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Remote sensing based on agricultural soil salinity assessment in Soc Trang province, Vietnam

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ABSTRACT

This study aimed to assess the spatial distribution of agricultural land use on saline soils in Soc Trang province in 2024. Multi-temporal Sentinel-1A radar satellite imagery was utilized for land-use classification through a supervised classification approach using the Random Forest algorithm implemented on the Google Earth Engine platform. The resulting agricultural land use map was then overlaid with saline soil data from the Department of Agriculture and Rural Development of Soc Trang province to analyze spatial patterns concerning salinity levels. The classification output identified 11 land use categories: (1) water bodies, (2) built-up areas, (3) aquaculture, (4) rice–shrimp farming, (5) double rice crop, (6) triple rice crop, (7) other perennial crops, (8) other annual crops, (9) forest, (10) coconut, and (11) sugarcane. The classification demonstrated high accuracy assessment with an overall accuracy (T) at 91.26% and a Kappa coefficient at 0.89. The results revealed clear spatial differentiation in agricultural land use based on different soil types. Areas with low to moderate soil salinity had mainly none to low-tolerant crops such as rice, annual crops, coconut, sugarcane, and other perennials. In contrast, high-salinity areas were mainly used for shrimp aquaculture. Coastal areas with very high salinity were associated with protective mangrove forests. This study highlights the effectiveness of Sentinel-1 radar imagery in land use classification and monitoring in saline environments. Furthermore, it provides a scientific basis for land-use planning, crop cultivation, and soil salinity management toward the region's adaptive and sustainable agricultural development.

Keywords: agriculture, saltwater intrusion, sentinel-1, Soc Trang province.

INTRODUCTION

The land is a crucial natural resource for human survival and development and a source of information for understanding the interaction between the environment and human activities (Pflugmacher et al., 2018). Land use influences biogeochemical cycles, climate change, soil erosion, and biodiversity. Land use and land cover changes (LULC) are essential for understanding global environmental changes, reflecting human-induced alterations to the Earth's surface change. Monitoring LULC dynamics is critical for predicting trends and informing sustainable policy decisions (Munthali et al., 2019). Furthermore, LULC changes are closely linked to economic development, with rapid growth accelerating these transformations (Gemitzi, 2021; Yin et al., 2010). Land cover refers to the physical characteristics observed on the Earth's surface, which results in the combined effects of human activities and the surrounding natural environment (FAO, 2016). Accordingly, providing accurate and timely information on land surface changes is essential for supporting land use planning, resource management, sustainable land management, landscape ecology, and climate-related studies (Hasan et al., 2024).

Soil salinity is a major abiotic risk factor for agricultural land worldwide, adversely affecting crop production and productivity. According to Shahbaz and Ashraf (2013), salt-affected soil is a serious agricultural problem mainly triggered by improper irrigation, adversely affecting crop productivity and quality. Over 800 million hectares, or more than 6% of the global status of salt-affected soil coverage areas, are damaged by soil salinity and/or soil solidity, and around 15–20 % of all irrigated cropland is affected by soil salinity (Safdar et al., 2019). Natural processes primarily cause soil salinity, whereas agricultural practices, improper irrigation, and illogical land use can bring on secondary environmental issues such as salinization, waterlogging, and nutrient depletion. Primary salinity increases spontaneously in soils and streams that occur naturally through various geological, hydrological, and pedological processes, leading to salt buildup over long periods (Mahmuduzzaman et al., 2014). Salinization processes negatively affect ecosystem services, as soil provides several crucial ecosystem services that contribute to maintaining biodiversity and the environment's health and participate in the nitrogen and water cycles. According to Zewdu et al. (2014), a rise in soil salinity significantly impacts both the environment and the livelihoods of farmers and smallholders, exacerbating declines in soil ecosystem services and reducing agricultural productivity, ultimately leading to decreased income. Low precipitation compared to evaporation in arid regions leads to soil salinization, negatively impacting natural vegetation and trees. Soil salinity negatively impacts every crop plant development stage, including germination, vigor, and overall productivity. Soil salinity negatively impacts crops by causing toxicity from specific ions, increasing osmotic pressure, and leading to nutrient imbalance, which hinders plant growth and development. This scenario likely refers to drought-resistant crop varieties or agricultural practices that reduce water usage, improving plant performance and potentially higher yields (Hernández, 2019). Applying sustainable management techniques can help mitigate the decline in yield caused by saline soil. These techniques focus on improving soil health, managing water resources effectively, and selecting appropriate crops. Adopting technologies or practices is often hindered by high costs, limited availability of resources, and exceptionally high-quality water. Reducing salinity stress in agriculture is a significant challenge, but several techniques can help mitigate its impact and further enhance plant resilience as a significant challenge (Hailu et al., 2020).

Various methods have been developed to investigate and map land use changes, among which remote sensing has become a powerful tool for detecting land cover changes across multiple spatial scales. Satellite imagery constitutes one of the principal sources of information for analyzing and extracting current land use patterns (Dhakal et al., 2022). Previous studies have successfully integrated diverse remote sensing datasets and leveraged the unique capabilities of different satellite platforms to produce highly reliable land-use maps (Nasiri et al., 2022). Remote sensing (RS) technology has rapidly advanced in analyzing LULC changes across different regions, providing reliable data for land classification and serving as the foundation for land use simulation. RS enables objective land use change monitoring by capturing and analyzing multi-temporal satellite imagery, with data stored, processed, and analyzed within geographic information systems (GIS) for various land use analysis and simulation models that can be directly integrated (Zhao, 2023). Due to its repetitive data acquisition, suitability for processing, and high precision in georeferencing, remote sensing data has indeed advanced in image processing, database management, and spatial analysis tools have enhanced to analyze these data for mapping and depicting LULC patterns (Krivoguz et al., 2023; Tempa et al., 2024).

Soc Trang, a coastal province in the Mekong Delta region of Vietnam, is situated in the Southeast and borders the East Sea, with a coastline of approximately 72 kilometers. The terrain is relatively flat, consisting mainly of alluvial and saline-affected soils, and is crisscrossed by a dense network of rivers, including the major branches of the Hau River. Due to its coastal location and low elevation, the province is highly vulnerable to saline intrusion, especially during the dry season when river water levels drop, allowing seawater to penetrate inland (Ngoc et al., 2024; Dang et al., 2025). Furthermore, the region's lack of long-term, high-resolution, and accurate LULC data has created challenges for sustainable resource management. Simulating LULC under the influence of saline intrusion is crucial to better understanding how climate change and environmental shifts affect land use and economic activities, particularly in agriculture.

This study aims to generate a land use map and to analyze land use patterns under the influence of saline intrusion in Soc Trang Province. The results will provide critical insights into how saline intrusion affects land use, thereby supporting the development of appropriate land management strategies and sustainable adaptation measures to protect land resources and ensure food security for the region.

MATERIALS AND METHODS

Study area

Soc Trang Province is situated in the southeastern region of the Mekong Delta, covering a total area of approximately 2.300 km², with an average population of 1.32 million (General Statistics Office of Vietnam, 2016) (Figure 1).

The province features a low-lying and relatively flat terrain, with absolute elevations ranging from 0.4 to 1.5 meters and an average slope of approximately 45 centimeters per kilometer. Topographically, the area resembles a basin, with higher elevations along the Hau River and the East Sea, gradually decreasing inland – particularly toward the western and northwestern regions (People's Council of Soc Trang Province, 2018). Due to its coastal location and downstream position along the Hau River, Soc Trang is highly susceptible to saline intrusion, which is causing significant challenges to local livelihoods and agricultural production (Le and Nguyen, 2011; Nguyen et al., 2017; Nguyen et al., 2019).

Data preparation

Satellite data

The dataset used in this study comprises Sentinel-1A GRD (Level-1 Ground Range Detected) imagery acquired from the Google Earth Engine platform between January 1, 2023, and December 31, 2023. A total of 24 scenes were collected, captured in Interferometric Wide (IW) swath mode, with a spatial resolution of 10 meters, and referenced to the WGS 84 / UTM zone 48N coordinate system (EPSG: 32648). The dataset obtained from Google Earth Engine underwent a five-step preprocessing workflow: (1) application of precise orbit files, (2) border noise removal, (3) thermal noise removal, (4) radiometric calibration, and (5) terrain correction. The resulting values represent the backscatter coefficient (σ°), expressed in decibels (dB) (Google Earth Engine, 2024).

Soil types data

The soil type data sources were collected from the Department of Agriculture and Environment

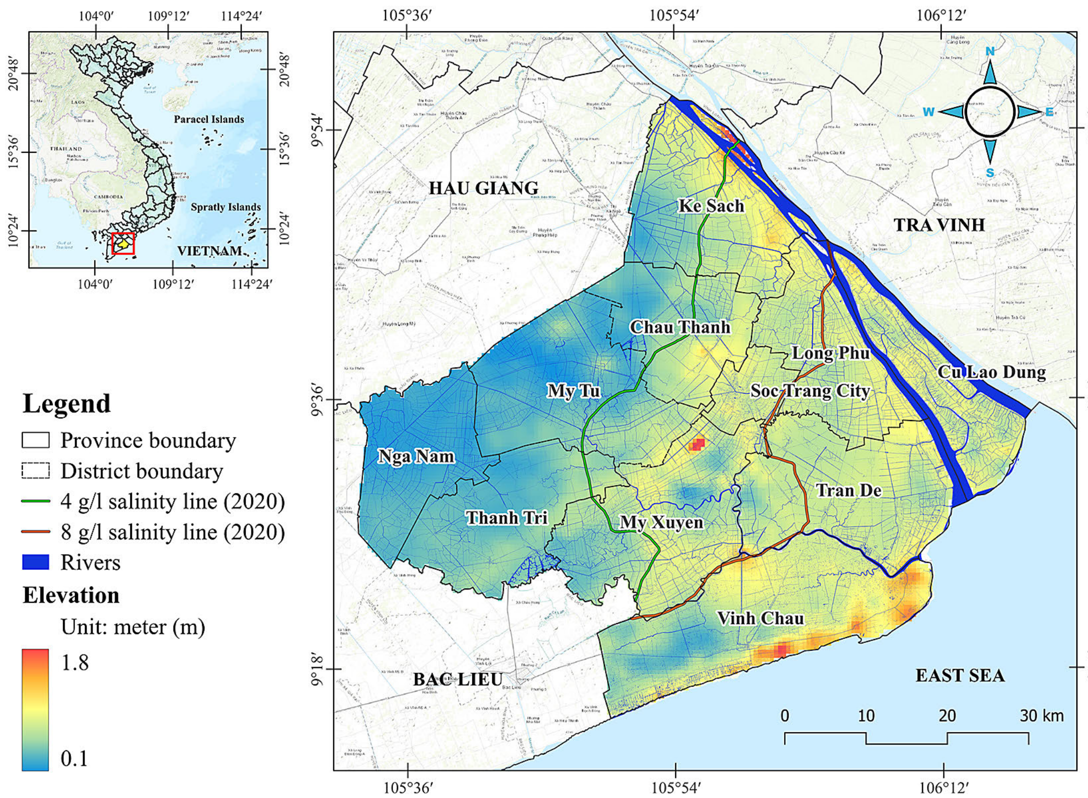

Figure 1. Map of the study area

of Soc Trang province (2024). The data were initially collected in image format (.png) and subsequently digitized into vector data (shapefile) using the QGIS tool.

Land use/land cover classification

Preprocessing

The Sentinel-1A imagery was denoised using the Lee Sigma filter (3 × 3 window) to reduce speckle noise inherent in radar image acquisition (Yommy et al., 2015). The study area was delineated using a shapefile uploaded to the Google Earth Engine (GEE) platform. The Sentinel-1A images were aggregated monthly, and single-polarization (VV) and dual-polarization (VH) values were extracted to observe temporal variations in backscatter coefficients (dB). In addition to monthly mean values, minimum, maximum, and standard deviation values were computed to serve as inputs for the classification model.

Subsequently, the image bands were combined using the to Bands function on the GEE. The list of bands used for classification is presented in Table 1, with 28 bands employed as model inputs. Notably, no imagery was available for July 2023 over the study area; thus, data for this month were excluded.

Random forest algorithm

This study utilized the random forest algorithm to classify land use status in the study area. As a supervised, non-parametric machine learning method, random forest has been widely recognized for its effectiveness in classifying multi-temporal satellite imagery (Jin et al., 2018). Compared to other machine learning classification approaches such as CART (Classification and Regression Trees), SVM (Support Vector Machine), kNN (k-Nearest Neighbors), and MLC (Maximum Likelihood Classification), Random Forest has shown superior performance across various remote sensing applications (Belgiu and Drăguț, 2016; Praticò et al., 2021). The algorithm operates by constructing an ensemble of decision trees, where each tree independently evaluates and assigns a land use class to each pixel (Dahhani et al., 2022).

For this study, the Random Forest model was configured with the following parameters: 800 trees, 22 variables considered at each split, a bagging fraction of 0.9, no specified maximum

Table 1. List of image bands used for classification

No.	Band	Description	No.	Band	Description
1	VH_1	Mean backscatter value in January (VH polarization)	15	VV_4	Mean backscatter value in April (VV polarization)
2	VH_2	Mean backscatter value in February (VH polarization)	16	VV_5	Mean backscatter value in May (VV polarization)
3	VH_3	Mean backscatter value in March (VH polarization)	17	VV_6	Mean backscatter value in June (VV polarization)
4	VH_4	Mean backscatter value in April (VH polarization)	18	VV_8	Mean backscatter value in August (VV polarization)
5	VH_5	Mean backscatter value in May (VH polarization)	19	VV_9	Mean backscatter value in September (VV polarization)
6	VH_6	Mean backscatter value in June (VH polarization)	20	VV_10	Mean backscatter value in October (VV polarization)
7	VH_8	Mean backscatter value in August (VH polarization)	21	VV_11	Mean backscatter value in November (VV polarization)
8	VH_9	Mean backscatter value in September (VH polarization)	22	VV_12	Mean backscatter value in December (VV polarization)
9	VH_10	Mean backscatter value in October (VH polarization)	23	VV_{max}	Maximum annual backscatter value (VV polarization)
10	VH_11	Mean backscatter value in November (VH polarization)	24	VV_{min}	Minimum annual backscatter value (VV polarization)
11	VH_12	Mean backscatter value in December (VH polarization)	25	VV_{max}-VV_{min}	Annual amplitude of backscatter (VV polarization)
12	VV_1	Mean backscatter value in January (VV polarization)	26	VH_{max}	Maximum annual backscatter value (VH polarization)
13	VV_2	Mean backscatter value in February (VV polarization)	27	VH_{min}	Minimum annual backscatter value (VH polarization)
14	VV_3	Mean backscatter value in March (VV polarization)	28	VH_{max}-VH_{min}	Annual amplitude of backscatter (VH polarization)

number of nodes, a minimum of one leaf node, and a random seed value of 0 (Sun and Ongsomwang, 2023).

The training data used as input for the classification model was built from survey points identified on Google Earth, which included the following land use types: (1) water bodies, (2) built-up areas, (3) aquaculture, (4) rice-shrimp, (5) double rice crop, (6) triple rice crop, (7) other perennial plants, (8) other annual crops, (9) forest, (10) coconut and (11) sugarcane.

Accuracy assessment

According to Islami et al. (2022), a reliable classification is consistently indicated by estimating the accuracy assessment between the classified image data and the field survey data using a confusion matrix approach. This reliability is assessed through two leading indices: overall accuracy (T%) and Kappa coefficient (K).

$$T = \text{Number of correctly classified pixels} / \text{Total Number of pixels in confusion matrix} \quad (1)$$

$$K = \frac{(T-E)}{(1-E)} \quad (2)$$

where: T is the overall accuracy provided by the confusion matrix; E is the quantity representing the expected accuracy, indicating the predictability of accurate classification in the actual classification process.

On the Google Earth Engine platform, the function ee.Classifier. Confusion matrix() identifies the confusion matrix and determines the overall accuracy and the Kappa coefficient. The classification error is classified into five levels, as shown in Table 2, which evaluates the interpretation results after classification.

Farmland showed widespread soil salinization distribution in most areas, as shown in Figure 2.

RESULTS AND DISCUSSION

Land use/land cover map

The classification results indicate a high level of reliability, with an overall accuracy of 91.26% and a Kappa coefficient of 0.89, confirming the strong agreement between the classified outcomes and actual land use conditions. In 2024, land use in Soc Trang Province was categorized into eleven classes: rice–shrimp, double rice crop, triple rice crop, other annual crops, other perennial plants, aquaculture, water bodies, built-up areas, forest, coconut, and sugarcane (Figure 3).

Among the land use types in Soc Trang Province, other perennial crops represented the most dominant, covering 132,665.06 hectares, or 40.39% of the province's total area (Figure 4). This category is widespread across districts and cities, with the largest concentrations in Ke Sach and Cu Lao Dung districts. Key perennial crops include durian, rambutan, mango, jackfruit, and pomelo, cultivated year-round (Soc Trang Provincial Statistics Office, 2023). Areas with dense perennial crop coverage are located along the Hau River, particularly in communes such as Xuan Hoa, An Lac Thon, An Lac Tay, Phong Nam, Nhon My, Thoi An Hoi, An My, Ke Sach Town, and the northern part of Cu Lao Dung.

Double rice cropping was the second most prominent land use type, accounting for 75,317.41 hectares (22.93%), mainly distributed in Tran De, Long Phu, Nga Nam Town, and parts of My Tu, Thanh Tri, Chau Thanh, My Xuyen districts, as well as Soc Trang City. Triple rice cropping covered 48,299.99 hectares (14.71%), concentrated in Ke Sach and parts of Chau Thanh, My Tu, Thanh Tri, and My Xuyen. In addition, the rice–shrimp rotation system occupied 1,718.14 hectares (0.52%), primarily in Gia Hoa 2 Commune of My Xuyen District.

Aquaculture was also significant, covering 29,568.08 hectares (9.00%), concentrated in coastal districts such as My Xuyen, Cu Lao Dung, Vinh Chau, and parts of Tran De. Water bodies covered 17,240.07 hectares (5.25%), and built-up areas accounted for 3,892.77 hectares (1.19%), mainly in urban centers, towns, and densely populated communes. Forest land, including production, protection, and special-use forests, occupied 7,723.46 hectares (2.35%), primarily in the coastal areas of

Table 2. Kappa Value Ranges (Congalton & Green, 1999)

No.	Accuracy	Kappa coefficient
1	Poor reliability	K < 0.2
2	Fair to poor reliability	0,2 =< K < 0.4
3	Moderate reliability	0,4 =< K < 0.6
4	Good reliability	0,6 =< K < 0.8
5	Very good reliability	0,8 =< K < 1.0

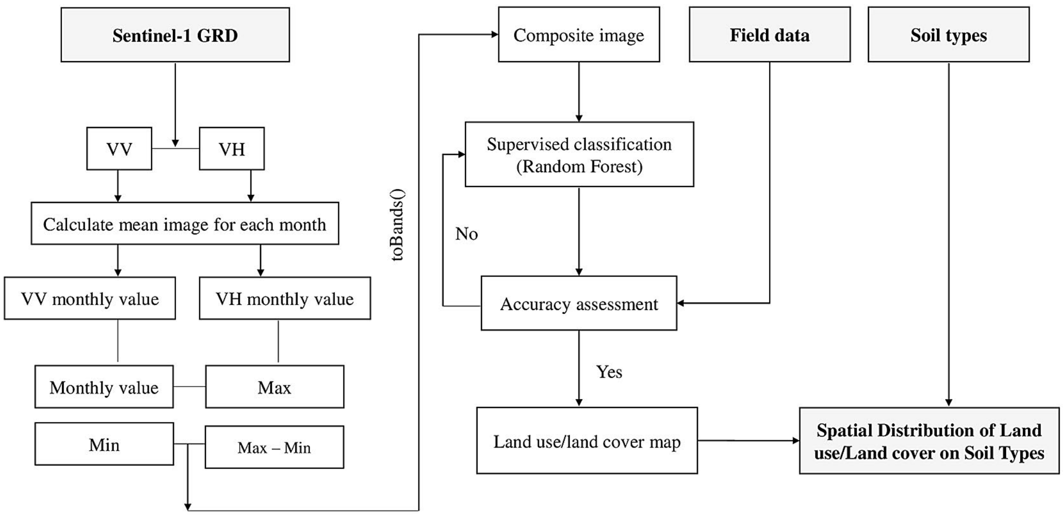

Figure 2. Comprehensive diagram for the spatial distribution of soil types on agriculture

Vinh Chau Town. Other annual crops covered 4,423.49 hectares (1.35%), including purple onion, radish, and watermelon. Coconut plantations accounted for 2,982.44 hectares (0.91%), primarily located in the northern region of Cu Lao Dung and the western part of Long Phu District. Meanwhile, sugarcane cultivation covered 4,626.63 hectares (1.41%), mainly concentrated in Cu Lao Dung District.

Soil types distribution in Soc Trang province

According to the Department of Agriculture and Environment of Soc Trang Province (2024), soil types include alluvial, active acid sulfate, potential acid sulfate, ridge, sandy, and saline soil (Figure 5). Alluvial soils are primarily located in the northern part of Ke Sach District, adjacent to the Hau River, representing areas with high agricultural potential due to their fertility. Active acid

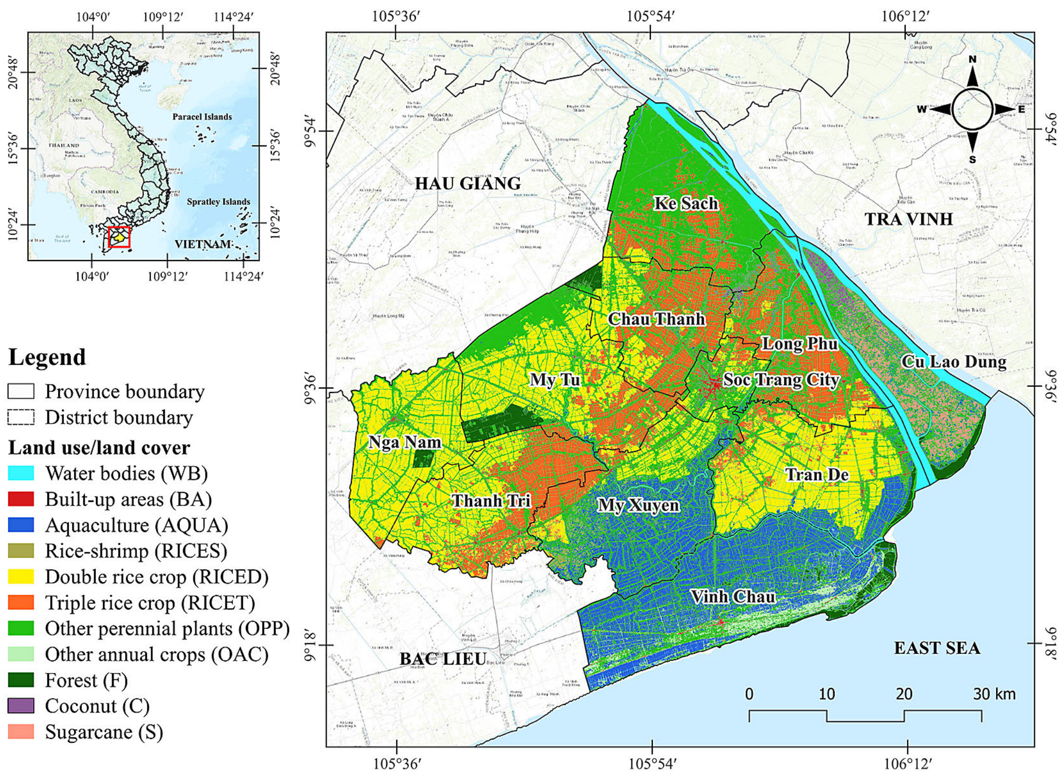

Figure 3. The land use map in Soc Trang province in 2024

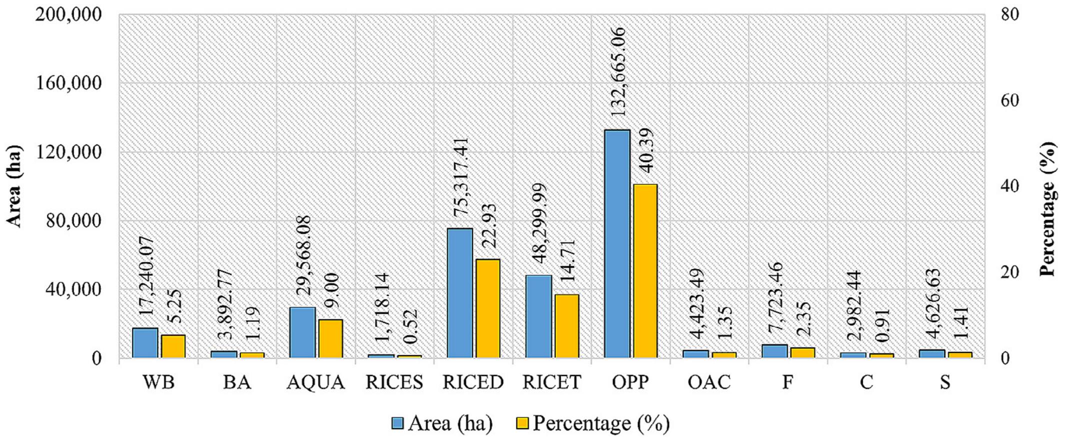

Figure 4. Land use area statistics Soc Trang province in 2024

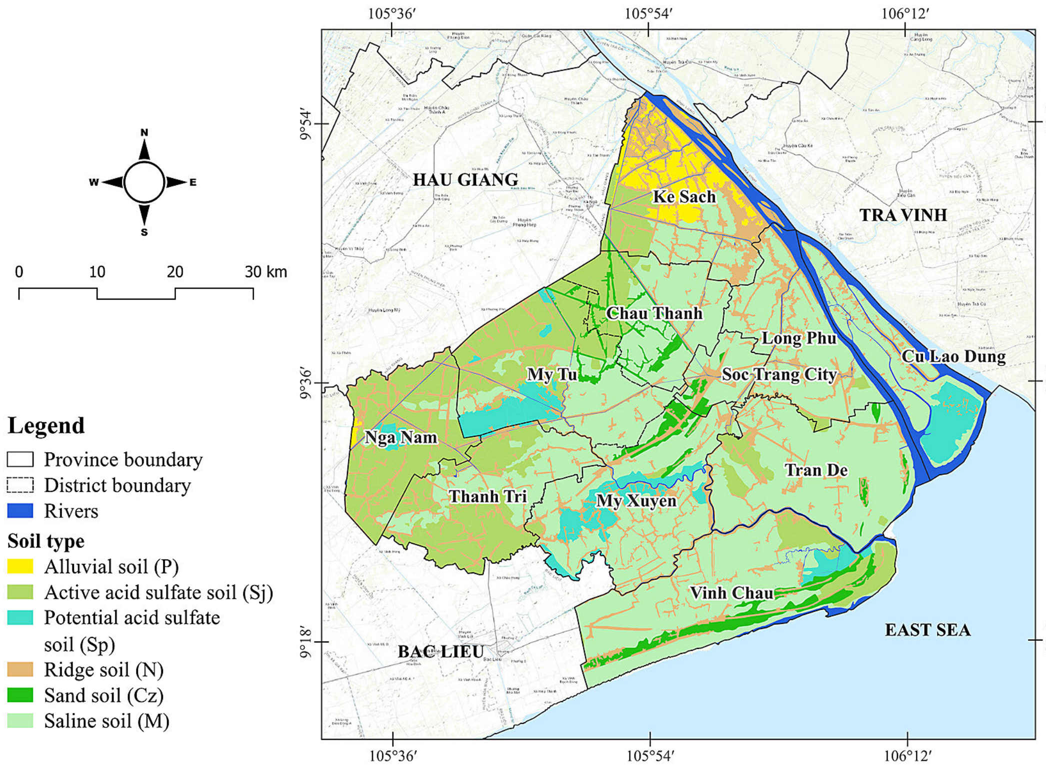

Figure 5. Soil types map in Soc Trang province in 2024

sulfate soils are widely distributed across several districts, including My Tu, Thanh Tri, My Xuyen, and Long Phu, posing challenges for agricultural production due to their high acidity. Potential acid sulfate soils are found sporadically in Thanh Tri and My Xuyen, with the risk of acidification upon drainage or oxidation. Ridge soils appear scattered throughout the province, often as elevated areas within acidic or saline zones, suitable for upland crops. Sandy soils are predominantly found in the coastal districts of Vinh Chau and Cu Lao Dung, where drainage is good, but water and nutrient retention are limited. Saline soils are extensive in the southern and eastern coastal regions, especially in Vinh Chau, Tran De, and Cu Lao Dung, where salt intrusion significantly influences land use, favoring aquaculture and salt-tolerant crops.

Figure 6 illustrates the area distribution of soil types in Soc Trang province. Saline soil (M) occupies the most significant area, covering 154,144.30 hectares. It is followed by active acid sulfate soil (Sj) with 62,614.55 hectares and ridge soil (N) with 54,085.34 hectares. Potential acid sulfate soil (Sp) covers 17,987.82 hectares, while sand soil (Cz) occupies 12,451.70 hectares. Alluvial soil (P) has the smallest area, with 8,317.04 hectares.

Soc Trang province is located along the coastal area in the Lower Mekong Delta, which is formed from young sediments, Holocene age, marine or mixed river-marine origin from alluvial products of the Mekong River system deposited in the marine environment due to marine sediments or the influence of saltwater overflow or coastal salinity of river mouths. Saline soils in the Mekong Delta are divided into three soil units, including saline soil of mangrove (Mm), highly saline soil (Mn), and medium and low saline soil (Mi). It is also consistent with the topographical location of the province, which has long coastlines and many funnel-shaped estuaries belonging to branches of the Mekong River system, in addition to the low-lying terrain (many places are lower than sea level). Thus, the possibility of saline intrusion is substantial (Vietnam Soil Science Association, 2000).

Agriculture cultivation distribution on saline soil

The land use map of Soc Trang province, based on saline soil conditions, illustrates a diverse distribution of agricultural practices, reflecting the region's adaptability to saline environments, especially in coastal areas (Figure 7). Saline soils in the province are generally classified into three sub-regions of which slightly saline, moderately saline, and highly saline soils.

According to Dao and Duc (2019), the slightly saline soils in mangrove forests are primarily present along the coastal areas and are home to protective forest ecosystems covering approximately 818.4 hectares. This soil type is characterized by high salinity, with an average chloride (Cl^-) concentration of around 1.33%, total soluble salt (TSS) content of 2.61%—indicating a highly saline condition—and an electrical conductivity (EC) value of 4.57 mS/cm. The mildly to moderately saline soils make up around 90% of the total saline soil area in Soc Trang province. This region supports various agricultural activities, including rice cultivation, perennial crops, annual crops, sugarcane, coconut, and aquaculture, with a total area of approximately 139,419.19 hectares (Figure 8). The Cl^- concentration ranges from 0.11% to 0.15%, TSS ranges from 0.49% to 0.60%, and EC values range from 1.47 to 1.71 mS/cm. This soil type falls within the low to moderate salinity range, with moderate fertility. It is only seasonally affected by salinity during the dry season, while the saline topsoil layer is significantly reduced during the rainy season due to dike systems and salt leaching, making it suitable for rice and vegetable cultivation. Lastly, the highly saline soil zone has an average Cl^- content of 0.65%, indicating predominantly chloride-based salinity. TSS varies widely from 0.24% to 4.18%, with an average of about 1.82%, and the EC value averages 4.42 mS/cm

According to the Vietnam Soil Science Association (2000), the saline soil of mangroves has a fairly average fertility level, which is an urgent requirement for the restoration and development of protective forest belts to stabilize and prevent coastal erosion while protecting and maintaining the mangrove ecosystem, which has high biological value. Saline soil has a relatively high fertility level, which can be used for aquaculture or sedge cultivation. After land improvement,

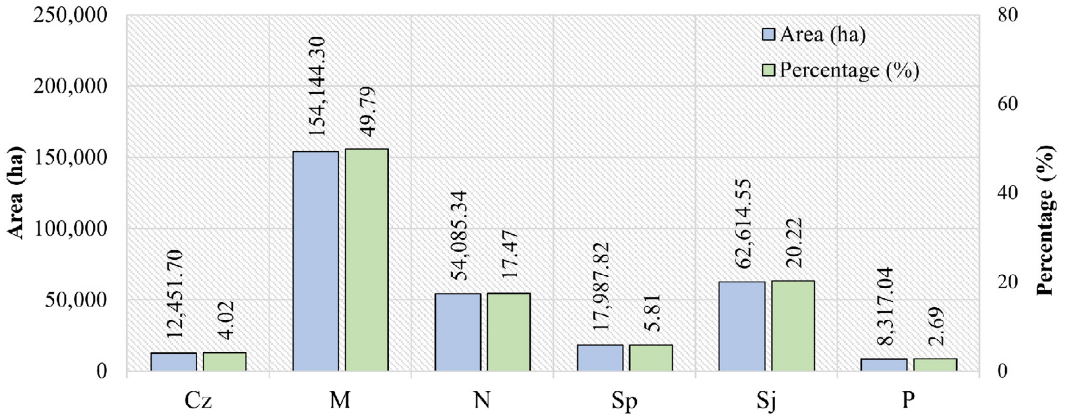

Figure 6. Soil types area in Soc Trang province

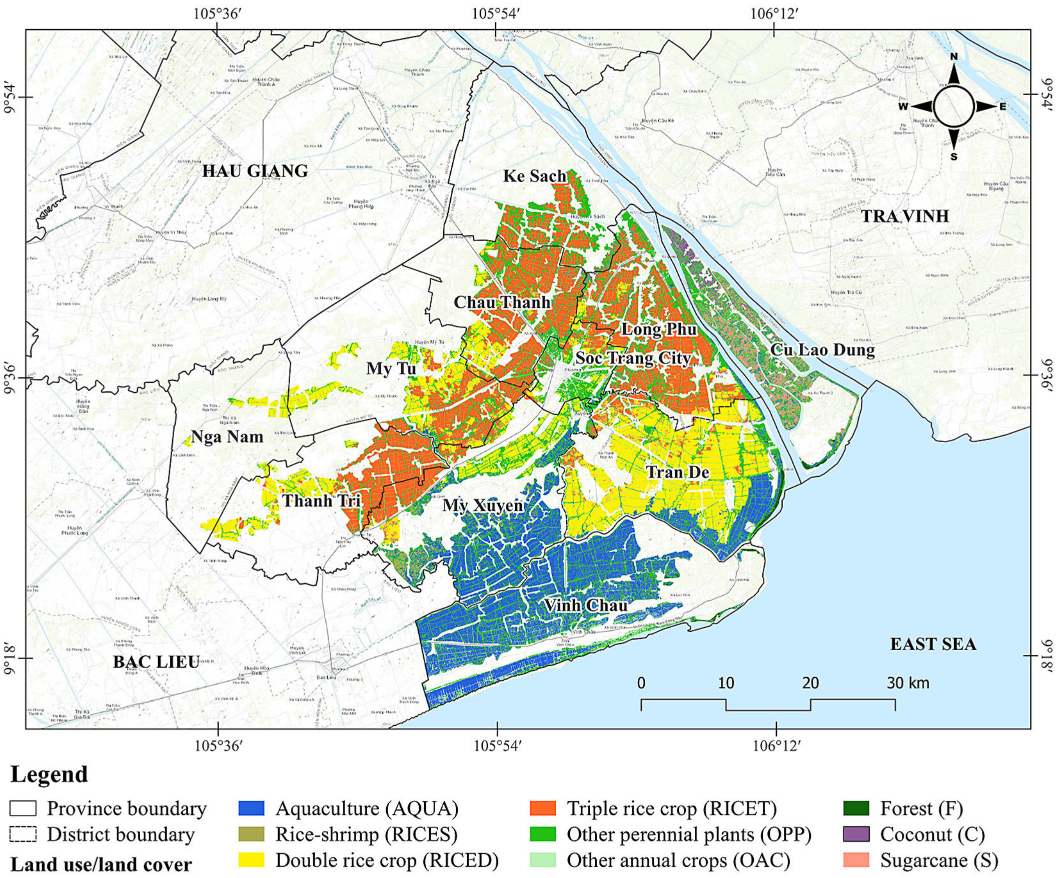

Figure 7. Map of the spatial distribution of agricultural land on saline soil

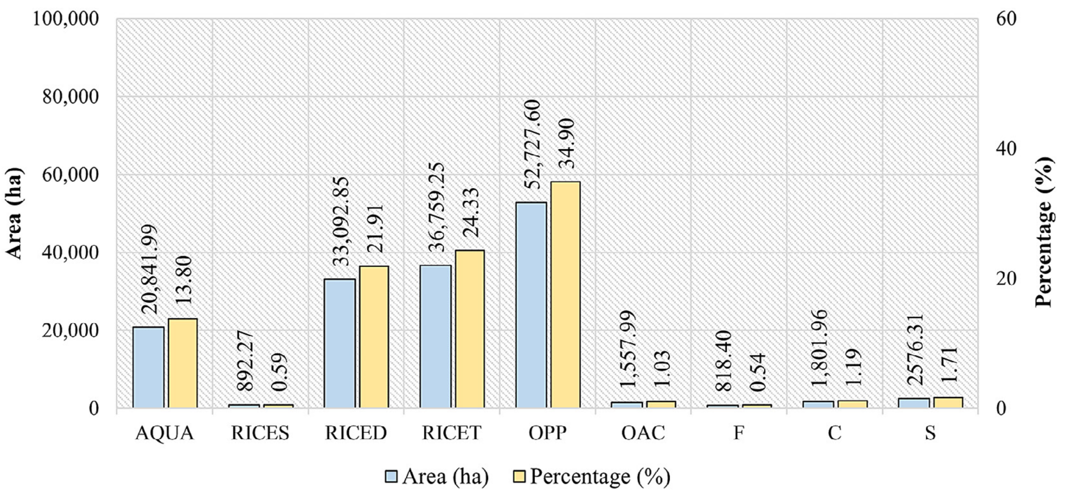

Figure 8. Agricultural area on saline soil

it is possible to grow double rice crops or one summer/autumn rice crop. Moreover, choosing salt-tolerant plant varieties and a fertilizer regime combined with acid drainage and salinity washing are top priority measures to ensure effective land use. Moderately and slightly saline soils have average fertility; most moderately and slightly saline soils are used for rice cultivation; in high terrain, it is possible to grow double-rice crops and mono-rice crops or upland crops. However, this soil type is effectively used to build dikes and banks to prevent salt overflow, combined with lime application and irrigation measures to wash away the salt.

In agroecosystems, crop productivity depends on favorable environmental and edaphic conditions to optimize yield and ensure economic viability. Among these factors, salinity in the rhizosphere is critical in regulating plant growth dynamics. The extent of salinity stress varies across plant species, depending on their intrinsic sensitivity or tolerance to salt. While low salinity levels generally have negligible effects on plant development, elevated salinity concentrations significantly impair growth and physiological functions (Lakhdar et al., 2009).

Soil salinity significantly increases the production of reactive oxygen species (ROS) in plants, including hydrogen peroxide, superoxide radicals, hydroxyl radicals, and singlet oxygen, collectively contributing to oxidative stress in plant tissues. This oxidative stress disrupts cellular homeostasis, leading to protein denaturation, lipid peroxidation, and nucleic acid damage, ultimately affecting plant metabolism and potentially resulting in cell death (Demidchik, 2014).

Sustainable land management practices are essential for maintaining and enhancing soil quality, preventing the degradation of natural resources, and improving agricultural land productivity. Abiotic stressors such as soil salinization represent a significant constraint to agricultural development, reducing crop yields and limiting the effective use of arable land. Significant agricultural losses are frequently attributed to high salinity levels and suboptimal soil moisture conditions. A comprehensive approach incorporating adaptive agronomic practices, policy interventions, and strategic management is required to mitigate the adverse impacts of salinity. Addressing soil salinization requires a combination of strategies, including implementing efficient irrigation systems, utilizing leaching practices to remove excess salts, cultivating salt-tolerant crops, and adopting integrated resource management frameworks.

CONCLUSION

The study developed an agricultural soil map utilizing *time-series Sentinel-1 SAR images and* identified various agricultural land types on saline soils in Soc Trang province. The results reveal a distinct spatial differentiation in land use according to salinity levels. Areas from low to moderate salinity are predominantly identified for rice cultivation, perennial crops, and annual crops, whereas highly saline zones are primarily designated for intensive aquaculture. Additionally, highly saline mangrove zones are mainly allocated for protective forest plantations.

The findings of this research provide a critical spatial database that can support agricultural land use planning aligned with local soil type conditions, specifically regarding the increasing impact of climate change and saltwater intrusion. Furthermore, the results offer valuable insights for policymakers in proposing sustainable management and reclamation strategies for saline soils, contributing to the broader goal of adaptive and long-term agricultural development.

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