Ecological Questions 35(2024)2 http://dx.doi.org/10.12775/EQ.2024.019

# Risk of Land Degradation: A Case Study of Phu Yen Province, Vietnam

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Received: 4 September 2023 / Accepted: 20 October 2023

**Abstract.** The issue of the land degradation vulnerability index (LDVI) is multifaceted, encompassing climate, soil, vegetation, policy formulation, and human actions. In Vietnam, the convergence of climatic fluctuations and human impact results in phenomena, such as soil sealing, erosion, salinization, and landscape fragmentation. These phenomena are recognized as significant triggers of land degradation. This paper seeks to present a method for assessing a land's susceptibility to degradation by utilizing ten ecological 10 criteria: NDVI; slope; bulk density (cg/cm$^3$); cation exchange capacity in the soil (CEC; mmol(c)/kg); Soil organic carbon stock (SOC; dg/kg), pH; Nitrogen (N; cg/kg); soil thickness (cm); soil surface temperature LST (0C); precipitation of the driest quarter (mm). The research results show that Song Hinh and Son Hoa communes are standing on the most land degradation vulnerability. Some criteria that are considered important in assessing land degradation by the analytic hierarchy process (AHP) technique are NDVI, followed by slope, nitrogen, bulk density, and soil thickness. The results of the study are consistent with records in localities that are often under pressure from drought. Extreme LDVI areas were larger identified on low mountains, slope terrain, and precipitation of driest quarter under 200mm, expanding on the agricultural areas with 40km$^2$ total province agriculture area, followed by grassland (20.3 km$^2$), natural forests (17.2 km$^2$), plantation forests (8.2 km$^2$), residences (8.2 km$^2$), and bare land (8.15 km$^2$). Poor land management practices, such as improper construction, inadequate water management, and lack of terracing, can contribute to soil erosion and land degradation. This LDVI assessment process can be applied to some tropical countries. The NDVI index combined with the slope, nitrogen, bulk density, and soil thickness can be exploratory indicators of land sensitivity to land degradation.

**Keywords:** Modeling, GIS technology, analytic hierarchy process, land degradation, soil map.

## 1. Introduction

Land degradation (LD) is a global problem in the 21st century because of its negative impacts on biological productivity, the environment, food security, and quality of life. Technogenic processes become more complex every year and worsen the ecological state of the soil due to the settling of toxic dust floating in the atmosphere (Ziarati et al., 2020; Vambol et al., 2019; Hussain et al., 2022a), pollution through waste (Hanoshenko et al., 2022; Hussain et al., 2022b; Vambol et al., 2023), application of plant protection chemicals (Vambol et al., 2020), watering from polluted sources (Khan et al., 2022; Zahorodniuk et al., 2019). The deterioration of soil purity leads to the production of low-quality products that are harmful to human health and activity (Karlova et al., 2017; Hulai et al., 2022). In addition to this, it is important to emphasize that soil quality goes down because of erosion that causes soil degradation (Eswaran et al., 2019). These lands have often become deserts, become polluted, or lost their forests to make room for farms, leading to many species. Some economists say that the effects of soil erosion and other forms of land degradation on the ground should not be able to stop national or international plans to protect people. They further argue that, for land managers, what should be concerned with is the factors affecting LD first.

On the other hand, agronomists say that land is a non-renewable resource and that some of the bad effects of degradation processes on soil quality, like less soil depth, can't be changed of plant roots. Land reclamation technology only provides a sense of security (Eswaran et al., 2019). The early use of biophysical models to measure land degradation led to an estimate that nearly 1 billion hectares of land worldwide are degraded and lying fallow. The results show that up to 490 million hectares of land in China and India are in the worst shape (Cai et al., 2011). There are four ways to evaluate degraded lands on a global scale: consulting experts, using satellite data, biophysical modelling, and taking an inventory of the land. All the research shows that improving our understanding of our global database is a way to deal with the lack of land around the world and develop policies for getting large amounts of land. The estimates give an idea of how much soil will get worse. Still, more importantly, they show how important it is to find new ways of doing things, which will probably require a combination of satellite data analysis and a land inventory.

The soil degradation index (SDI) was created using climate variables, land use, topography, and soil properties. This was done with the help of satellite images from different times. Machine learning algorithms predict soil properties like clay, cation exchange capacity (CEC), and soil organic matter (OM) in different places. SDI was validated using the OM prediction map. The area with the least amount of organic matter (OM) had the most degradation (Nascimento et al., 2021). Tolche et al. (2021) identify and map soil degradation vulnerability using precipitation, NDVI and surface temperature (LST), topography (slope), and geological features (i.e., soil depth, soil pH, soil texture, and soil drainage). Assessing the dangers of the soil and where they are in space is important for building up the baseline data needed for effective control measures. The analytic hierarchy process (AHP) approach to modelling soil risk zones has been extensively studied in many studies (Tolche et al., 2021; Saha et al., 2019; Arabameri et al., 2018). Recent advances in remote sensing and GIS technology allow us to assess large spatial extents of soil degradation with greater accuracy.

From what the research team found on the ground, this study was done in Phu Yen province, where land degradation has become a big problem. Remote sensing data and AHP method were used to assess land degradation through the land degradation vulnerability index (LDVI) in the area. This paper helps make clear, area by area, which parts of the province are most at risk because of land degradation. This is useful information for the management and development of sustainable land use.

## 2. Materials and methodology

### 2.1. Study area

Phu Yen is a coastal province in the south-central part of Vietnam. Its latitude goes from 12°42'36" to 13°41'28" north, and its longitude goes from 108°40'40" to 109°27'47" east; Fig. 1). Phu Yen has a relatively convenient geographical position and transportation for socio-economic development. Natural area: 5,045 km$^2$, coastline length: 189 km. The climate is tropical monsoon, hot and humid, with oceanic influences. There are two distinct seasons: the rainy season from September to December and the dry season from January to August. The average temperature is 26.5°C, and the average annual rainfall is about 1,600–1,700 mm. The province's western region is affected by a huge drought every year, affecting people's lives (Phu Yen Statistical Yearbook).

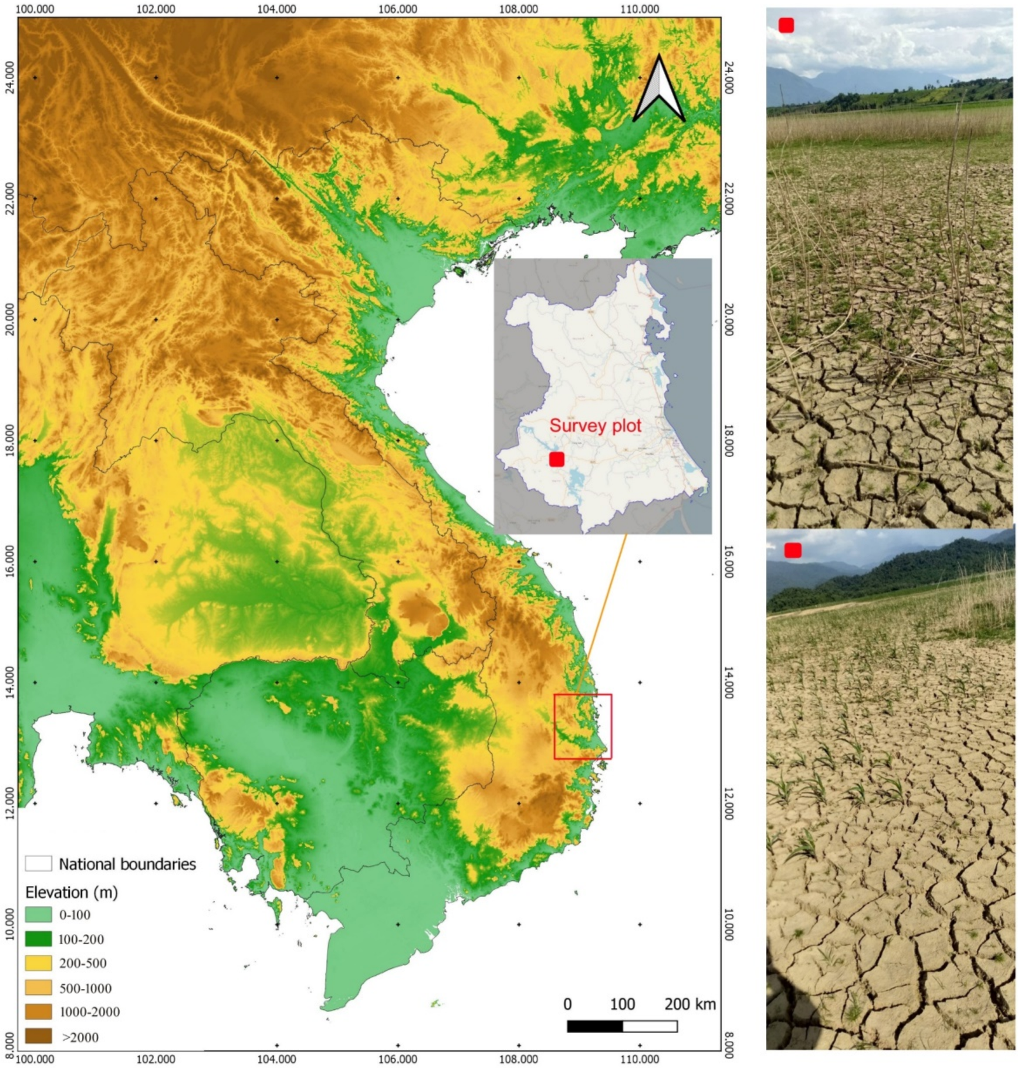


**Figure 1.** Study area (The area marked by a small red region on the map is the most affected by drought and land degradation through the field survey investigation)

## 2.2. Materials

This study comprised the implementation of a field survey during the months of April 2020 and May 2021, with the goal of gathering samples relating to the geographical coordinates of existing land-use land-cover sites. The purpose of the data gathering was to assist in the development of a comprehensive LULC map for the province. A total of 78 different locations were surveyed. After an initial assessment, a total of 70 locations were chosen to serve as the input data for the building of a current LULC map. GPS coordinates are used to record the locations, followed by entering statistics into Excel software and then implementing the data into QGIS 3.11.13. After the completion of the field survey, a focus group decision team was established, including ecologists, experts in soil degradation, and agronomists. The group participated in a discussion process with the aim of developing a comprehensive framework to generate a map that depicts land deterioration. This includes determining the criteria for land evaluation. Finally, 10 LDVI evaluation criteria were developed based on the documents (Table 1).

**Table 1.** Criteria for LDVI Model.

| Criteria | Related scientific literature |
| --- | --- |
| **LULC** | Land use status is important because it shows how much vegetation cover is needed to stop erosion and keep the soil from worsening (Albaladejo et al., 2021). Nascimento (2021) developed a land degradation index using multi-temporal remote sensing images (Nascimento et al., 2021). Changing the land's use status makes it more likely that the land will get worse. Symeonakis (2007) has shown a reciprocal relationship between land use and cover change (LULC) and land degradation (Symeonakis et al., 2007). |
| **Slope** | The slope is a major factor affecting soil water erosion, as lower inclination results in lower soil erosion rates (Quan et al., 2020). |

| | |
|---|---|
| **BDOC** Bulk density | FAO (1980) suggested that the increase in soil bulk density from year to year is one way to measure the physical degradation of soil. The main physical properties of soil erosion are an increase in bulk density and a decrease in the rate at which water can pass through the soil. Bulk density increases with deforestation, and farming increases soil bulk density. Infertile soils are characterized by higher bulk density, lower porosity, and lower soil moisture (Aminu & Jaiyeoba, 2015; Al-Shammary et al., 2021). |
| **CEC** Cation exchange capacity (mmol(c)/kg) | Acidification, salinization, the loss of nutrients, and a lower cation exchange capacity (CEC) are all signs of soil degradation; Signs of soil degradation include higher pH values and low CEC values (Aminu & Jaiyeoba, 2015). Soil cation exchange capacity (CEC) was considered an indicator of soil degradation (Sinoga et al., 2012). CEC is a good indicator of the degradation of soil surface formations, as it is directly related to soil organic carbon storage capacity. |
| **SOC** Soil organic carbon (dg/kg) | SOC stocks are central to soil health, fertility, quality, and productivity. Soil organic carbon stock as an indicator for monitoring soil and soil degradation. Soil organic carbon (SOC) loss seriously impacts soil nitrogen storage. An increase in SOC stock can improve soil health, reduce soil erosion, give energy to soil biota, improve the soil's ability to store things, help filter and break down nutrients and pollution, and increase carbon dioxide sequestration (Lorenz et al., 2019; Hengl et al., 2017). |
| **pH** | pH is one of the factors that have the greatest influence on the microbial community in the soil. |
| **N** Nitrogen (cg/kg) | Soil degradation is an environmental problem that depletes soil nitrogen, directly affecting soil quality, fertility, yield, and overall quality (Dlamini et al., 2014; Hengl et al., 2017). |
| **ST** Soil thickness | Soil degradation has a close relationship with soil thickness. The physical thickness of the soil is an indication of significant soil loss (Ewunetu et al., 2021). |

| | |
|---|---|
| **LST** Land surface temperature ($^{0}C$) | LST is considered one of the most important climatic factors that reflect soil quality. Its intensity and distribution are directly related to the vegetative conditions of a particular ecosystem. LST temperature extremes degrade soil quality, affecting vegetation's proper growth. The soil degradation vulnerability is relatively high in areas with high LST temperatures (Tolche et al., 2021). |
| **Bio17** (mm) | Bio17 is the total rainfall in the driest three months of the year obtained on Worldclim in 30s resolution. Precipitation is an important climatic factor affecting soil productivity; Low and erratic rainfall limits vegetation cover and acts as a limiting factor for crop growth. Therefore, it is considered an integrated parameter to quantify soil degradation. (Tolche et al., 2021). |

### 2.3. Remote sensing

*Land Use/Land Cover (LULC) map*: Creating a LULC map using the Random Forest algorithm in Google Earth Engine involves several steps. The process includes data preprocessing, training the model, classifying the image, and visualizing the results. The study region is distinguished by the dominance of seven land use and land cover types, including agriculture, water bodies, bare land, grassland, plantation forests, residences, and natural forests. The training and validation samples were obtained by a process of manual visual interpretation of high-resolution images sourced from Sentinel-2. This approach is extensively utilized and published in academic articles. In addition, to reduce the impact of spatial autocorrelation while still gathering the variation in land cover types within each category, we selected training samples in the shape of small polygons. These polygons cover a collection of pixels that demonstrate a relatively consistent land cover type. In contrast, validation samples were selected as individual points. When validation samples are chosen near the training polygons, there is a higher probability of overfitting detection. As a result, we employed a random selection process to choose validation points, ensuring that they were at least one hundred meters away from the nearest training polygon to reduce spatial autocorrelation. In the final analysis, our dataset consisted of 50 training polygons and 20 validation points. This map provides a valuable database for analysing the impact generated by land degradation on different types of land use and land cover.

*LST map:* MODIS MOD11A2 composite images with 1 km spatial resolution were downloaded (https://earthexplorer.usgs.gov) and processed. Then, the equation (2) below is used to change the data from DN (numerical value) to °C (degrees Celsius):

$$LST\ (°C) = 0.02 \times DN - 273.15 \quad (2)$$

To create the time series monthly maximum value composite image (2000–2016), "Cell Statistics" is a tool in ArcGIS used to make a long-term LST raster image for the study area from the average seasonal LST dataset.

### 2.4. GIS method

Soil parameters play an important role in identifying areas vulnerable to land degradation. The SoilGrids data provides global predictions of soil properties at standard depth levels (Hengl et al., 2017). Important soil parameters like Bulk Density (BD), Cation Exchange Capacity (CEC), Soil Organic Carbon Stock (SOC), PH, Nitrogen (N), and pH were downloaded from SoilGrid (https://soilgrids.org/, 250 m resolution, WGS 84). Soil thickness parameter from the soil map of the province (scale 1:100.000) (Fig. 2, 3). DEM and Bio17 were downloaded from Woldclim (https://worldclim.org/). The data from DEM was used to make a slope map using spatial analysis tools in ArcGIS 10.8 (Fig. 4, 5).

### 2.5. Analytical hierarchy process

Secondary data layers contain remote sensing data after being normalized by QGIS software. The Analytical Hierarchy Princess (AHP) method is a mathematical method used in multi-criteria decision analysis to measure LD soil degradation (Tolche et al., 2021) by making the LDVI index. Saaty (2016) revealed that the main criteria and sub-criteria depend on the purpose of the study. We use the 9-point scale of Saaty to evaluate the pairwise comparison matrix to compare how important each one was. Based on expert knowledge and references, a spatial decision support system (Table 1) decided how much each criterion mattered. The AHP method uses maths to figure out how consistent pairwise comparisons are. The consistency index (CI) and the consistency ratio (CR) are found. Where RI is the random index, CR is the consistency ratio, CI is the consistency index, n is the number of elements compared in the matrix, and max is the main eigenvalue of the matrix (eq. 3-4).

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (3)$$

$$CR = \frac{CI}{RI} \quad (4)$$

In this study, the CR value for the evaluated criteria is less than the maximum recommended value of (<0,1) (Saaty, 2016).

To map the LDVI soil degradation vulnerability index, the following formula is used to provide weights to the model's input parameters. These weights are based on the AHP approach (eq. 5):

$$\text{LDVI} = \sum_{i=1}^{n} \sum_{j=1}^{m} W_i . W_j \qquad (5)$$

Where *Wi* is the weight of the criterion from the AHP technique, *Wij* is the weight of the *j* sub-criteria for *i* criterion from the AHP technique, n is the total number of criteria, and m is the total number of sub-criteria in criterion *i*.

## 3. Result and discussion

### 3.1. Environmental parameters

The study aimed to focus on developing a formula to calculate the LDVI index. There are plenty of references that concern the gold of research that has been statistically analysed. Four main criteria and 10 sub-criteria were selected and scored according to the expert group discussion method. There was agreement among the scores between experts with the consistency index (CR<0.1, as appropriate). Each sub-criteria were classified into 4-5 categories, and each category was added to the expert's score (9: very high impact on the process of land degradation; 7: high impact; 5: moderate impact, 3: low impact; 1: very low impact). The result provided 10 maps of 10 sub-criteria, according to the findings in Table 2.

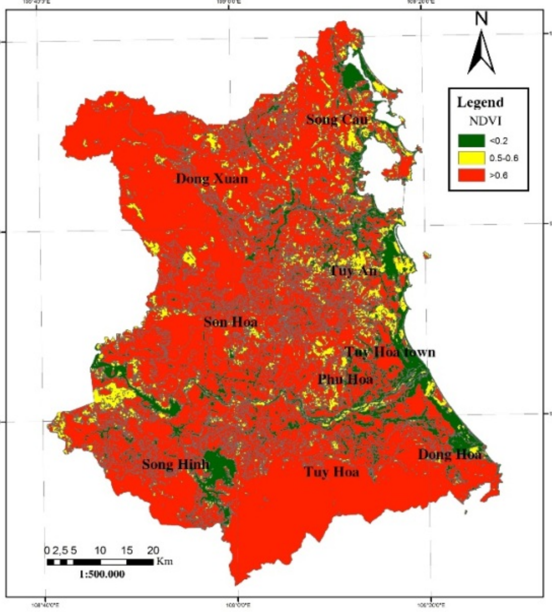


**Figure 2.** NDVI

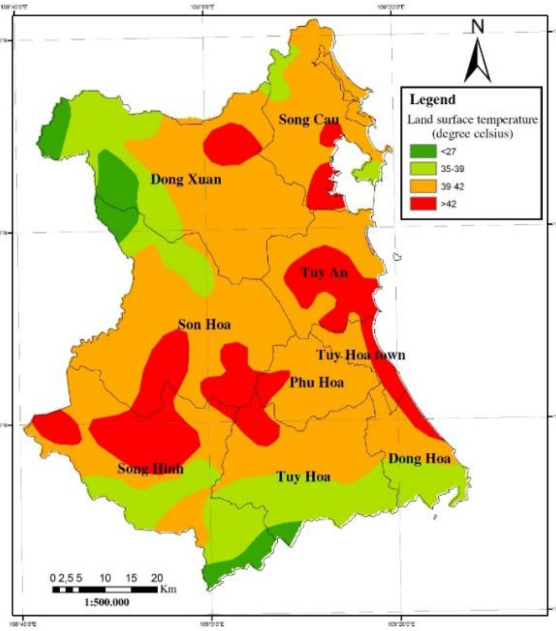


**Figure 3.** LST

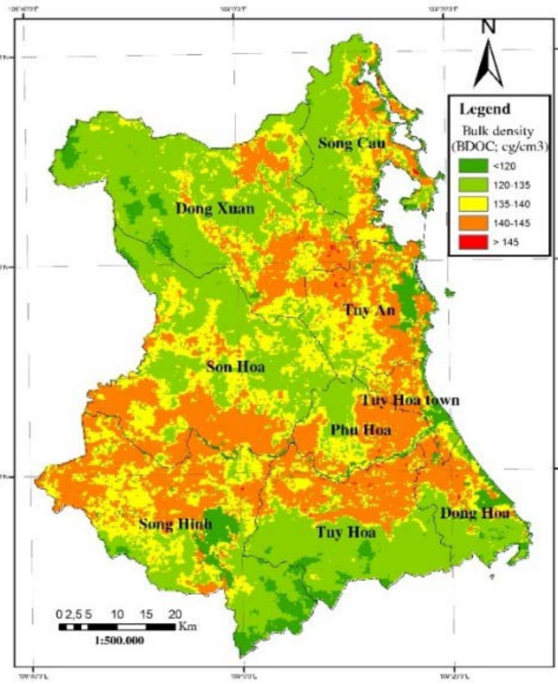


**Figure 4.** Bulk density of soil

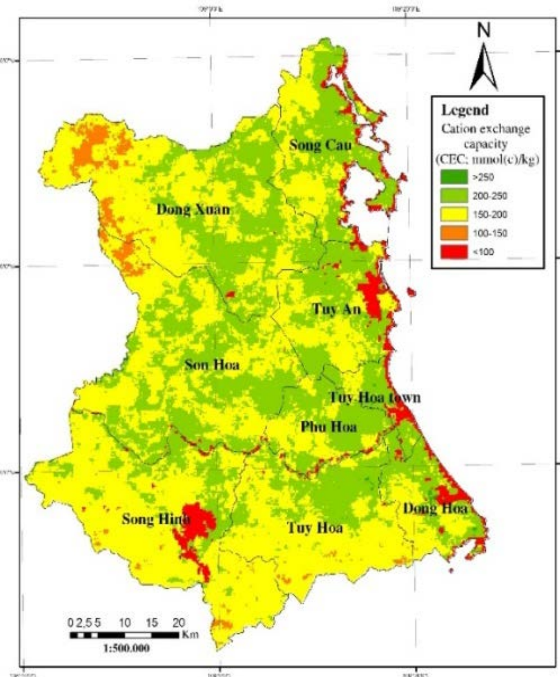


**Figure 5.** CEC of soil

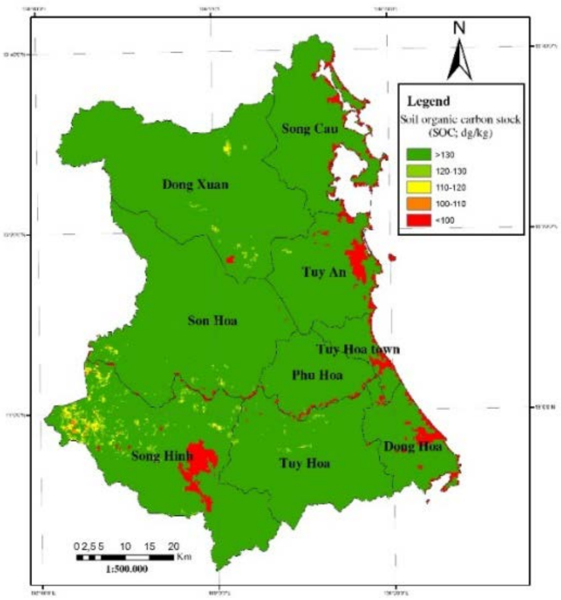


**Figure 6.** SOC of soil

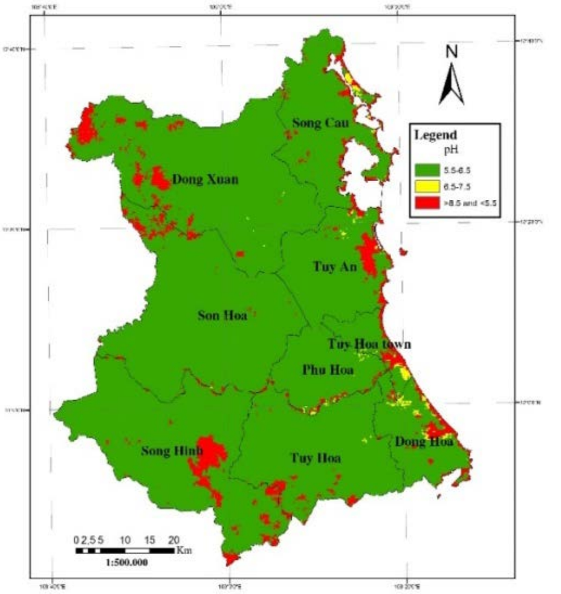


**Figure 7.** pH

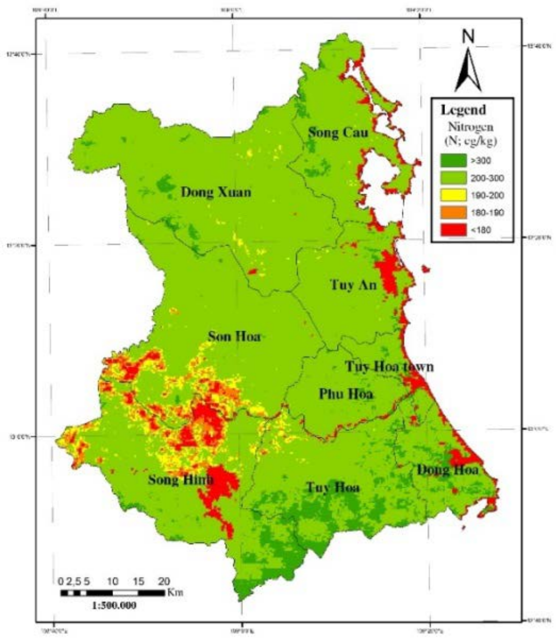


**Figure 8.** Nitrogen of soil

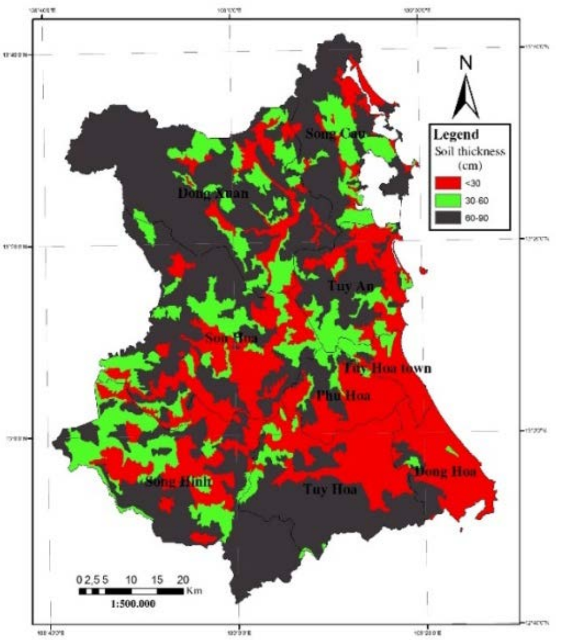


**Figure 9.** Soil thickness of soil

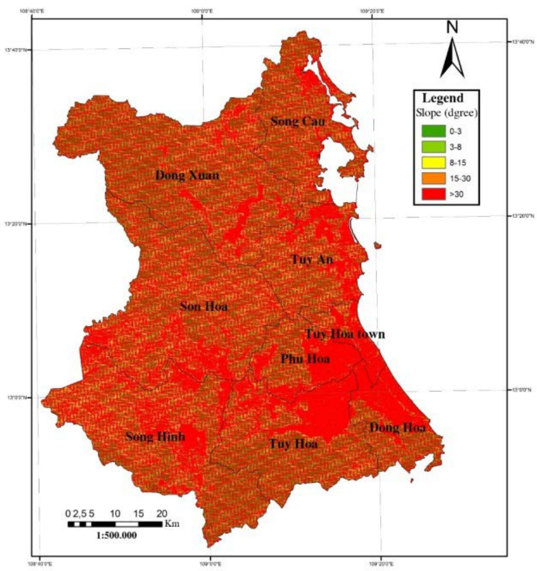


**Figure 10**. Slope

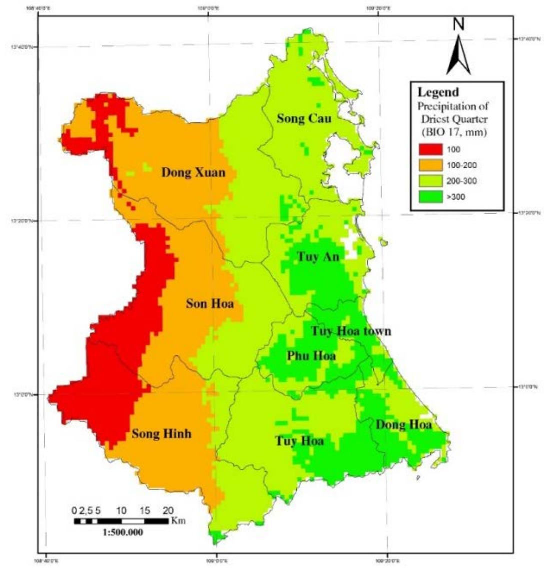


**Figure 11**. Bio17

The results of the weighting process for the 10 sub-criteria are presented in Table 2. Among these variables, the NDVI had the highest score, followed by slope, nitrogen content, bulk density, soil thickness, pH value, precipitation during the driest quarter, cation exchange capacity (CEC), soil organic carbon (SOC), and land surface temperature (LST). The mean NDVI values of the study area were divided into three sub-criteria (Fig. 2). The highest area (75%) falls under layer NDVI >0.6, followed by <0.2 (13%), and the lowest area NDVI: 0.2-0.6 (12%). NDVI is sensitive to changes in vegetation cover, density, and health. It is particularly useful for detecting changes in vegetation over time, such as deforestation, reforestation, and land use changes. Healthy ecosystems usually exhibit higher NDVI values due to a greater abundance of green vegetation. As land degradation typically involves changes that negatively impact vegetation, monitoring NDVI can provide insights into the overall health of an ecosystem (Khalil et al., 2014). NDVI can help identify areas prone to soil erosion. Erosion often leads to the removal of topsoil, which negatively affects vegetation growth. Monitoring changes in NDVI can help identify erosion-prone areas and track the effectiveness of erosion control measures. While NDVI directly measures vegetation health, it indirectly provides information about soil quality. Healthy vegetation is often indicative of good soil conditions, including nutrient availability and water retention. By tracking NDVI changes, researchers and land managers can infer changes in soil quality and fertility (Sandeep et al., 2021).

The mean slope values of the study area were divided into five layers. The highest area (35%) falls under layer >25°, followed by 15-30° (23%), 0-3° (20%), 3-8° (17%), and 8-15° (16%). Large areas of hills and high slopes in the southern of Phu Yen province pose significant risks for land loss in agricultural production areas and near roads due to the increased vulnerability to erosion and other forms of land degradation. The mean nitrogen values of the study area were divided into five layers. The highest area (71%) falls under layer 200-300 cg/kg, followed by <180 cg/kg (13.3%), >300 cg/kg (7.2%), 190-200 cg/kg (5%), 180-190 cg/kg (3.5%). The mean bulk density values of the study area were divided into five layers. The highest area (40%) falls under layer 120-135 cg/cm$^3$, followed by <140-145 cg/cm$^3$ (37%), 135-140 cg/cm$^3$ (13%), <120 cg/cm$^3$ (8%), >145 cg/cm$^3$ (2%). The mean soil thickness values of the study area were divided into three layers. The highest area (47%) falls under layer 60-90cm, followed by <30cm (28%), 30-60cm (25%). The remaining layers play a less important role in the evaluation process. The weighted criteria are ranked from high to low as follows: pH > Precipitation of driest quarter (Bio17) > Soil organic carbon stock (SOC) > Cation exchange capacity (CEC) > Land surface temperature (LST).

**Table 2.** Weights of the criteria and sub-criteria.

| **Criteria** | **Sub-criteria** | **Value** | **Score** | **Weight** |
|---|---|---|---|---|
| **Vegetation** | **1. NDVI** | <0.2 | 9 | **0.230** |
| | | 0.2-0.3 | 7 | |
| | | 0.4-0.5 | 5 | |
| | | 0.5-0.6 | 3 | |
| | | >0.6 | 1 | |
| **Soil** | **2. Slope** (Slope; degree) | >30 | 9 | **0.212** |
| | | 15-30 | 7 | |
| | | 8-15 | 5 | |
| | | 3-8 | 3 | |
| | | 0-3 | 1 | |
| | **3. Bulk density** (BD; cg/cm$^3$) | > 145 | 9 | **0.094** |
| | | 140-145 | 7 | |
| | | 135-140 | 5 | |
| | | 120-135 | 3 | |

| | | | | |
|---|---|---|---|---|
| | | <120 | 1 | |
| | **4. Cation exchange capacity** *(CEC; mmol(c)/kg)* | <100 | 9 | 0.055 |
| | | 100-150 | 7 | |
| | | 150-200 | 5 | |
| | | 200-250 | 3 | |
| | | >250 | 1 | |
| | **5. Soil organic carbon stock** (SOC; dg/kg) | <100 | 9 | 0.055 |
| | | 100-110 | 7 | |
| | | 110-120 | 5 | |
| | | 120-130 | 3 | |
| | | >130 | 1 | |
| | **6. pH** | >8.5 and <5.5 | 9 | 0.061 |
| | | 8-8.5 | 7 | |
| | | 7.5-8 | 5 | |
| | | 6.5-7.5 | 3 | |
| | | 5.5-6.5 | 1 | |
| | **7. Nitrogen** *(N; cg/kg)* | <180 | 9 | **0.113** |
| | | 180-190 | 7 | |
| | | 190-200 | 5 | |
| | | 200-300 | 3 | |
| | | >300 | 1 | |
| | **8. Soil thickness** *(cm)* | <30 | 7 | **0.072** |
| | | 30-60 | 5 | |
| | | 60-90 | 3 | |
| | | >60 | 1 | |
| **Land surface temperature** | **9. LST** *(degree Celsius)* | >42 | 9 | 0.048 |
| | | 39-42 | 7 | |
| | | 35-39 | 5 | |
| | | 27-31 | 3 | |
| | | <27 | 1 | |
| **Precipitation** | | 100 | 7 | 0.059 |

| | | | | |
|---|---|---|---|---|
| | **10. Precipitation of Driest Quarter** (*BIO 17*, *mm*) | 100-200 | 5 | |
| | | 200-300 | 3 | |
| | | >300 | 1 | |

### 3.2. LDVI map

Fig. 12 and Fig. 13 revealed that the degradation area was mainly concentrated southwest of Phu Yen province, focused on Song Hinh and Son Hoa districts. This result was in agreement with the results of the sub-criteria maps. Such areas with low hills and low mountains that are mainly dedicated to agroforestry experience high soil degradation due to a combination of factors related to both the landscape characteristics and human activities. The presence of low hills and mountains contributes to soil erosion, especially in areas with steep slopes. Rainwater run off can gain momentum on these slopes, leading to increased erosion and sediment transport. Agroforestry areas are often intensively cultivated to maximize agricultural production. This can lead to repeated disturbance of the soil through practices like ploughing, which can lead to compaction and decreased soil structure stability. Compacted soil is more prone to erosion and reduced water infiltration.

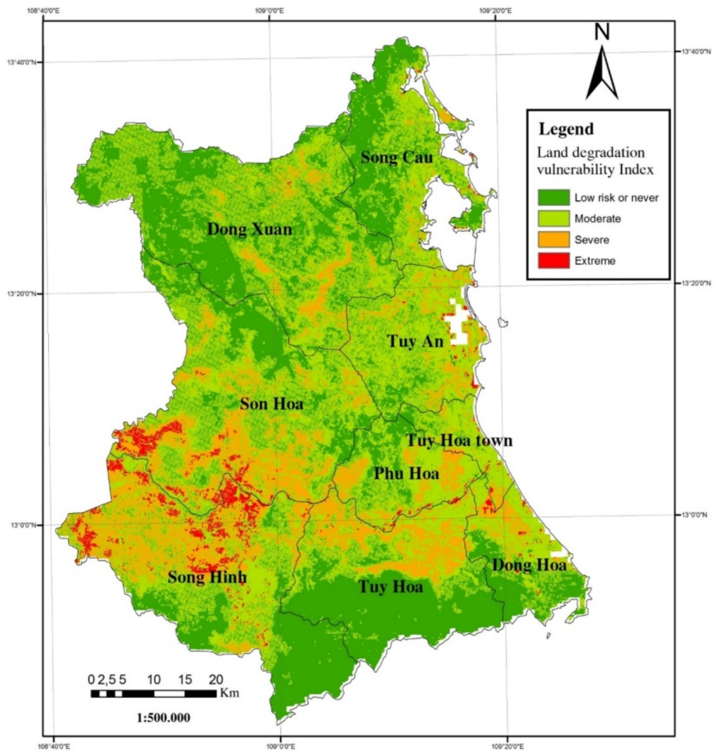

**Figure 12.** LDVI map of the study area

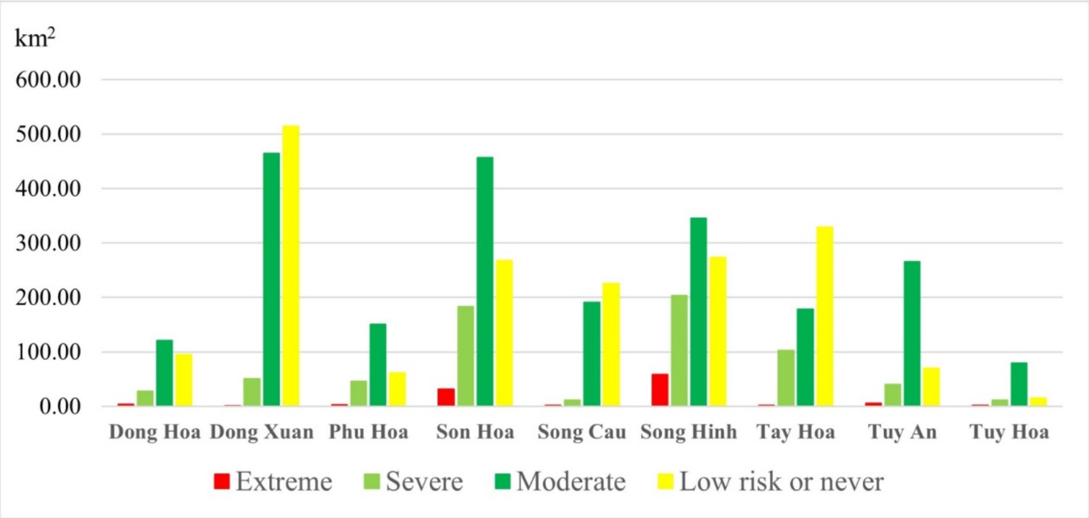


**Figure 13**. Areas of soil degradation classified among districts

Climate plays a significant role in soil degradation. Soil degradation refers to the deterioration of soil quality and productivity, often resulting from various human activities and natural processes. The changes in nutrients, soil organic matter, soil structure, soil morphology, soil ion concentration, and soil chemistry can collectively contribute to soil degradation and reduced soil productivity. Low rainfall (Fig. 11, 100–200 mm in the dry season) was one cause of drought. The high bulk density of the soil (135–145 cg/cm3) also makes it harder for water to get into the soil. In general, the soil surface temperature (LST) is high (>42$^{0}$C), especially in the middle of Song Hinh and Son Hoa districts (Fig. 3). All these factors can interact and reinforce one another, leading to a downward spiral of soil degradation. As the soil becomes less productive, it can't support healthy vegetation, leading to reduced crop yields, degraded ecosystems, and increased vulnerability to erosion and desertification.

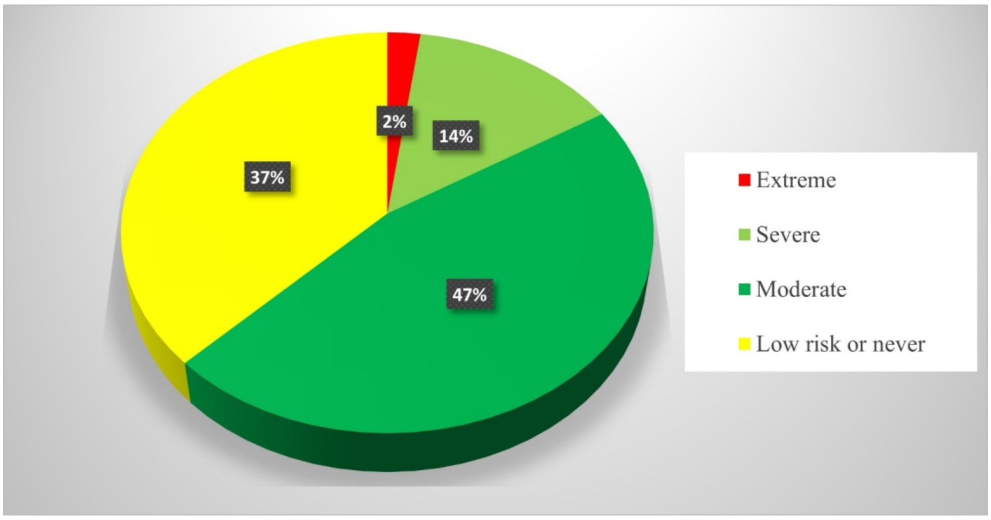


**Figure 14.** Areas of soil degradation classified among Phu Yen province

Figure 14 shows the areas of soil degradation classified in Phu Yen province. The area identified as facing the extreme of LDVI amounts to roughly 2%. The areas were recorded at the remaining rates as follows: severe LDVI (14%); moderate (47%); low risk or never (37%). In general, some of the most important issues that happen when land degrades are faster erosion, reduction of the soil organic carbon (SOC) pool and loss of biodiversity, loss of soil fertility and imbalance of elements, acidification, and salinization. Trends in soil degradation can be stopped by changing how the land is used and using the best management techniques. The plan is to reduce soil erosion and create positive SOC and N budgets (Lal, 2015; Lorenz et al., 2014). SOC is a crucial component of soil organic matter and plays a significant role in supporting plant growth, improving soil structure, enhancing water retention, and sequestering carbon dioxide from the atmosphere (Dlamini et al., 2014).

### 3.3. The type of land cover in relation to LDVI

Figure 15 is the result of land use classification from the LULC map with 7 types of land cover detected in the area: natural forests, agriculture, water bodies, bare land, grassland, plantation forests, and residences.

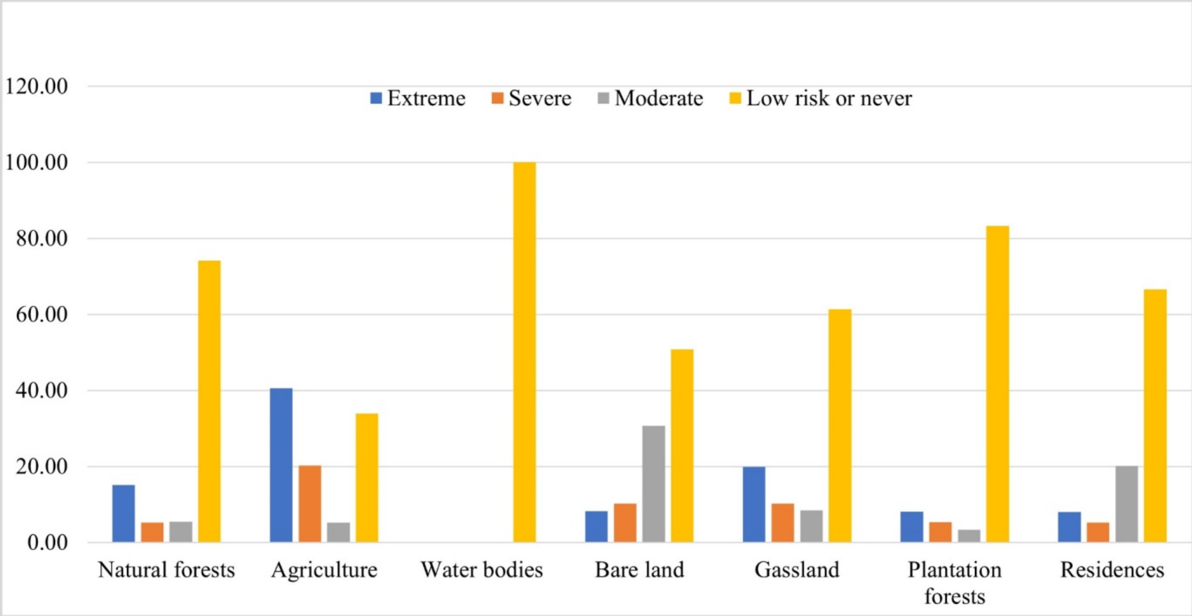


**Figure 15.** Areas of LULC classified among soil degradation categories (km$^2$)

According to Fig. 15, LDVI is mainly concentrated in agricultural areas with 40 km$^2$ total province agriculture area. The findings of this step provided significant practical guidance for managers in Phu Yen, as they highlight the importance of prioritizing environmental policies and carrying out effective strategies for land reclamation in agricultural regions. The extreme LDVI strongly reduced from agricultural areas to grassland (20.3 km$^2$), natural forests (17.2 km$^2$), plantation forests (8.2 km$^2$), residences (8.2 km$^2$), and bare land (8.15 km$^2$). Similarly, the severe LDVI also witnessed a slight decrease from agricultural areas (20 km$^2$) to grassland (10.15 km$^2$), bare land (9.9 km$^2$), plantation forests (5.05 km$^2$), natural forests (5 km$^2$), residences (8.2 km$^2$). Meanwhile, water bodies and bare land were found to be affected by the lowest levels of LDVI.
The LDVI is also faced with substantial concern regarding the preservation of natural forests in this particular area. The findings indicate that natural forests are ranked third among categories of vulnerability, behind agricultural land and red fields, which experience the most significant effects from LDVI. This finding suggests that the aforementioned analysis can be assigned to the elevated land surface temperature (LST) observed throughout the whole province, including regions with high forest cover. The province's forest area is currently experiencing challenges related to drought and land degradation. Further research is necessary on the subject of forest degradation in order to expand and improve our knowledge in this respect.

## 4. Conclusion

In the present study, 10 thematic maps (NDVI, slope, nitrogen, bulk density, soil thickness, pH, Precipitation of driest quarter, SOC, CEC, LST) were taken into a model for LDVI assessment. The analysis revealed that 2% of the area falls under extreme degradation, followed by 13.9% of the area falling under severe degradation, 46.4% of the area falling under moderate degradation, and 37.3% of the area falling under low risk. The LDVI index was developed using secondary data sources, which was carried out on soils in the province of Phu Yen that were in danger of becoming degraded. The research employed expert knowledge to construct an LDVI evaluation model by integrating AHP methodology into GIS technology to analyse geographical data layers. The results have shown that LDVI can estimate how likely the soil is to get worse during the pre-survey stage and make detailed plans for building land reclamation methods. The research helps to explain in detail, which areas are most at risk of land degradation. Two mountainous districts Song Hinh and Son Hoa were indicated that have a lot of extreme risk areas in low mountains, concentrating the farm in slope terrain and precipitation of driest quarter under 200 mm, especially in agricultural areas with 40 $km^2$ total province agriculture area, followed by grassland (20.3 $km^2$), natural forests (17.2 $km^2$), plantation forests (8.2 $km^2$), residences (8.2 $km^2$), and bare land (8.15 $km^2$). Research on land degradation provides the factual foundation upon which effective planning and development strategies can be built. It empowers decision-makers to take proactive measures to protect and enhance the health of ecosystems, promote sustainable land use practices, and ensure a balanced approach to development that benefits current and future generations.

## Acknowledgments

The authors express gratitude to the villagers of Phu Yen province for their valuable contributions in giving crucial information for the conduction of the field survey and investigation regarding the issue of land degradation.

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