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Long-Term Flood Inundation Trends and Their Effects on Diverse Agricultural Systems in Ben Tre of Vietnam

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ABSTRACT

The Vietnamese Mekong Delta (VMD), a critical agricultural hub, faces recurrent flooding that poses substantial threats to livelihoods and productivity. Ben Tre province, with its low-lying coastal terrain, is particularly vulnerable. Effective risk management and sustainable agricultural development necessitate a thorough understanding of these flood dynamics. This study leveraged the Google Earth Engine (GEE) platform and Sentinel-1 Synthetic Aperture Radar (SAR) imagery to analyze flood inundation patterns and their impacts on diverse agricultural land uses in Ben Tre province from 2015 to 2023. The methodology involved SAR data pre-processing, Otsu thresholding for water body delineation from VH polarization data and change detection using a 2020 land use map to quantify annual flooded areas and their impact on specific agricultural categories. The total inundated area peaked in 2018 at 58,334 ha, a significant increase from 27,934 ha in 2015, before stabilizing around 42,000–44,000 ha in 2021–2023. Flooded agricultural land mirrored this trend, increasing from 18,615 ha (2015) to a peak of 39,514 ha (2018), then decreasing to 28,841 ha (2023). Notably, wet rice cultivation experienced a 37.8% increase in its flooded area over the study period, while other annual crops and perennial crops saw increases of 38.9% and 68.4%, respectively. This research demonstrates the GEE platform's efficacy with Sentinel-1 SAR for robust, long-term flood monitoring and impact assessment, revealing escalating flood pressure on key agricultural systems and an expansion of flooding beyond traditional low-lying zones, providing crucial data for adaptive land use planning.

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1. Introduction

Flooding, a globally pervasive natural hazard, inflicts considerable economic losses and poses significant threats to human lives and livelihoods [1, 2]. Deltaic regions, characterized by low-lying topography, fertile lands, and high population densities, exhibit particular susceptibility to flood impacts [3, 4]. These impacts are frequently exacerbated by climate change-induced sea-level rise, intensified rainfall, and anthropogenic modifications to river systems, including upstream dam construction and localized land-use changes [4–6]. The Vietnamese Mekong Delta (VMD), often termed Vietnam's "rice bowl," exemplifies such a vulnerable environment [7, 8]. This expansive region, covering approximately 40,000 km² and home to over 17.4 million people [9], is pivotal for Vietnam's food security and export economy, primarily through intensive rice cultivation, aquaculture, and fruit production. Understanding and managing flood risk in the VMD is therefore of paramount national importance.

The inherent low elevation and intricate river network of the VMD render it prone to annual flooding. However, recent decades have witnessed significant alterations in flood regimes—changes in timing, duration, and magnitude—often linked to regional land-use modifications and the overarching impacts of climate change [6, 10, 11]. These shifts, coupled with ongoing sea-level rise and an increased frequency of extreme weather events, amplify risks to agricultural production, critical infrastructure, and socio-economic stability throughout the delta [12]. Ben Tre province, situated in the coastal part of the VMD, faces compounded flood risks due to its direct interface with the East Sea (Bien Dong) and its agricultural systems' reliance on freshwater resources that are sensitive to inundation and salinity intrusion [13, 14]. Consequently, accurate flood mapping, monitoring, and impact assessment are paramount for effective risk management and sustainable agricultural development in Ben Tre and the broader VMD.

To provide a theoretical framework for understanding flood impacts and guiding response strategies, the DPSIR (Driving Forces – Pressures – State – Impact – Response) model is highly relevant. Developed by the OECD and EEA, this model is widely applied in environmental management and policy development [15]. In the context of Ben Tre, Driving forces include climate change (leading to sea-level rise, altered rainfall) and socio-economic development pressures. These drivers exert pressures such as intensified rainfall events, higher river discharges during flood seasons, and increased tidal influence. These pressures alter the state of the environment, leading to increased flood extent, duration, and depth. The impacts on agricultural systems are diverse, including direct crop damage, loss of agricultural land, reduced productivity, soil degradation, damage to infrastructure, and negative effects on farmers' livelihoods and income [14]. Finally, responses involve measures to mitigate these impacts, such as developing early warning systems, constructing flood defenses, promoting flood-resilient crops and farming systems, and implementing adaptive land-use planning.

Remote sensing technology, particularly when integrated with platforms like Google Earth Engine (GEE), plays a crucial role in monitoring the 'State' and quantifying the 'Impact' components of the DPSIR framework. Traditional flood monitoring, relying on ground-based gauges and field surveys, provides point-specific data but often lacks the spatial comprehensiveness and timeliness required for effective regional assessment and rapid response [3, 16]. Remote sensing offers a powerful alternative, providing synoptic views, frequent revisit capabilities, and the ability to map flood extent over large and often inaccessible areas [17]. While optical sensors (e.g., Landsat, Sentinel-2) are valuable for delineating water bodies under cloud-free conditions [18], their utility during major flood events in tropical regions like the VMD is often hampered by persistent cloud cover. Synthetic Aperture Radar (SAR) sensors, such as those aboard the Sentinel-1 satellites, operate in the microwave spectrum, enabling them to penetrate clouds and acquire imagery day or night [19, 20]. This all-weather, day-and-night capability makes SAR exceptionally well-suited for flood monitoring in tropical monsoon regions.

The advent of cloud computing platforms like GEE has revolutionized the processing and analysis of large-volume satellite data archives [21]. GEE provides access to petabytes of satellite imagery, including the complete Sentinel-1 archive, and offers powerful parallel processing capabilities. This enables large-scale, long-term environmental monitoring without requiring extensive local computational resources or specialized software [22, 23]. GEE has been increasingly utilized for flood mapping globally and specifically within Vietnam [24–26]. For instance, Mai et al. [26] demonstrated the utility of Sentinel-1 data processed on GEE for delineating urban flood extent and impacts in Thai Nguyen city. The synergy of SAR's all-weather capability and GEE's processing power is highly pertinent for assessing agricultural flooding in the frequently cloud-covered VMD. GEE facilitates the systematic analysis of SAR time-series data, allowing for the delineation of inundated areas and, when combined with land use information, the direct assessment of flood impacts on different agricultural systems. This approach directly links the observed 'State' (flood extent) to specific 'Impacts' (flooded agricultural land types), providing critical information for the 'Response' phase of the DPSIR cycle.

This study differentiates itself from previous research by focusing on a long-term (2015-2023) analysis of flood inundation dynamics specifically within Ben Tre province, utilizing the GEE platform and Sentinel-1 SAR imagery to assess impacts across a diverse range of its agricultural land use types. While broader VMD flood studies exist, this research provides detailed, high-resolution insights into a particularly vulnerable coastal province, quantifying trends in flood extent and its differential effects on specialized wet rice, other annual crops, perennial crops (a significant component of Ben Tre's agriculture), and aquaculture. The specific objectives are: (1) to map annual flood inundation extents in Ben Tre province from 2015 to 2023 using Sentinel-1 SAR data processed on GEE; (2) to quantify the total inundated area and analyze its spatio-temporal trends; and (3) to assess the specific impact of flooding on various agricultural land use types by overlaying flood maps with a detailed land use map. By examining these trends, the research seeks to understand the evolving flood risk to Ben Tre's vital agricultural sector and provide data-driven insights for informed decision-making in land use planning, flood management strategies, and climate change adaptation, thereby contributing to the 'response' element of the DPSIR framework. The findings are expected to highlight the increasing vulnerability of diverse agricultural systems and demonstrate the efficacy of the GEE-SAR combination for long-term flood monitoring and impact assessment in complex deltaic landscapes.

2. Materials and Methods

2.1. Study Area

Ben Tre province, one of 13 provinces in the Vietnamese Mekong Delta (VMD), is situated approximately 85 km southwest of Ho Chi Minh City. It encompasses an area of 2,379.7 km^2 and is characterized by three main islets (An Hoa, Bao, and Minh) formed by major VMD distributaries—the Tien River, Ham Luong River, Ba Lai River, and Co Chien River—before they discharge into the East Sea (**Figure 1**). The province's topography is predominantly flat and low-lying, with average elevations ranging from 1 to 2 meters above mean sea level, exhibiting a gradual slope from northwest to southeast. This coastal geography, coupled with an extensive coastline and a dense network of rivers and canals, renders Ben Tre highly susceptible to annual flooding, tidal influences, and saltwater intrusion, particularly during the May to November monsoon season [27].

The regional climate is tropical monsoon, featuring stable high temperatures (average 26 °C–27 °C) and two distinct seasons: a rainy season from May to November and a dry season from December to April. Annual rainfall averages 1,400–1,500 mm, with 90–93% occurring during the rainy season. Agriculture, including rice, coconuts (a provincial specialty), fruits (pomelo, durian, rambutan), and aquaculture (shrimp, fish), forms the mainstay of the provincial economy [9]. These diverse agricultural systems are intricately linked to the hydrological regime, making them inherently vulnerable to alterations in flood patterns and intensity.

This study utilized C-band Sentinel-1A/B Synthetic Aperture Radar (SAR) Ground Range Detected (GRD) data, acquired in Interferometric Wide Swath (IW) mode. The IW mode provides a 250 km swath width with an original spatial resolution of 5 m x 20 m, which is resampled by the processor to 10 m pixel spacing for GRD products. Sentinel-1 data were accessed via the Google Earth Engine (GEE) data catalog (COPERNICUS/S1_GRD). With its two-satellite constellation, Sentinel-1 offers a revisit frequency of approximately 6 days over Vietnam, ensuring frequent observations. For this study, images covering Ben Tre province from **June to December** for each year between 2015 and 2023 were selected. This period was chosen as it corresponds to the typical VMD flood season, allowing for a comprehensive assessment of peak inundation and its progression. Both VV (vertical transmit, vertical receive) and VH (vertical transmit, horizontal receive) polarizations are available. VH polarization, being more sensitive to volumetric scattering from vegetation and surface roughness changes due to inundation beneath vegetation canopies, was primarily used for flood delineation, although VV polarization can also be effective for detecting open water surfaces[19, 20].

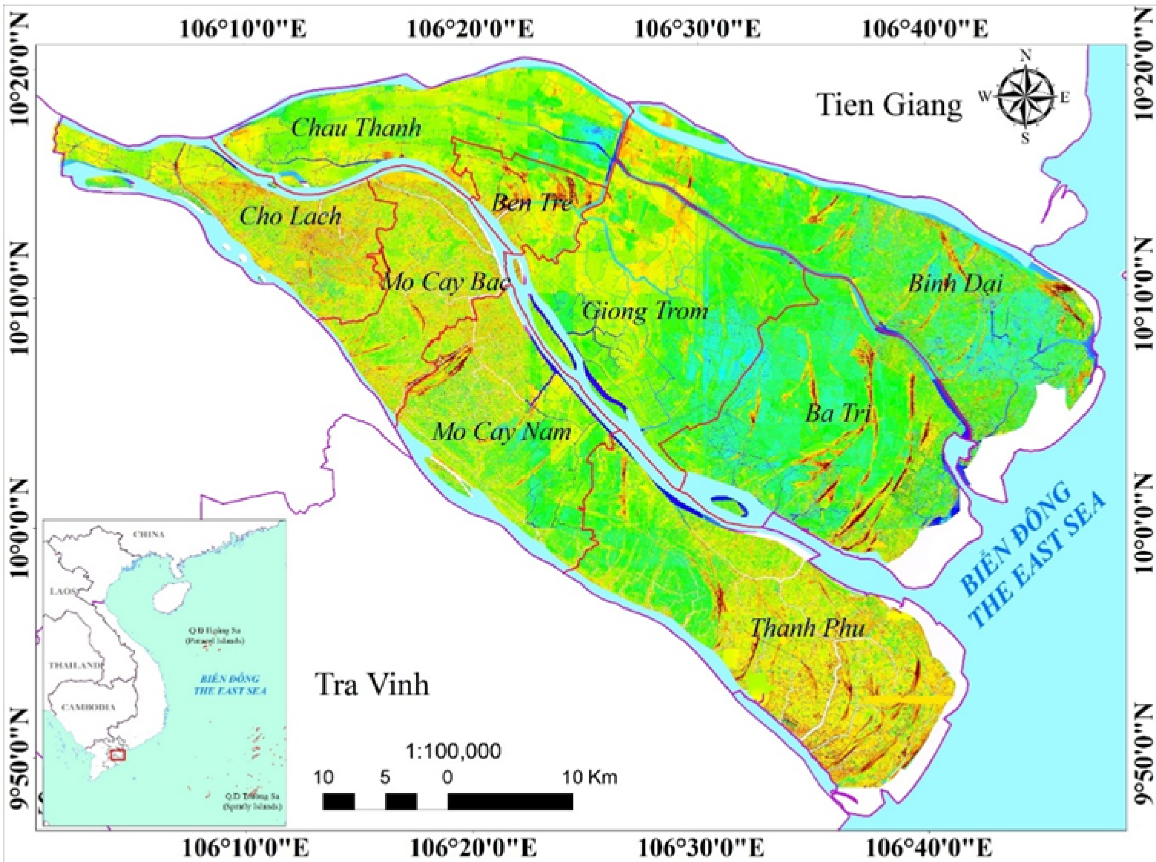

Figure 1. The map of the study area belongings to Ben Tre Province, Vietnam

2.2. Data Acquisition

This study utilized C-band Sentinel-1A/B Synthetic Aperture Radar (SAR) Ground Range Detected (GRD) data, acquired in Interferometric Wide Swath (IW) mode. The IW mode provides a 250 km swath width with an original spatial resolution of 5 m × 20 m, which is resampled by the processor to 10 m pixel spacing for GRD products. Sentinel-1 data were accessed via the Google Earth Engine (GEE) data catalog (COPERNICUS/S1_GRD). With its two-satellite constellation, Sentinel-1 offers a revisit frequency of approximately 6 days over Vietnam, ensuring frequent observations. For this study, images covering Ben Tre province from June to December for each year between 2015 and 2023 were selected (**Table 1**). This period was chosen as it corresponds to the typical VMD flood season, allowing for a comprehensive assessment of peak inundation and its progression. Both VV (vertical transmit, vertical receive) and VH (vertical transmit, horizontal receive) polarizations are available. VH polarization, being more sensitive to volumetric scattering from vegetation and surface roughness changes due to inundation beneath vegetation canopies, was primarily used for flood delineation, although VV polarization can also be effective for detecting open water surfaces[19, 20].

Land Use Map: A land use map for Ben Tre province for the year 2020 was obtained from the provincial Department of Natural Resources and Environment. This map provided the spatial distribution of various land use categories: rice paddy land (RPL), other annual crops (OAC), perennial crops land (PCL), aquaculture land (AL), coastal aquaculture land (CAL), salt production land (SPL), other agricultural land (OAL), and irrigation land (IL). This dataset was crucial for analyzing the specific impact of flooding on different agricultural land types. It is acknowledged that using a static 2020 land use map for the entire 2015–2023 period is a limitation, as land use can change over time. However, this was the most updated and reliable comprehensive dataset available at the time of study initiation.

Table 1. Dataset used in this study.

Primary Satellite Data					
GEE Access Address	**Datasets**	**Period**	**Resolution**	**Provided by**	**Purpose**
COPERNICUS/S1_GRD	Sentinel-1 (SAR) satellite data	June–December (2015–2023)	10 m	European Space Agency (ESA)	To extract flood extent

Secondary Data			
Datasets	**Provided by**	**Time**	**Purpose**
Flooded data	Measurement in Ben Tre Province	2022	Accuracy assessment
Land Use Status Quo Map	Department of Natural Resources and Environment of Ben Tre Province	2020	To extract flooded agricultural land

Validation Data: High-resolution optical satellite imagery available on Google Earth for corresponding flood periods, along with available field survey reports or news articles describing flood events in Ben Tre, were used for the qualitative validation of the generated flood maps. Quantitative accuracy assessment was also performed using field survey data collected in June 2022, consisting of 514 ground truth points, which yielded a Kappa coefficient of approximately 0.85 when compared to the SAR-derived flood extent for that period, indicating good agreement.

2.3. Flood Mapping and Impact Assessment

The GEE platform provides Sentinel-1 GRD data that has undergone initial pre-processing. The standard GEE Sentinel-1 pre-processing workflow applied in this study included:

Apply Orbit File: Updates orbit metadata for accurate geolocation.

GRD Border Noise Removal: Removes low-intensity noise and invalid data at image swath edges.

Thermal Noise Removal: Corrects for thermal noise, particularly significant for cross-polarized channels like VH.

Radiometric Calibration: Converts digital number (DN) values to radar backscatter coefficients (Sigma Nought, σ°) in linear units, which are then converted to decibels (dB) for analysis (σ°_dB = 10 * log10(σ°)). This represents the calibrated radar reflectivity.

Terrain Correction (Range Doppler Terrain Correction): Geocodes imagery using a Digital Elevation Model (DEM)—typically the Shuttle Radar Topography Mission (SRTM) 30 m DEM—to correct for geometric distortions caused by terrain.

Speckle Filtering: A Lee filter (or a similar filter like Gamma MAP) with a 3 × 3 or 5 × 5 pixel window was applied to the calibrated dB imagery to reduce speckle noise inherent in SAR data. This enhances image interpretability and improves the accuracy of subsequent water delineation. The entire flood mapping and impact assessment process was implemented within the GEE cloud-computing platform, following the key steps outlined in **Figure 2**.

Water Body Delineation using Otsu Thresholding: Water surfaces typically exhibit low backscatter in SAR imagery due to specular reflection, causing them to appear dark. Histogram-based thresholding is a common and effective method for separating water from non-water pixels[16]. This study employed the Otsu thresholding algorithm[28], which automatically determines an optimal threshold value to separate the image histogram into two classes (water and non-water) by minimizing the intra-class variance. This method was applied to the pre-processed VH polarization backscatter coefficient images (σ°_VH_dB). Pixels with backscatter values below the Otsu-derived threshold were classified as water/inundated land, while those above were classified as non-water/dry land, resulting in a binary water mask (0 for land, 1 for water). This approach is widely recognized as effective for SAR-based water mapping [29, 30].

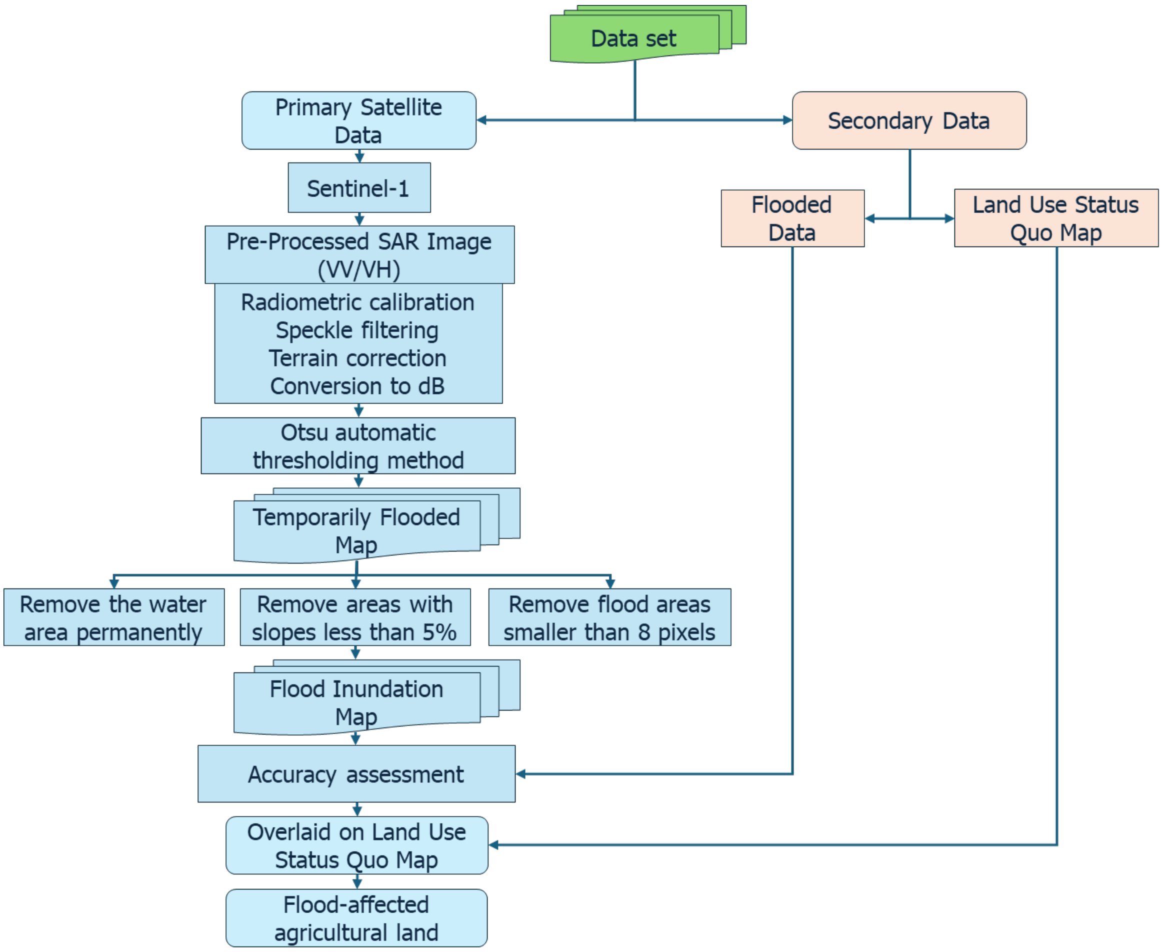

Figure 2. The flowchart of the process steps of conducting study.

Flood Inundation Mapping (Change Detection): To distinguish floodwater from permanent water bodies and refine the flood extent, an implicit change detection approach was adopted. Flood maps were generated based on the composite of image interpretation results of inundated areas throughout the June to December flood season for each year. This involved identifying all pixels classified as water during this period. The final annual flood map was then refined through the following steps:

Slope Masking: Areas with a slope greater than 5% (derived from the SRTM DEM) were generally excluded, as they are less likely to experience prolonged inundation. This step has a minor impact in Ben Tre's predominantly flat terrain but is standard practice.

Permanent Water Body Removal (Refinement): A mask of permanent water bodies (derived from dry season SAR imagery or a static, reliable water layer for the region) was used to subtract these areas from the seasonal water mask. This step isolates pixels representing actual flood inundation from those that are permanently water-covered.

Small Pixel Removal: Small, isolated patches of classified water (e.g., less than 8 connected pixels, corresponding to approximately 800 m^2) were removed using a morphological filter to reduce noise and minor misclassifications often associated with SAR imagery in complex landscapes.

Flood map accuracy was assessed both qualitatively and quantitatively. Qualitative validation involved comparing the delineated annual flood extents with contemporaneous high-resolution optical imagery available on Google Earth and cross-referencing with available field survey reports or news articles describing specific flood events in Ben Tre (**Table 1**). For quantitative assessment, as mentioned earlier, field survey data from June 2022 (514 points) were compared against the derived flood map for that period, yielding a Kappa coefficient of approximately 0.85, indicating a high level of agreement and robust classification accuracy.

Generated annual flood inundation maps for the period 2015–2023 were overlaid with the 2020 Ben Tre land use map. This analysis was performed using GIS functionalities within GEE or, for more detailed statistical compilation, by exporting raster layers for analysis in desktop GIS software. This overlay allowed for the annual quantification of the area of each agricultural land use type affected by flooding. Statistics on flooded areas per land type were compiled annually and analyzed to identify temporal trends and assess the varying flood impacts on different agricultural systems within the province.

3. Results and Discussion

This section presents the primary findings of the study, commencing with an overview of the spatio-temporal dynamics of flood inundation in Ben Tre province from 2015 to 2023. Subsequently, it details the specific impacts of this flooding on various agricultural land use types.

3.1. Spatio-Temporal Flood Dynamics in Ben Tre Province (2015-2023)

The GEE-based analysis of the Sentinel-1 SAR time-series imagery from 2015 to 2023 revealed significant inter-annual variability in both the extent and spatial distribution of flood inundation across Ben Tre province. The total inundated area, as summarized in **Table 2** (and visualized annually in maps similar to **Figure 3** for 2015), exhibited a clear trend. It surged from approximately 27,936.7 ha in 2015 to a pronounced peak of 58,349.8 ha in 2018. This represents a more than twofold increase, indicating that 2018 was a particularly severe flood year for the province, with nearly a quarter (24.5%) of its total area inundated. Following this 2018 peak, the total flooded area generally showed a decreasing trend, albeit with fluctuations; for example, 2020 also experienced extensive flooding (55,046.8 ha). In the most recent years of the study (2021-2023), the total inundated area stabilized around 42,000 - 44,000 ha (specifically 42,128.6 ha or 17.7% of the province in 2023). This temporal pattern suggests a period of heightened flood activity culminating in 2018, followed by a phase of relative moderation. However, it is crucial to note that recent flood extents, even in these moderate years, remain substantially higher than the levels observed at the beginning of the study period in 2015.

Spatially, flood inundation was consistently observed along the major river branches and within the low-lying coastal zones of Ba Tri, Binh Dai, and Thanh Phu districts. These areas are inherently more vulnerable due to their lower elevation and direct exposure to both fluvial and tidal flood influences. A key observation during high-flood years, such as 2018 and 2020, was the noticeable expansion of floodwaters further inland from these primary floodplains and coastal regions. This encroachment impacted areas that are not typically inundated during milder flood years, indicating an increasing spatial reach of significant flood events.

Table 2. Flooded area statistics in Ben Tre Province, 2015–2023.

Year	Flooded Area (ha)		Flooded Agricultural Land Area (ha)	
2015	27936.7	11.7%	18614.8	7.8%
2016	53956.0	22.7%	36365.8	15.3%
2017	36493.5	15.3%	24743.9	10.4%
2018	58349.8	24.5%	39499.5	16.6%
2019	47441.3	19.9%	32216.2	13.5%
2020	55046.8	23.1%	37947.0	15.9%
2021	42740.6	18.0%	28870.9	12.1%
2022	43907.7	18.5%	30013.1	12.6%
2023	42128.6	17.7%	28841.0	12.1%

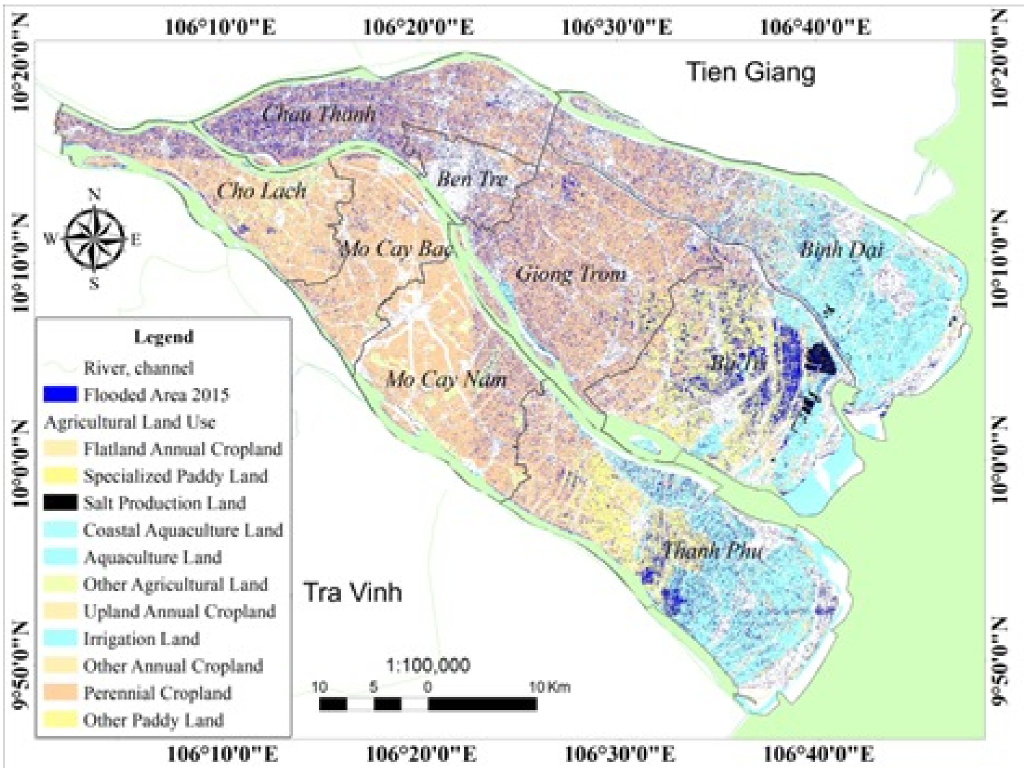

Figure 3. Flood inundation map of Ben Tre Province in 2015.

3.2. Impact of Flooding on Agricultural Land Use Types

The overlay analysis of the annual flood inundation maps with the 2020 agricultural land use data provided critical insights into the flood impacts on different farming systems within Ben Tre province (**Tables 2** and **3**). The total area of agricultural land affected by flooding closely mirrored the temporal pattern observed for total inundation. It increased from 18,614.8 ha in 2015 to a peak of 39,499.5 ha in 2018. Following fluctuations, including another high in 2020 (37,947.0 ha), the flooded agricultural area subsequently declined to 28,841.0 ha by 2023. Despite this recent decline from peak years, the extent of flooded agricultural land in 2023 remained over 50% higher than in 2015, signifying a persistent and elevated risk to the agricultural sector.

Analysis by specific agricultural land use types (**Table 3**) revealed varying degrees of impact and concerning trends over the 2015-2023 period:

Rice Paddy Land (RPL): The flooded area of RPL land increased from 2,828.8 ha in 2015 to 3,898.6 ha in 2023, a substantial relative increase of 37.8%. This indicates growing pressure on traditional rice-growing areas.

Other Annual Crops (OAC): Flooding in areas designated for other annual crops (e.g., vegetables, maize) rose from 102.2 ha in 2015 to 119.6 ha in 2023 (a 17.0% increase, though absolute values are smaller).

Flatland Annual Cropland (FAL): This category saw its flooded area increase from 432.8 ha in 2015 to 601.3 ha in 2023, a 38.9% rise, similar to RPL.

Perennial Crop Land (PCL): Perhaps the most alarming trend was observed for PCL, which predominantly includes high-value fruit orchards (e.g., coconut, durian, pomelo). The flooded area within PCL surged from 11,155.7 ha in 2015 to 18,787.0 ha in 2023, an increase of 68.4%. This signifies a major expansion of flood risk into areas cultivated with longer-gestation, higher-value crops that are often less flood-tolerant than rice.

Aquaculture Land (NACL - Freshwater/brackish ponds; MVT - Coastal Aquaculture): Flooded areas within NACL expanded from 3,328.0 ha in 2015 to 4,282.8 ha in 2023 (a 28.7% increase). Coastal aquaculture (MVT) showed a decrease from 11.6 ha to 8.6 ha, though this is a very small land use type in terms of flooded area.

Other Agricultural Lands: Salt production land (SPL), other agricultural land (OAL), and irrigation land (IL) also experienced significant increases in flooded areas: SPL from 149.8 ha to 209.3 ha (39.7%), OAL from 196.6 ha to 326.2 ha (65.9%), and IL from 407.0 ha to 603.1 ha (48.2%) between 2015 and 2023.

Table 3. Agricultural land inundation statistics in Ben Tre Province, 2015–2023.

Land Types		**Agricultural Land Area Affected by Flooding (ha)**								
		2015	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**
Rice Paddy Land	RPL	2828.8	4354.9	3820.7	4248.7	3686.6	3185.3	4186.3	3437.5	3898.6
Other Paddy Land	OPL	2.2	9.3	4.5	8.7	5.1	6.0	6.2	8.1	4.6
Flatland Annual Land	FAL	432.8	794.8	518.2	875.1	601.0	626.2	615.8	599.2	601.3
Other Annual Cropland	OAC	102.2	276.9	145.2	298.7	151.7	205.3	190.1	205.1	119.6
Perennial Crop Land	PCL	11155.7	23889.9	15752.0	26878.4	22287.9	28354.9	17743.4	21087.9	18787.0
Aquaculture Land	NACL	3328.0	5658.7	3497.4	5805.7	4342.6	4217.3	4995.2	3632.3	4282.8
Coastal Aquaculture Land	MVT	11.6	15.5	5.5	12.1	12.4	12.3	11.7	11.4	8.6
Salt Production Land	SPL	149.8	234.5	167.8	134.1	118.6	182.0	181.6	64.4	209.3
Other Agricultural Land	OAL	196.6	454.4	275.8	498.5	391.3	533.0	332.2	401.6	326.2
Irrigation Land	IL	407.0	676.8	556.8	739.7	619.1	624.7	608.4	565.6	603.1
Total		18614.7	36365.8	24743.9	39499.5	32216.2	37947.0	28870.9	30013.1	28841.0

4. Discussion

4.1. Summary of Key Results

The GEE-based Sentinel-1 SAR analysis effectively quantified a significant overall increasing trend in both total flood extent and, critically, the extent of agricultural land affected by flooding in Ben Tre province between 2015 and 2023. This occurred despite considerable inter-annual fluctuations, with 2018 emerging as a year of exceptionally severe and widespread inundation. The most alarming finding from an agricultural and economic perspective is the substantial relative increase (68.4%) in the flooding of Perennial Crop Land (PCL), which primarily comprises high-value fruit orchards. While traditional rice areas (RPL) and other annual croplands (OAC, FAL) also experienced considerable increases in flooded extent (37.8% and 38.9% respectively for RPL and FAL), the encroachment into PCL territories is particularly concerning.

This sharp increase in PCL flooding suggests that flood events are not merely becoming more extensive within traditional floodplain areas (like rice paddies) but are also expanding into areas previously considered less prone to inundation, where higher-value, longer-gestation perennial crops are cultivated. This indicates an expansion of floodwaters into potentially higher-elevation or better-protected zones traditionally considered safer for orchard cultivation. This trend has direct and severe economic implications for farmers, as perennial crops represent significant long-term investments and often yield higher returns than annual crops; their loss or damage due to flooding can lead to substantial income reduction and require considerable time and resources for recovery [14]. This phenomenon could be attributed to a combination of factors: more intense rainfall events driven by climate variability, potential impacts of upstream river regulation on downstream flood dynamics, localized land subsidence (a documented issue in the VMD [Minderhoud et al., 2019, as cited in original OCR, though not in provided reference list]), and potentially localized changes in drainage patterns due to infrastructure development. The increasing flood pressure on all major agricultural land groups—rice, annual crops, and perennial crops—has significant implications for Ben Tre's overall agricultural sustainability and the livelihoods dependent upon it.

The widespread nature of these increasing flood impacts across diverse agricultural systems underscores the escalating vulnerability of Ben Tre's vital agricultural sector. This directly threatens provincial food security, the economic stability of its farming communities, and broader rural livelihoods. The findings necessitate urgent attention from local authorities and agricultural planners. The spatially explicit information generated on flood patterns and their differentiated impacts on rice, annual crops, and particularly perennial orchards provides a critical evidence base for developing targeted flood mitigation and adaptation strategies. This includes promoting climate-resilient land use planning—perhaps reconsidering the suitability of certain highly vulnerable areas for sensitive perennial crops without adequate flood protection—and guiding investments in adaptation measures to safeguard agricultural productivity. Such measures could range from improving drainage infrastructure and constructing localized defenses to promoting flood-tolerant crop varieties and adjusting cultivation practices [11, 12].

4.2. Limitations of the Study

The flood delineation relied on SAR backscatter thresholding using the Otsu method. While robust and automated, this method can be affected by factors such as wind-roughened water surfaces (which can increase backscatter, mimicking land) or dense emergent vegetation (which can obscure underlying water), potentially leading to under- or over-estimation of flood extent in some localized areas.

The use of a static land use map (from 2020) to assess impacts over the 9-year study period (2015-2023) is a limitation. Land use itself can change significantly over such a period due to socio-economic drivers, policy changes, or farmers' responses to previous floods. Employing dynamic annual land use maps, if they become available, would improve the accuracy of agricultural impact assessments in future studies.

The validation of flood maps was primarily qualitative, supplemented by a quantitative check for one period (June 2022). A more rigorous, systematic quantitative accuracy assessment using extensive ground truth data collected across multiple years and flood events would further strengthen the findings and provide more precise error estimates.

This study focused on mapping flood extent. Information on flood depth and duration, which are critical parameters for assessing the severity of agricultural damage and economic losses, was not derived. Integrating these parameters would provide a more comprehensive risk assessment.

Despite these limitations, the study clearly demonstrates the power of GEE and Sentinel-1 SAR for consistent, large-scale, and all-weather monitoring of flood dynamics and their agricultural impacts in complex deltaic environments like Ben Tre.

5. Conclusions

This study successfully leveraged the Google Earth Engine platform and a nine-year (2015-2023) archive of Sentinel-1 SAR imagery to systematically assess flood inundation dynamics and their impact on diverse agricultural land use types in Ben Tre province, a vulnerable coastal region of Vietnam's Mekong Delta. The key findings reveal a concerning overall trend of increasing flood extent affecting vital agricultural lands, with significant inter-annual variability. Critically, perennial crop areas, which include economically important fruit orchards, exhibited the most substantial relative increase in inundation over the study period. This highlights an alarming expansion of flood impacts beyond traditional floodplains into areas cultivated with higher-value, longer-gestation crops, posing a significant threat to agricultural income and sustainability.

The research underscores the escalating vulnerability of Ben Tre's diverse agricultural sector to flooding. The consistent, large-scale, and all-weather monitoring capability offered by the combination of Google Earth Engine and Sentinel-1 SAR provides a powerful and efficient tool for understanding these complex hydro-environmental challenges. The spatially explicit information on flood patterns and their differentiated impacts generated in this study provides a critical evidence base for local authorities and agricultural planners. This information is essential for informing targeted flood mitigation strategies, promoting climate-resilient land use planning, and guiding strategic investments in adaptation measures designed to safeguard agricultural productivity and enhance the resilience of rural livelihoods in this vulnerable deltaic province.

Future research should aim to address the limitations of this study by incorporating dynamic land use data, conducting more extensive quantitative accuracy assessments, and integrating flood depth and duration into the impact analysis. Furthermore, combining remotely sensed flood evolution data with hydrological modeling and socio-economic impact analyses could provide a more holistic understanding of flood risk and facilitate the development of flexible, site-specific adaptation scenarios. Nevertheless, this study provides a robust baseline and demonstrates an effective methodology for long-term flood monitoring, which is crucial for supporting Ben Tre's efforts to adapt to the complex effects of climate change and other environmental pressures in the coming years. The implications of these findings extend beyond Ben Tre, offering insights for other deltaic regions globally facing similar challenges of increasing flood risk to agriculture.

Author Contributions

Data process and analysis, P.T.D.Q. and T.X.D.; results interpretation and discussion, P.T.D.Q. and T.X.D; manuscript design, T.X.D.; manuscript revision, P.T.D.Q. ;submission steps, P.T.D.Q. All authors have read and agreed to the published version of the manuscript.

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Confict of Interest

The authors declare no conflict of interest.

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