Volume 10, Issue 7, pp. 66-70, July 2026.
International Journal of Scientific Engineering and Science
ISSN (Online): 2456-7361

An Interpretable Sentinel-2 and GIS Framework for Rapid Screening of Cropland Salinity Stress: A Case Study in Ben Tre Province, Vietnam

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Abstract**—*Coastal agriculture in the Vietnamese Mekong Delta requires spatially explicit screening of salinity-related crop stress, but dense field observations are rarely available at provincial scale. This study developed a transparent Sentinel 2 and geographic information system workflow to map relative salinity-stress indications in annual cropland across Ben Tre Province during the 2025 dry season. Surface-reflectance imagery acquired from 1 December 2024 to 31 May 2025 was cloud masked and composited in Google Earth Engine. Cropland was delineated with ESA WorldCover class 40, open water was excluded with the modified normalized difference water index, and three complementary indicators were converted to binary evidence layers: low vegetation vigor, low moisture, and a visible-band salinity proxy. Their sum produced four screening classes from no indication to high indication. The mapped cropland covered 21,339.40 ha, or 8.93 percent of the study extent. A total of 5,501.96 ha, representing 25.78 percent of mapped cropland, showed at least one adverse spectral signal; moderate and high indications were concentrated toward Ba Tri, Thanh Phu, and eastern Binh Dai. The workflow is computationally light, interpretable, and suitable for prioritizing monitoring locations. It does not estimate measured electrical conductivity or salt concentration, and the resulting classes should be treated as screening evidence until calibrated with field observations and crop-stage information.*

Keywords**—** *Ben Tre, cropland, GIS, salinity stress, Sentinel 2, spectral indices.*

I. Introduction

Salinity intrusion is a recurrent pressure on water security and agricultural production in the Vietnamese Mekong Delta. Its severity is shaped by the interaction of dry-season freshwater discharge, tidal propagation, channel geometry, local water management, drought, and land-use decisions. A regional review showed that salinity intrusion has already contributed to major agricultural transitions across the delta, while recent satellite and monitoring analyses confirm that drought-salinity episodes are associated with shifts in cultivated land and cropping systems [1], [2]. The problem is especially consequential in low-lying coastal provinces where riverine and marine processes meet and where crop response can change rapidly within one dry season.

Ben Tre Province is a suitable test area because its agricultural landscape is distributed among low-lying interdistributary islands and is directly connected to the coastal branches of the Mekong system. Field-calibrated studies in Ben Tre have demonstrated that remote-sensing covariates and machine-learning models can predict soil salinity and that higher salinity generally occurs toward the eastern coastal sector [3]. At the wider delta scale, remote sensing combined with monitoring or machine learning has also supported salinity-intrusion prediction under data limitations [4], identified salinity-related spectral behavior in neighboring Tra Vinh Province [5], and documented long-term land-use responses to hydrological change [6]. These studies establish the value of Earth observation, but their data demands and model complexity may limit routine operational use by local agencies.

Internationally, soil-salinity mapping has evolved from single spectral indices toward multivariate and machine-learning approaches. Reviews emphasize that salt, soil moisture, vegetation condition, surface roughness, and crop phenology may produce overlapping spectral responses, making a single index insufficient for causal attribution [11]. Sentinel 2 has nevertheless enabled salinity prediction in hyper-arid areas, coastal wetlands, and other data-constrained landscapes when spectral information is combined with environmental evidence or calibrated models [12]-[15]. The common lesson is that satellite data can support screening, but the meaning of mapped classes depends on the availability and quality of field reference data.

A practical gap therefore remains between high-performance field-calibrated models and simple maps that can be updated rapidly during the dry season. Many local applications use salinity labels that imply measured concentration even when the classification is derived only from vegetation, moisture, and visible reflectance. This creates a risk of overinterpretation. The present study addresses that gap by reformulating the supplied Ben Tre workflow as an explicitly relative, evidence-based screening method for annual cropland. The contributions are threefold: (1) a reproducible dry-season Sentinel 2 processing chain with cloud, water, and cropland masks; (2) an interpretable score that integrates vegetation vigor, moisture, and a visible-band salinity proxy without claiming direct salt concentration; and (3) quantified spatial priorities for field monitoring, accompanied by clear statements of uncertainty and transferability.

II. Materials and Methods

A. Study Area and Analytical Scope

The study covered Ben Tre Province in the lower Vietnamese Mekong Delta. The province is characterized by low relief, a dense river and canal network, extensive coastal exposure, and strong dry-season interactions between declining

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freshwater supply and tidal salinity. The processed provincial extent was 238,980.70 ha. Because the ESA WorldCover class used in the supplied analysis represents cropland rather than all agricultural systems, the analytical population was restricted to mapped annual cropland. Coconut plantations, orchards, aquaculture, settlements, and other land-cover types were outside the primary area statistics unless they were represented as class 40.

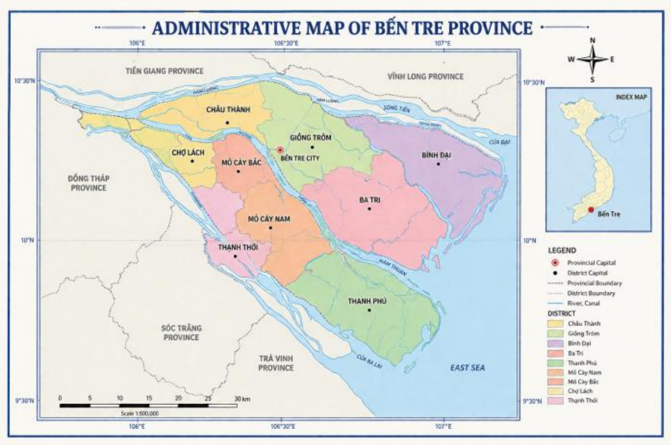

Fig. 1. Study area and provincial administrative units of Ben Tre province

B. Input Data

TABLE I. Input Data and Processing Configuration

Component	Source	Configuration
Optical imagery	Sentinel 2 SR Harmonized	1 Dec. 2024-31 May 2025; median composite
Cloud screening	Scene metadata and SCL	Cloudy pixels <40%; SCL 1, 3, 8, 9, 10, 11 removed
Boundary	FAO GAUL 2015 level 1	Ben Tre provincial polygon
Cropland mask	ESA WorldCover 2021 v200	Class 40; 10 m
Output grid	Google Earth Engine	10 m; B11 evaluated on 10 m grid

Sentinel 2 provides multispectral observations suited to vegetation, moisture, soil, and water analysis [7]. The COPERNICUS/S2_SR_HARMONIZED collection was accessed through Google Earth Engine, whose cloud infrastructure supports reproducible compositing and large-area raster analysis [8]. The Sentinel 2 B2, B3, B4, and B8 bands have 10 m native resolution, whereas B11 has 20 m resolution. Continuous B11 reflectance was evaluated at the 10 m output grid using bilinear resampling. ESA WorldCover v200 supplied the 10 m cropland mask [16].

C. Image Preprocessing

Images were filtered to the 2025 dry-season window and to scenes with less than 40 percent metadata cloudiness. The Sentinel 2 scene-classification layer was used to remove defective pixels, cloud shadows, medium- and high-probability clouds, cirrus, and snow or ice, corresponding to SCL classes 1, 3, 8, 9, 10, and 11. A median surface-reflectance composite was then calculated to reduce residual cloud contamination and transient noise. The composite was clipped to the provincial boundary. Water pixels were removed using MNDWI, and the remaining land pixels were intersected with WorldCover cropland class 40. Fig. 2 summarizes the processing and interpretation chain.

D. Spectral Indicators

Four spectral transformations were used. NDVI represented green vegetation vigor, NDMI represented vegetation and surface moisture, a visible-band salinity proxy represented relative changes in blue, red, and green reflectance, and MNDWI separated open water. NDVI and NDMI follow established normalized-difference formulations, while MNDWI improves the discrimination of open water in mixed land-water settings [9], [10]. For Sentinel 2 surface-reflectance bands, the indicators were calculated as follows:

$$NDVI = (B8 - B4) / (B8 + B4) \quad (1)$$

$$NDMI = (B8 - B11) / (B8 + B11) \quad (2)$$

$$VSP = (B2 \times B4) / B3 \quad (3)$$

$$MNDWI = (B3 - B11) / (B3 + B11) \quad (4)$$

VSP denotes the operational visible-band salinity proxy used in this paper. It is not treated as a standardized salinity index or a direct estimator of electrical conductivity. The use of a relative proxy is consistent with the broader constraint that soil salinity is difficult to isolate spectrally without reference samples because moisture, soil type, roughness, vegetation cover, and management can generate similar responses [11].

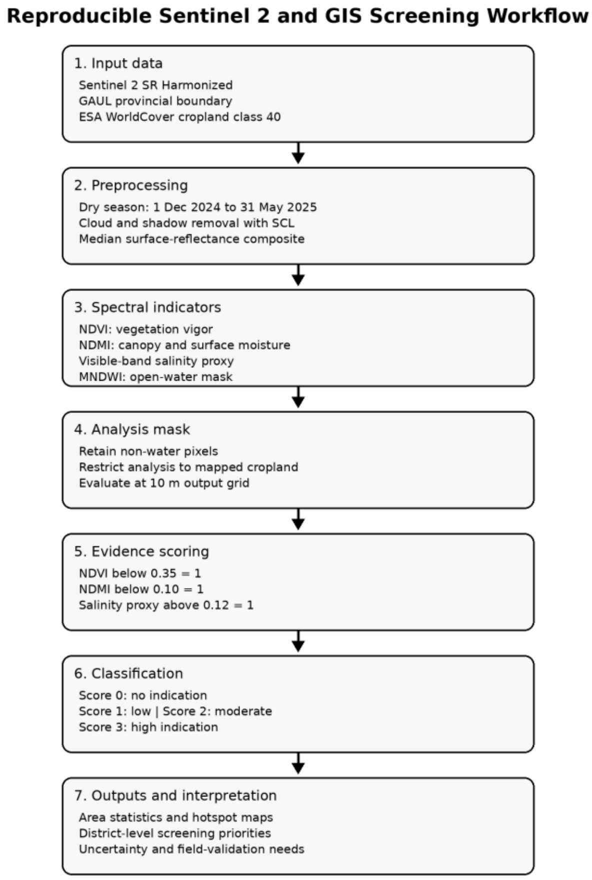

Fig. 2. Workflow for generating relative cropland salinity-stress indications from Sentinel 2 and GIS data.

E. Thresholding and Evidence Score

The supplied operational thresholds were retained to reproduce the reported area statistics, but they were interpreted as screening cutoffs rather than universal biophysical boundaries. A pixel received one evidence point for low vegetation vigor, one for low moisture, and one for an elevated visible-band proxy. MNDWI was applied only as a land-water mask. The evidence score was:

$$S = I(NDVI < 0.35) + I(NDMI < 0.10) + I(VSP > 0.12) \quad (5)$$

where I is an indicator function equal to one when the stated condition is satisfied. Only pixels with MNDWI less than or equal to 0.05 and WorldCover class 40 were analyzed. Scores

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International Journal of Scientific Engineering and Science
Volume 10, Issue 7, pp. 66-70, July 2026. ISSN (Online): 2456-7361

from zero to three were assigned to no, low, moderate, and high spectral indication classes, respectively. Table II lists the decision rules. This nomenclature deliberately avoids the concentration labels previously attached to the map because no field electrical-conductivity observations were available to justify thresholds in parts per thousand or decisiemens per meter.

TABLE II. Evidence Rules and Screening Classes

Item	Rule	Interpretation
Vegetation	NDVI < 0.35	Low vegetation vigor
Moisture	NDMI < 0.10	Low moisture signal
Surface proxy	VSP > 0.12	Elevated visible response
Land mask	MNDWI <= 0.05	Retain non-water pixels
Score 0-3	Sum of three flags	None, low, moderate, high

F. Area Statistics, Spatial Interpretation, and Validation Boundary

Pixel counts were converted to hectares using the 100 m2 area of a 10 m output pixel. Results were summarized for the province and interpreted by district using the source map and administrative boundaries. The spatial pattern was compared qualitatively with published Ben Tre and Mekong Delta studies, particularly the documented east-to-west salinity gradient [1], [3], [4]. This comparison is a plausibility assessment, not an independent accuracy test. Overall accuracy and Kappa statistics were therefore not reported, because such measures require georeferenced reference labels and a documented sampling design. The appropriate next validation step is a stratified field campaign measuring soil or irrigation-water electrical conductivity, crop type, crop stage, and moisture across all four mapped classes.

III. RESULTS

A. Cropland Extent

The WorldCover mask identified 21,339.40 ha of cropland, equal to 8.93 percent of the 238,980.70 ha provincial study extent. Other mapped cover types accounted for 217,641.30 ha. This result defines the scope of all subsequent percentages: they refer only to WorldCover cropland class 40, not to the full agricultural economy of Ben Tre. The cropland pixels were concentrated in Ba Tri, Thanh Phu, and eastern Binh Dai, with additional fragmented patches farther inland (Fig. 2).

B. Spectral Evidence Classes

TABLE III. Cropland Area By Spectral Evidence Class

Class	Area (ha)	Share (%)
No indication	15,837.44	74.22
Low indication	2,279.05	10.68
Moderate indication	2,069.92	9.70
High indication	1,152.99	5.40
Total cropland	21,339.40	100.00

Most mapped cropland showed no combined adverse signal, but 5,501.96 ha, or 25.78 percent, satisfied at least one evidence rule. The low and moderate classes were similar in area, whereas the high class represented the smallest but most concentrated priority group. The high class indicates simultaneous agreement among the vegetation, moisture, and visible-reflectance rules. It should not be read as a measured salinity concentration.

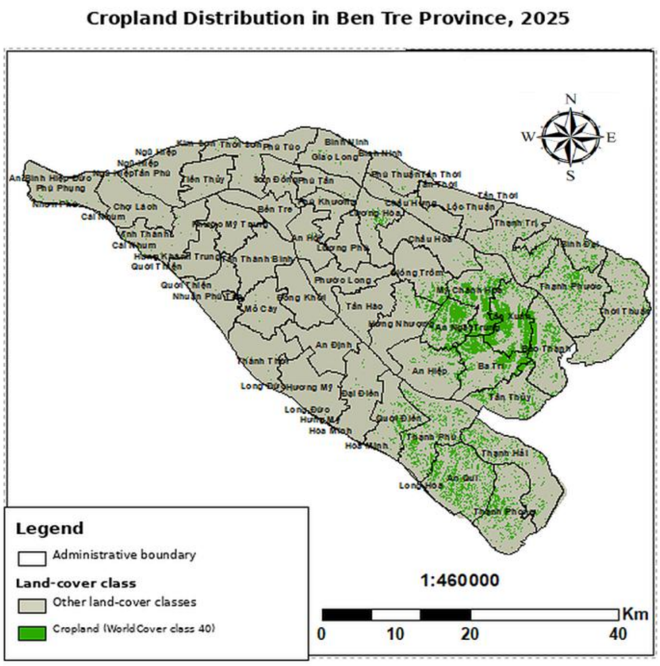

Fig. 2. Distribution of ESA WorldCover cropland class 40 within Ben Tre Province

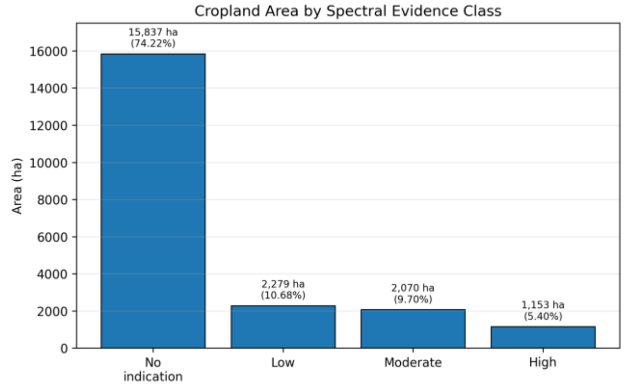

Fig. 3. Area and percentage of mapped cropland in each spectral evidence class.

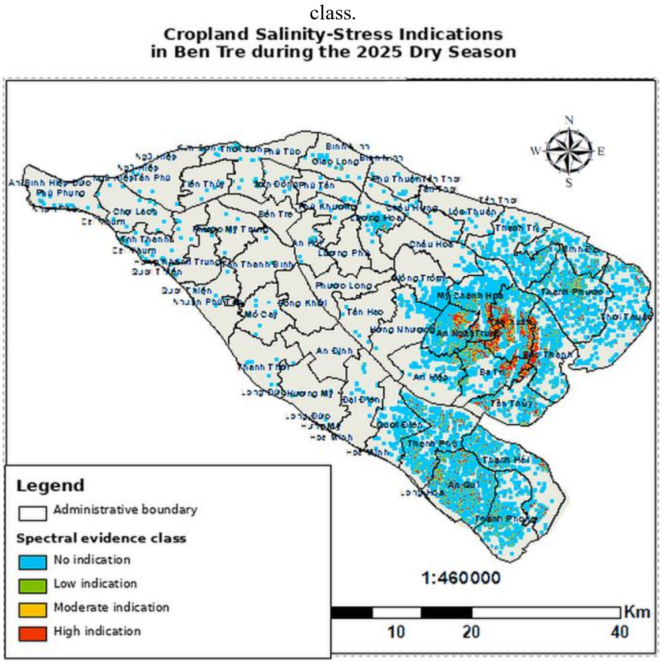

Fig. 4. Relative spectral evidence classes on the cropland mask. Classes represent screening indications and not measured salt concentration.

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Volume 10, Issue 7, pp. 66-70, July 2026. ISSN (Online): 2456-7361

C. Spatial Pattern and Hotspots

The screening map displayed a clear coastal concentration of moderate and high indications (Fig. 4). The most persistent clusters occurred in Ba Tri and Thanh Phu, with a strong eastward pattern in Binh Dai. Moderate-to-high indications were reported around Giao Thanh, An Ngai Trung, Bao Thuan, An Thuy, Thanh Hai, and Binh Thoi. Low-to-moderate indications occurred in parts of An Thuan, Thanh Phong, Quoi Dien, and My Hung. Inland localities in Giong Trom, Cho Lach, Chau Thanh, Mo Cay Bac, and western Mo Cay Nam were dominated by no or low indication.

TABLE IV. District-Level Spatial Interpretation

District	Dominant pattern	Screening implication
Ba Tri	Moderate-high coastal clusters	Priority field sampling and irrigation-water checks
Thanh Phu	Moderate-high along estuarine and coastal zones	Monitor crop stress and freshwater access
Binh Dai	Marked east-west gradient	Sample across coastal-inland transition
Giong Trom	Mainly no-low indication	Potential comparison or reference zone
Inland districts	Mostly no indication	Continue surveillance; avoid assuming zero salinity

IV. DISCUSSION

A. Meaning of the Coastal Gradient

The concentration of moderate and high indications in eastern and coastal Ben Tre is consistent with the spatial tendency documented by field-calibrated soil-salinity models in the province [3] and with broader accounts of dry-season salinity intrusion in the Mekong Delta [1], [2], [4]. The pattern is physically plausible because coastal districts are closer to estuarine saline-water pathways and may experience greater dry-season freshwater constraints. The result is also consistent with research showing that long-term hydrological changes and salinity-related disturbances can reorganize agricultural land use across the delta [2], [6].

Nevertheless, spatial agreement does not prove that salt alone caused the observed reflectance. Low NDVI and NDMI may also result from crop harvest, fallow land, drought without salinity, crop disease, sparse planting, or soil exposure. Visible soil reflectance is affected by mineralogy, texture, organic matter, roughness, and moisture. These confounding factors are central limitations in remote sensing of soil salinity [11]. Consequently, the map is most defensible as a triage layer that identifies where field measurements should be intensified, rather than as a substitute for salinity monitoring stations or laboratory measurements.

B. Value and Limits of the Rule-Based Approach

Compared with hybrid machine-learning models developed for Ben Tre and other settings [3], [12]-[15], the rule-based score has lower data requirements and greater interpretability. Every class can be traced to three explicit conditions, which is useful for operational agencies that need a repeatable method and transparent decision logic. The method can be updated quickly in Google Earth Engine and can be implemented without a large training dataset. Its limitations are equally explicit: fixed thresholds may not transfer between seasons, crops, soil backgrounds, or atmospheric conditions, and equal weighting assumes that all three indicators contribute the same information.

The distinction between screening and quantitative salinity mapping is important. Field-calibrated research in Tra Vinh and Ben Tre has shown that remote-sensing variables can support salinity estimation when paired with observations and appropriate models [3], [5]. However, interpretation of purely spectral salinity indices has also been debated, particularly where the training and validation design does not isolate salinity from co-varying moisture and land-cover effects [18]. The present study therefore removes concentration labels and avoids unsupported accuracy statistics. This editorial correction improves scientific validity even though it makes the claims more conservative.

C. Management Implications

The map can support a tiered monitoring strategy. Moderate and high clusters in Ba Tri, Thanh Phu, and eastern Binh Dai should receive the highest density of soil and irrigation-water sampling near the peak of the dry season. Transitional zones should be sampled along coastal-inland transects to determine whether spectral class changes correspond to electrical conductivity, crop stage, or water availability. Areas with no indication remain useful as comparison sites but should not be considered salinity-free without measurement. When combined with local water-gate operations, canal observations, and crop calendars, monthly updates could help target freshwater storage, irrigation scheduling, and extension advice.

D. Uncertainty and Research Priorities

Four uncertainties constrain interpretation. First, the analysis represents one dry season and cannot separate an anomalous year from a persistent trajectory. Second, 10 m pixels mix narrow fields, canals, roads, and tree cover, while the 20 m B11 band introduces additional spatial smoothing. Third, WorldCover class 40 excludes many perennial systems important to Ben Tre, particularly coconut and orchards, so the reported 21,339.40 ha should not be called total agricultural land. Fourth, no independent field dataset was available. Future work should use stratified random sampling across the four classes, record crop type and phenological stage, measure soil and water electrical conductivity, and test alternative thresholds or calibrated regression models. Multi-date imagery should then be used to distinguish persistent salinity stress from temporary harvest or drought signals.

V. CONCLUSION

This study demonstrates a defensible role for Sentinel 2 and GIS as an early screening layer for salinity-related stress in data-limited coastal agriculture. Its main value is not the assignment of a salt concentration to each pixel, but the integration of three interpretable spectral signals within explicit cropland and water masks. The resulting pattern identifies coastal Ben Tre as the primary location for intensified field surveillance and provides a transparent basis for allocating limited monitoring resources. By replacing concentration labels and unsupported accuracy claims with relative evidence classes, the paper establishes a more scientifically cautious and operationally useful product. The next step is to convert this screening map into a quantitative decision tool through crop-specific field calibration, repeated dry-season observations, and integration with river salinity, rainfall, and water-management data.

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