Landsat 5-TM 3,4,5	01-01-2010, 12-31-2010
2015	Landsat 8-OLI 4,5,6	01-01-2015, 12-31-2015
2018	Landsat 8-OLI 4,5,6	01-01-2018, 12-31-2018
2023	Landsat 8-OLI 4,5,6	01-01-2023, 12-31-2023

Table 2.

The factors used for mapping the PEF and EEF.

	Factors	Data type, resolution	Database, method
F1	Slope	Raster, 30 m	Worldclim
F2	Annual mean precipitation	Raster, 250 m	Worldclim
F3	Fluvial Hierachy	Raster, 250 m	Strahler method
F4	Percentage of sand in soil	Raster, 250 m	Soilgrids,
F5	Geological Domains	Polygons	Atlanta Vietnam
F6	Landscape (LC)	Raster, 250 m	From this study

Table 3.
Expert scores for EF evaluation factors.

N^0	**Factors**	**Sub-factors**	Scores	Weight (%)
F1	Slope	0-6%	1	27.5
		6-12%	3	
		12-20%	5	
		20-30%	7	
		above 30%	9	
F2	Annual mean precipitation	1,250-1,350 mm/year	3	14
		1,300-1,350 mm/year	3	
		1,350-1,400 mm/year	3	
		1,400-1,450 mm/year	7	
		1,450-1,678 mm/year	7	
F3	Fluvial hierachy	5-7th order	1	11
		-	3	
		3-4th order	5	
		2th order	7	
		1th order	9	
F4	Percentage of sand in soil at 5 cm depth	<15%	1	4.5
		15-20%	3	
		20-25%	5	
		25-35%	7	
		>35%	9	
F5	Geological Domains	Undeformed Granitoids, Deformed Granitoids	1	3
		Archean Gneisses và Migmatite	3	
		Metasedimentary Rocks, Paragneisses Complex, River and Lake	5	
		Sedimentary Rocks	7	
		Cenozoic Detrital Lateritic Covers	9	
F6	LC	Natural forest; Forest plantations;	1	40
		Annual industrial crop; crops/ shrubs/grass	3	
		Water	5	
		Rice	7	
		Urban/Built-up; other non-vegetated areas	9	