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Spatial-social evaluations of ecosystem services of adaptive aquaculture models using SAR and multivariate analyses: a case in the Vietnamese Mekong Delta

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Abstract The presented study is conducted to investigate the efficiency of two important aquaculture models of the Vietnamese Mekong Delta (VMD)'s Soc Trang province via quantifying and mapping the supporting ecosystem services (ES). The study targets the two most prevalent rearing practices, intensive and semi-intensive, covering four rural districts: My Xuyen, Tran De, Cu Lao Dung, and Vinh Chau. A mixed-method approach was applied, combining remote sensing, grass-root social survey, and multivariate statistical analyses. First, image analysis using Sentinel-1A time-series data was conducted to detect the aquaculture areas across the study area based on temporal changes of VV backscatter of different land use/land cover (LULC) types, in which aquaculture receives relatively low backscatter values compared to other LULC categories except river and deeper water surfaces. Our analysis yields an overall accuracy of 91% with a kappa coefficient of 0.82. Second, using semi-structured questionnaires, a total of 140 shrimp farming households across the four focused districts were interviewed for their rearing experience. Thereupon, the collected responses were analyzed using two multivariate analyses, including

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principal component analysis (PCA) and hierarchical cluster analysis (HCA). In general, the intensive model could have generated more economic values of ecosystem services than the artisanal/semi-intensive model. Our analyses also took note of the potential barriers hindering the semi-intensive farmers from achieving higher economic income. These include (i) geographical factors, i.e., locations; (ii) social factors, i.e., experience, farming calendar, education; (iii) financial factors, i.e., investments; and (iv) technical factors, i.e., farm areas, productivity, rearing concentration. Since semi-intensive food is more appropriate for small-scale farming households, it is recommendable that addressing these factors can enhance the efficiency of this model as a profitable livelihood option.

Keywords Ecosystem services · Livelihood transformation · SAR · Mekong Delta

Introduction

As Tammi and Polizzi remarked, there has been widespread adoption of the ecosystem-based approach as an overarching framework for environmental management discourse during the past decades, especially in the academic conversations (Loc et al., 2017; Loc et al., 2018; Polizzi et al., 2015; Tammi et al., 2017). The adoption and operationalization of the ecosystem-based approaches are, in turn, closely linked with the conceptual entity of ecosystem services (ES), and the assessment of these nature-derived human benefits (Loc et al., 2021, Yee et al., 2021). Not only has the number of studies concerning ES valuation been constantly on the rise, especially after the monumental publication of Costanza et al. (1997) in nature, the field of ES also sees exponential growth in terms of relatable disciplines, rapidly diversifying the scope of applications. Originally positioned as an assessment framework for biodiversity, ES has been traditionally approached via the concept of natural capital, its stocks, flows, and their values (Costanza et al., 1997). However, scientists from many other earth science-related disciplines have started to incorporate ES into their respective research fields, including both natural and social sciences.

In part, the rapidly evolving application scope of ES can be attributed to the inherently spatial nature of these benefits and functions (Schägner et al., 2013), even though not all types of services can be mapped with the same accuracy, precision, and resolution. Alongside the constantly growing popularity of geospatial techniques, i.e., geographic information systems (GIS) and remote sensing (RS) in both academic and non-academic spheres, the past few years have seen an exponential growth of exploratory studies adapting ES into various new research fields, other than biodiversity or conservation studies. Notable contributions of such include urban planning (Gómez-Baggethun & Barton, 2013), ecotourism management (Huu et al., 2018), and more recently, ecological livelihoods management (Huu et al., 2018; Loc et al., 2017, 2018a, b). In addition, consideration must also be given to changes in environments that will impact agricultural activities and potential human health risks (Ozel et al., 2019; Park et al., 2020; Tran et al., 2021). Therefore, it is necessary to consider multi-criteria to make policies suitable for each region. Notwithstanding the integration of GIS and RS has important added values to the studies concerning ES visualizing and communicating research findings to decision-makers concerned with natural resources management (Cetin, 2015; Polizzi et al., 2015), the bridge between these two agendas is yet to exist (Primmer & Furman, 2012). Therefore, there is an urgent need for knowledge binding between research and policies on focused research areas, thus promoting the validity and legitimacy of ES in related decision-making contexts and processes (Loc et al., 2020; Vierikko et al., 2016).

In this study, we present novel evidence of how the adaptation of ES concept can substantially streamline better-informed decision-making processes, focusing on the field of ecological agricultural management. The chosen study site for this study is the Vietnamese Mekong Delta (VMD), downstream of one of the world's most important river deltas. With a total area of more than 4 million ha, the VMD houses 20% of the country's population, most of which are working in agriculture and related sectors. The sustainable development of the VMD, however, is under several critical environmental stressors (Arias et al., 2019), among which, the intrusion of saline water is the main threat towards agricultural production as it directly contaminates the essential freshwater resources, while simultaneously degrading the soil (Loc et al., 2021; Park et al., 2020; Pham et al., 2020;

Tan et al., 2020). Every year, more than two million ha of agricultural land are prone to the risks of salinity intrusion (SI) (Toan, 2014). Plus, SI can also disrupt the supply of freshwater for both domestic (e.g., household daily use) and industrial consumers, especially in the coastal areas.

The SI menace is even more critical as the VMD agricultural production accounts for half of the country's food supplies. With the current productivity of ~ 25 million tons of rice every year, the VMD not only safeguards the country's food security but also contributes about 18.7% of the national GDP through agricultural products exports (Loc et al., 2021; Piesse, 2019; Tran et al., 2021). In recent years, how to deal with the ever-intensifying intrusion of seawater while protecting the agricultural production area has emerged as a challenge for the local government across the VMD. The strategies so far have included both hard and soft measures. While the former includes the construction of salinity mitigation infrastructures, such as sluice gates, the latter relates to the constant shift from rice-focused agriculture into more diversified agriculture that incorporates salinity tolerant/adaptive crops and livestock (Loc et al., 2021a, b, c). Among the salinity adaptive agricultural models recently introduced, ecological shrimp/prawn farming is the most important one, in part, due to their high economic values (Nguyen et al., 2015; Pham et al., 2020).

In this paper, we employed the evaluation and mapping of ecosystem services associated with agricultural production to investigate the efficiency of two important salinity adaptive shrimp farming models, i.e., artisanal/semi-intensive and intensive. Although targeting similar harvests, these models are of virtual difference in many aspects. While most farmers operating the former systems as a small- to middle-scale family business thus tend to be less invested and organized, those associated with the latter are predominantly industrial farms with substantially higher levels of technology-induced operations. Another important difference between these two models relates to the stocking approaches. While the artisanal/semi-intensive model is usually associated with larger ponds (3 to 5 ha) and low stocking density (4–6 PL per m^2), the intensive model is more concentrated with smaller pond sizes (0.2 to 0.5 ha) and much higher stocking density (40–90 PL per m^2). Using a case study of Soc Trang Province, one of the most important aquaculture production areas of the VMD, this paper targets the evaluation and spatial distribution related to values of the ES supporting these farming systems for the first time. The results are of particular relevance to the local government to realize the opportunities as well as the risks emerging from the local ecosystems associated with each model. The second significance of the paper relates to its potential contribution to the substantial absence of ES-related studies in the Mekong Delta, which so far only has a handful of peer-reviewed publications. Finally, this paper also contributes an important methodological implication related to the application of ES accounting and mapping to sustainable agricultural management. Although important, this is still a relatively new concept among many publications in the traditional fields, including biodiversity and conservation-related disciplines.

Study area

The province of focus is Soc Trang, located on the east coast of the Vietnamese Mekong Delta, adjacent to Hau Giang province in the Northwest, Tra Vinh in the Northeast, and Bac Lieu in the Southwest (see Fig. 1). Out of 331,118 ha of land areas of Soc Trang, 83.64% or 276,958 ha is agricultural, including 146,970 ha of rice fields, 54,500 ha of aquaculture of various kinds, and 43,000 ha of perennial crops. Soc Trang province has a 72-km coastline, discharging to the East Sea (also known as the South China Sea) in three major estuaries: Dinh An, Tran De, and My Thanh. Such geographical conditions substantially expose Soc Trang province to the perennial intrusion of saline water from the East Sea, making it favorable for the development of brackish water aquaculture production, especially white-legged shrimp and tiger shrimps. In fact, the provincial government has, since 2010, prioritized aquaculture development towards higher economic valued crops (prawns and shrimps) while minimizing negative impacts on environmental ecosystems. For this study, we collected responses from farmers of four coastal districts: Vinh Chau, Tran De, Cu Lao Dung, and My Xuyen. These four areas are representative of the two most prevalent shrimp farming models in Soc Trang: artisanal/semi-intensive and intensive. The fundamental differences between

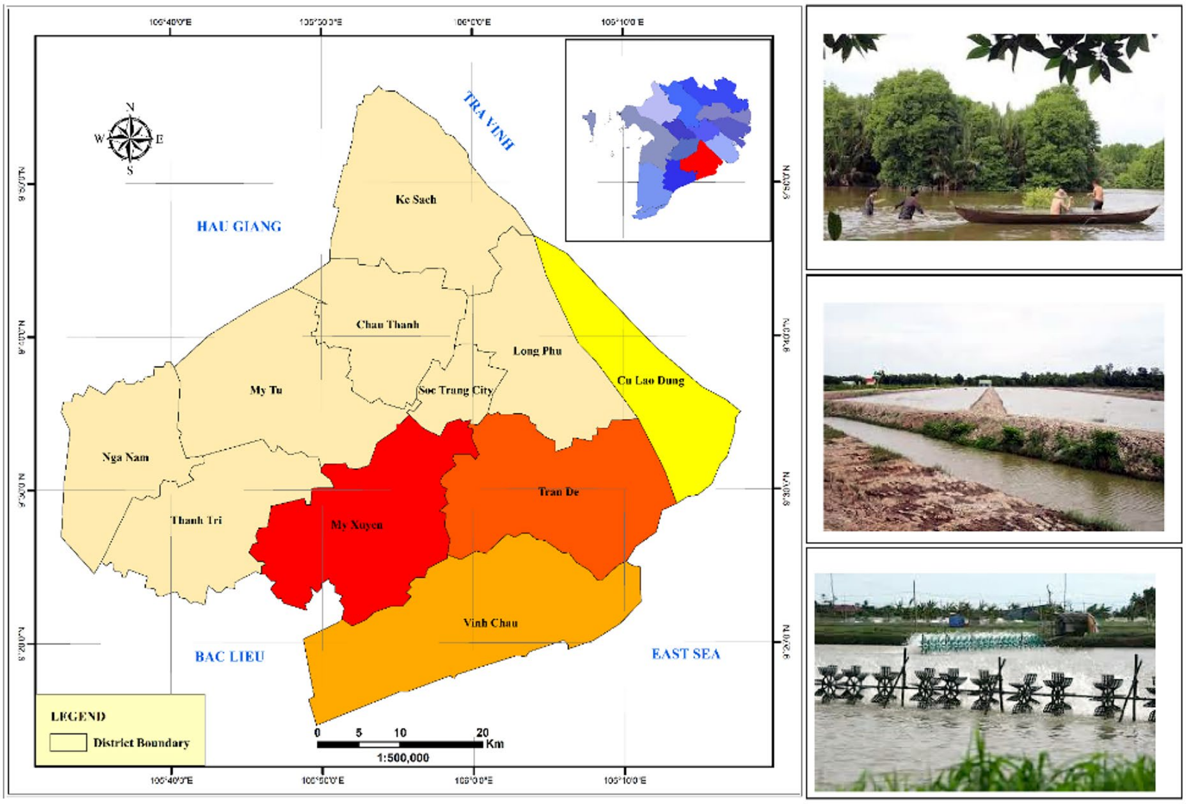

Fig. 1 **A** Study area including four coastal districts: Vinh Chau, Tran De, Cu Lao Dung, and My Xuyen. **B–D** Sample images of three kinds of shrimp farming practices: artisanal (**B**), semi-intensive (**C**), and intensive (**D**)

these models include the stocking density, investment requirement, and technology involvement. More specifically, artisanal/semi-intensive has substantially low stocking density, and usually does not incur high-technology involvement while relying mostly on human labors. Within the first group, the artisanal farming model is most associated with the conservation of mangrove forests along the coastline. The second sub-tier, the semi-intensive model, is mostly associated with small-scale farmers' households. Finally, the intensive is essentially an industry-induced model, having the highest density of stocking, thus requiring technologies and investments the most. In recent years, intensive farms have even employed state-of-the-art technologies, such as real-time systems for water quality monitoring and shrimp/prawn feeding. From plain sight, the intensive shrimp farming model is usually distinguished by the use of mechanical aerators (see Fig. 1D).

Methods

Classification of land cover using remote sensing

Data

Sentinel-1A time-series was used to identify land use/land cover (LULC) as a basis to extract aquaculture areas on the entire study site. Sentinel-1 (S1) is a C-band synthetic aperture radar (SAR) satellite with dual polarization. Sentinel-1 has been a popular source of images in various applications, including investigation of aquaculture/agriculture landscape in the VMD, mostly due to its capability to overcome the most critical challenges associated with the optical satellites such as the Landsat (Kuenzer et al., 2013; Leinenkugel et al., 2013).

For this study, we acquired 54 Sentinel-1 images in 2017 of the Ground Range Detected High Resolution (GRDH) product, captured in Interferometric

Wide-Swath Mode (IW) over the mainland region. A single VV polarization (vertical transmit/vertical receive) was utilized to aggregate a time-series image since this polarization is broadly applied in water-related studies with a higher accuracy against vertical transmit/horizontal receive polarization (VH) (Li et al., 2018; Twele et al., 2016).

Image classification and validation

In this study, derived aquaculture areas from earth observation served as critical information to orient and define the social survey campaigns, which focused on the primary aquacultural cultivation areas. Additionally, it is also a base map to visualize economic values of ecosystem services for better knowledge transfer. Aquaculture areas were extracted from land use/land cover data classified by Sentinel-1 time-series data. Sentinel-1 owns high spatial and temporal resolution with a free-of-charge acquisition; its products have large volumes and require a high-performance client to process such images to generate time-series data. For this study, we employed Google Earth Engine (GEE)—a cloud computing platform that stores earth observation, geospatial data, and numerous algorithms. The available Sentinel-1 IW GRDH product is preprocessed using S1 Toolbox to produce calibrated and ortho-corrected images. It therefore solely needs to perform a plane smoothing to remove speckle noises using a morphological reducer with a radius of the kernel ($R = 100$). The VV backscatter images were subsequently combined into one multitemporal time-series image starting from 11 January 2017 ($DOY = 11$) to 26 December 2017 ($DOY = 360$).

The images were then classified by an unsupervised classifier of the K-means algorithm (Durduran, 2015; Nijhawan et al., 2017; Novillo et al., 2018; Ragettli et al., 2018) which indicated that a large enough number of clusters even improve the classification over data quality. We tried a set of initial clusters, $K = (10, 11, \ldots, 30)$, to recognize the most appropriate number of clusters. The small numbers of clusters were neglected to limit misclassification between rice systems in Soc Trang province, where it is isolated into subregions with diverse crop calendars due to hydrological traits. An optimal number of clusters were 20 classes. The unlabeled image then was assigned a LULC type for each cluster based on temporal fluctuation of backscatter signals over the investigation period along with the assistance of spatial distribution of each LULC type through the field survey. For instance, sugarcane is a typical LULC type in Cu Lao Dung islet, while mangrove is along the coastline; double rain-fed rice crop is extensively distributed in Tran De and My Xuyen, while upland vegetables (shallot, gourd, and melon) are well-known in Vinh Chau district. The similar land cover types were combined before this data came to majority analysis (kernel size: $k = 5$) to remove potentially minor misclassification pixels that originated from noise on SAR data.

Finally, the results from image classification were validated with 600 ground truth points, equally divided between aquaculture and non-aquaculture. Of the 300 aquaculture points, 176 points are “real” points. The real ground truth points were collected alongside the social surveys using GPS, while the virtual points (both aquaculture (134) and non-aquaculture (300)) were generated using very-high-resolution (VHR) images on Google Earth (Son & Thanh, 2018). Thereupon, the ground truth information was turned to a two-class raster dataset, i.e., aquaculture vs non-aquaculture areas. This data was then overlaid with truth points to construct a confusion matrix. To quantitatively validate the classification results, we calculate the overall accuracy index and Kappa coefficient from the confusion matrix to validate the classified result (Congalton, 1991; Congalton & Green, 2019).

Social surveys

Data collection

We employed face-to-face interviews using semi-structured questionnaires to collect responses from shrimp/prawn farmers in four focused districts: Vinh Chau, Tran De, Cu Lao Dung, and My Xuyen. Such an approach for social primary data collection was preferred to other online surveys to have a higher response rate. To increase the validity and representativeness of our sampled population, we had, in each district, a local facilitator who is working in an agriculture-related government agency or local municipality to identify potential respondents for our study (Loc et al., 2021a, b, c). A total number of 140 respondents were identified and interviewed in April 2020. Out of which, the majority is intensive, with 108 questionnaires collected, while 32 are associated with artisanal/semi-intensive models. The sampled population, though admittedly imbalanced, substantially reflects the landscape of Soc Trang's agricultural production in recent years moving towards the intensification and higher valued rearing system. Artisanal/semi-intensive models, on the hand, are on the verge of being diminished given their comparatively lower financial profits as discussed above (Nguyen et al., 2015).

The structure of the questionnaire used in this study (after being pre-tested) includes three main sections. The first section comprises questions to collect data related to (i) the respondent's shrimp/prawn rearing experience and knowledge and (ii) farming areas, stocking density, species (white-legged shrimp vs tiger prawn), and rearing calendar. The second section of the interview explores information related to the financial aspects of the farming practices, including fixed costs (investments), season costs (food, agrochemicals, etc.), and the farmers' opportunity costs. The last section collects conventional socio-demographic information, i.e., age, gender, farming experience (in years), and education. For this study, all respondents remain anonymous during and after the data collection. The structure of the questionnaire is the previous studies in exploring the economic dimension of the VMD's agriculture landscape (Kilicoglu et al., 2020; Loc et al., 2017; Pham et al., 2020).

The economic values of ecosystem services

Within the scope of our study, only ES that are related to shrimp/prawn farming production are considered. These include but are not limited to *provisioning services*, water and nutrition, and *regulating service*s, nutrition circulation and climatic regulation. In essence, these services combined with rearing activities can create crop yields that are directly beneficial to the farmers. Regardless of the farming models, these ES are the fundamentals to facilitate any forms of agricultural activities, including shrimp rearing (both intensive and artisanal/semi-intensive).

In Vietnam, the economic valuation of agriculture-associated ES is still very limited (Loc et al., 2017), thus the absence of any forms of established markets for these virtual benefits. The reasons behind the hesitance to adopt ES and their economic valuations vary but the following two could have been among the most important ones. Firstly, although emerged strongly in various science-policy discourses, ES has not made it way to any regulations, rules, or planning articles yet. As a result, the concept is still predominantly seen as "for-research" with limited real-world applications in policy planning (Loc et al., 2020). Secondly, the VMD has some of the longest histories in agricultural production in Asia being one of the major rice bowls. Thus, to an extent, policy makers can be conservative to new approaches such as ES (Loc et al., 2018). However, with the impacts of climate change, in this case, salinity intrusion creates unprecedented opportunities to streamline ES into policy planning and decision-making agenda. Therefore, in this study, a proxy of total annual crop yields per unit area was employed to quantify the values of the ES concerned. Thereupon, the economic accounts for these ES values were estimated via the EU's resource rent approach (Loc et al., 2017). Such an approach has been applied in various developing countries, for instance, Indonesia (Sumarga et al., 2015) and Vietnam (Loc et al., 2017; Pham et al., 2020). The economic values of ES are estimated using the following formula:

$$RR = TR - (FC + VC + OC) \tag{1}$$

where *RR* is the resource rent, *TR* is the total revenue from shrimps, *FC* is the fixed costs, *VC* is the variable costs, and *OC* is the opportunity costs. More specifically, we consider that FC include initial and long-term investments, i.e., of canals and ponds dredging cost, machinery purchase, and irrigation system development. VC, on the other hand, refers to harvest-based or periodical expenses such as stocking, labors, food, and other crop-protection agrochemicals. Finally, OC reflects the benefits foregone by adopting agricultural production, which was estimated by the average land rental cost of the respective communes/hamlets. Similar to Loc, the inclusion of OC in the formula facilitates the evaluation of the natural ecosystem's capacity to support the people's primitive livelihoods (Loc et al., 2017). All of the values in (1), either revenues or costs, are collected in the local currency, i.e., VND, yet reported as USD/ha/year in this paper for convenient reference of the international readers.

Statistical analysis

This study builds upon and expands the analytical framework proposed by Loc et al. (2017) in exploring the ES values and socio-demographic attributes of the farmers. Even though such investigations of human-nature links are commonly used in social studies, including ES-related, the applications are mostly associated with the non-material services, such as cultural or spiritual benefits (Chan et al., 2012; Martín-López et al., 2012; Ryan, 2011). In this paper, we realize this target by a two-step analytical analysis.

First, the traditional descriptive statistics were conducted with the collected responses to provide a qualitative description of the sampled population concerning their socio-demographic attributes and their prawn/shrimp farming practices (i.e., rearing densities, stockings, and production costs). As for the inferential statistics, we first employed χ^2 (Chi-squared) to verify potential associations between the respondent's background information and the economic values of ES. We then took one step further and conducted principal component analysis (PCA) and hierarchical cluster analysis (HCA), both of which are commonly used in ES-related studies (Huu et al., 2018; Kilicoglu et al., 2020; Loc et al., 2018a, b). Before the multivariate analyses, a Bartlett's test of sphericity or homogeneity of variances was conducted (Bartlett, 1937). For this study, the initial sets of 8 explanatory variables include FC, VC, OC, farm areas, stocking density, crop productivity, selling prices, and total revenues. We also integrate four qualitative factors as supplementary variables: districts, stocking alternatives (white-legged shrimp vs tiger prawn vs combined), annual harvests (how many crops per year), and farming models (intensive vs semi-intensive). The multivariate analyses were conducted using the FactoMineR package (Lê et al., 2008; Team, 2013).

Results

Land use/land cover classification

Figure 2A shows a typical backscatter image (DOY = 11) obtained from S1-GRDH product and preprocessing procedures, in which backscatter values vary from low to high, corresponding to dark-bright tones on a single band image depending on the scattering mechanisms. A rougher and wetter surface (e.g., plowed and irrigated field) more reflects coming energy back to the SAR sensor compared to flatter and drier target (e.g., glass and dry, bare soil). Yet, it is an exception for rivers and water bodies on the S1 image since these surfaces are similar to a widely smooth surface absorbing incoming pulse.

Based on this basis, the classified image was grouped into 8 LULC types by considering their temporal changes to backscatter values (Fig. 2B). The eight detectable LULC types in this classification consist of aquaculture, perennial trees (orchards and mangroves), rice fields, rice-shrimp, river, sugarcane, upland vegetation, and urban areas. More explicitly, backscatter from urban features is double bounce, so its values are always stably higher (−4.2 to −1.9) compared to other LULC types. Among eight LULC types focused in the study areas, aquaculture is a major land cover of about 37,325 ha, equivalent to 25.7% of the total areas. Vinh Chau has the largest aquaculture areas with 22,754 ha (60.94% of total aquaculture areas). My Xuyen is the second main district rearing aquaculture with a surface area of up to 11,017 ha (29.52%). Tran De and Cu Lao Dung account for 8.03% (2997 ha) and 1.51% (563 ha), respectively.

Vegetated surfaces reflect medium coming energy (−14.1 to −6.9) since it is bounced by moist canopy and leaves. The backscatter fluctuation over time is a critical basis to discriminate those LULC types in detail. A primary rice system in the four coastal districts is double-cropped rice fed by natural rain (Nguyen et al., 2015). The rice cultivation areas were recognized with a double peak profile corresponding to the two highest growth stages of rice in August and December. Additionally, rice's backscatter profile is also characterized by two abysses depicted by a fallow period after each crop in June and October. Farmers often plow the fields and irrigate to sow for the next crop; therefore, backscatter values of rice fields are down even equivalent to those values handed by water surfaces (−21.6). Rice-shrimp is an adaptive farming system based on seasonal traits and advantages (Loc et al., 2017). In this culture, they cultivate shrimp in the dry season and salt-tolerant rice in the rainy season when salinity drops below the shrimp tolerance. Its backscatter variation has one peak in December, similar to the second crop of rice

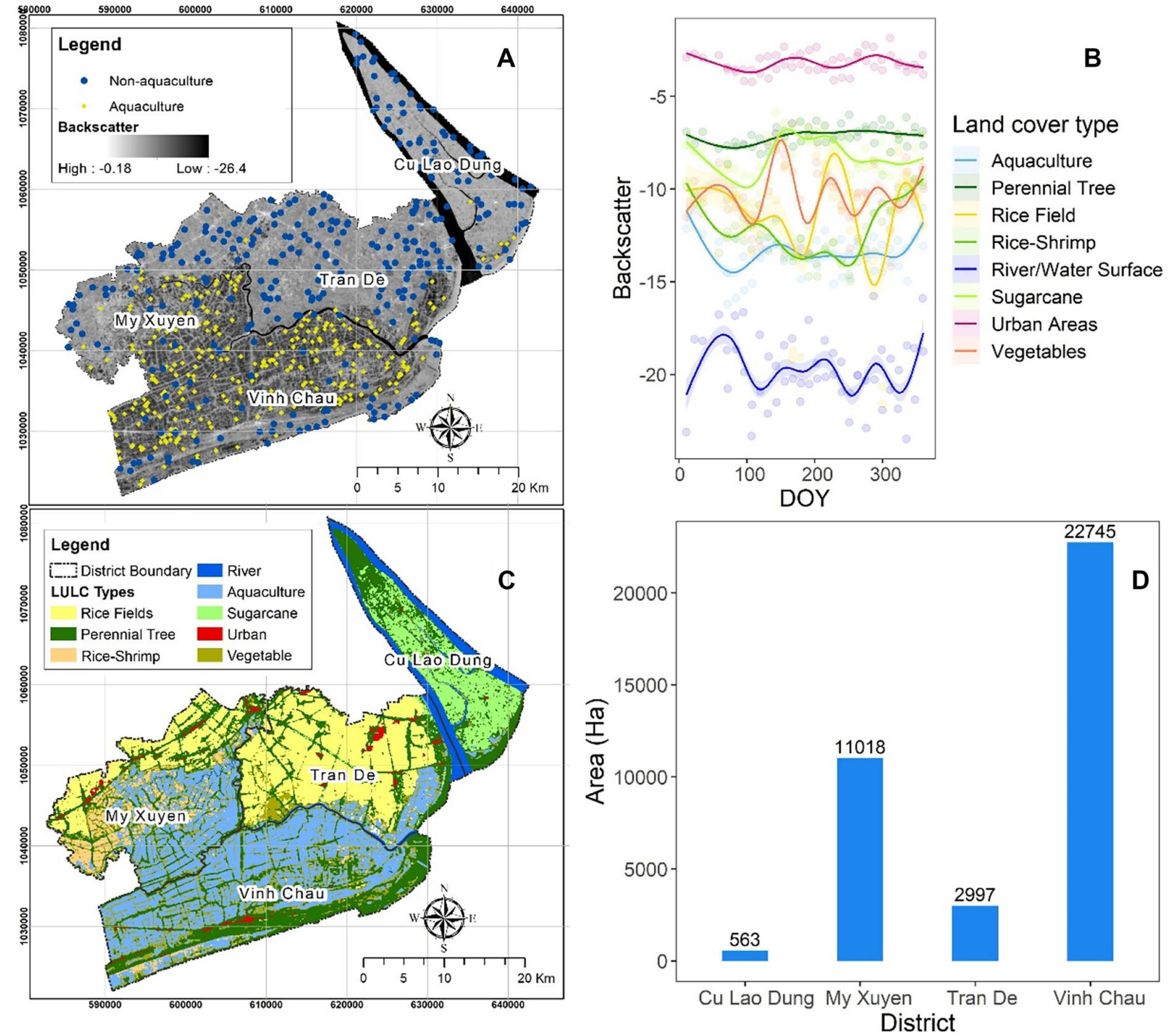

Fig. 2 **A** A single backscatter S1-GRDH image on 11 January 2017 with low backscatter value in dark tone and high backscatter value in light tone and truth points of aquaculture and non-aquaculture. **B** Smooth lines present backscatter fluctuation of eight LULC types over the investigation period. **C** LULC map consists of eight LULC types across the entire study area. **D** Bar chart presents the district's aquaculture area

cultivation areas. After the rice crop, rice residues remained to form an eco-friendly environment for shrimp farms. It therefore visibly looks like a temporal wetland from space. Sugarcane is also detected by one peak profile, yet its values are generally higher than these values of rice systems, e.g., -10.9 to -5.9. Sugarcane's growing period is longer than a typical rice rotation, about 5 months from April to September. Vegetables are characterized by multiple peak variations as this culture is cultivated a few crops per year with short cultivating time. On the contrary, the backscatter of perennial trees remains unchanged at a high level (-8.7 to -6.0).

Descriptive statistics of the sampled population

Out of 140 farmers' responses collected, My Xuyen hamlet accounts for 36.43% ($n=51$), followed by Vinh Chau with 30.71% ($n=43$), Cu Lao Dung with 18.57% ($n=26$), and Tran De with 14.29% ($n=20$). The distribution of the sample is substantially in line with that of the aquaculture areas in each hamlet (see

Fig. 2). There are also significant differences regarding the farming practices between the four focused districts, as summarized in Table 1.

Given the semi-purposive sampling facilitated by the local facilitators, the distribution presented in Table 1, in part, also reflects the aquaculture landscape of these districts. In general, intensive farming is the predominant model of the two, regardless of the hamlets considered. We conducted the χ^2 (Chi-squared) and verified the association between the hamlets and models ($p = 2e^{-10} < 0.05$), in which Cu Lao Dung and Tran De are more associated with intensive practice, whereas Vinh Chau and My Xuyen are more associated with the artisanal/semi-intensive practices.

Regarding the socio-demographic characteristics of the respondents, most of them are middle-aged males, reflecting typical attributes of rural households, with men being the family heads. More specifically, 95% of respondents are males, and 56% are in their mid-30 s to 40 s. The limited amounts of younger and older respondents can be attributed to (i) the youngsters that do not have sufficient capital and experience and (ii) the labor required to look after the farms being too hard a burden for elders. Experience-wise, there are also significant differences between the two models. In this study, the respondent's number of years of experience is divided into four sub-groups, i.e., under 5, 6–10, 11–20, and over 20. For intensive farming, the three middle groups (1–5, 6–10, and 11–20) are almost equal, with the percentages being 32%, 31%, and 33%, respectively. For artisanal/semi-intensive farming, the 11–20 years-of-experience group is substantially more prominent with 53.1% than the other groups. Even though no statistical analysis can be facilitated given the imbalanced sample size, these distribution differences imply that intensive farming is more standardized. Hence, farmers can adapt without requiring too much experience as compared to the artisanal/semi-intensive models that are more empirically based.

Table 1 Distribution of respondents by rearing practices and by districts of focus

Districts	Artisanal/ semi-intensive	Intensive	Total
My Xuyen	13	38	51
Vinh Chau	15	28	43
Cu Lao Dung	1	25	26
Tran De	3	17	20
Total	32	108	140

Economic evaluations of ecosystem services

The production costs

Figure 3A–C compare the production costs incurred with the two types of rearing practices across the four concerned districts. In general, between the two rearing practices, the intensive model has considerably higher FC than the artisanal/semi-intensive model, which can be attributed to higher initial investments, e.g., pumps, mechanical aerators, and pipes. The averaged FC of the intensive model and artisanal/semi-intensive model are 3214 USD/ha.year^{-1} and 1735 USD/ha.year^{-1}, respectively. The standard deviations of these two measurements are 2730 USD/ha.year^{-1} and 1508 USD/ha.year^{-1}

For the VC, however, the differences between intensive and semi-intensive are inconsiderable. More specifically, the averaged VC of the intensive model and artisanal/semi-intensive model are 30,613 USD/ha.year^{-1} and 30,470 USD/ha.year^{-1}, respectively. However, the standard deviation of the latter measurement is 52,810 USD/ha.year^{-1}, much larger than the former being 17,538 USD/ha.year^{-1}. From the open discussions with the respondents, we observe that the magnitude of VC is more associated with the climatic conditions of a specific cropping year than the type of rearing practice, such as weather, water quantity, and quality, or seasonal diseases.

The OC, as estimated via the land leases, is more correlated with the geographical locations than the type of rearing practice. Of the four investigated districts, My Xuyen and Vinh Chau have the most advantages in terms of geographical locations and transportation networks (close to the national highway), hence the highest OC. In particular, these two districts have the average OC of 647 USD/ha.year^{-1} and 862 USD/ha.year^{-1}, relatively higher than those of Cu Lao Dung with 517 USD/ha.year^{-1} and Tran De with 560 USD/ha.year^{-1}.

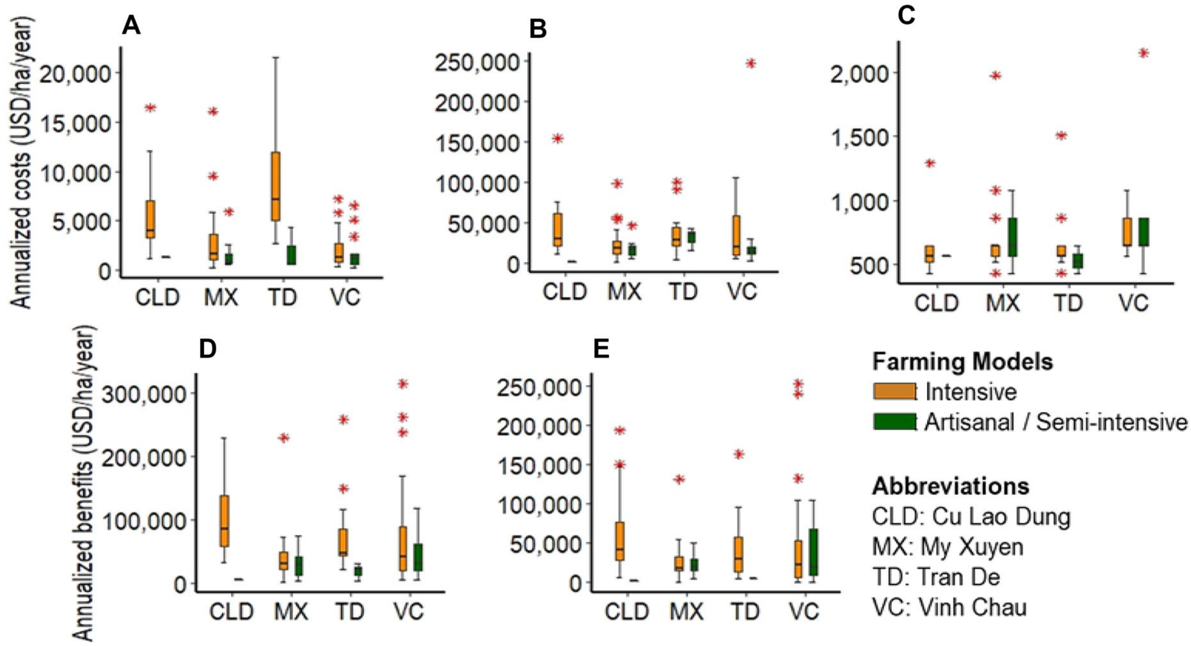

Fig. 3 Annualized economic valuations of ES associated with the two rearing models across the four focused districts. **A** Fixed costs, **B** variable costs, **C** opportunity costs, **D** total revenues, **E** economic values of ES (after removing the negative values)

Total revenues and economic values of ecosystem services

Due to the substantially higher stocking densities, the average productivity for intensive shrimp farms is 3194 kg/ha.year^{-1}, almost three times as much as that of the artisanal/semi-intensive, being 998 kg/ha.year^{-1}. However, the selling prices of the latter are marginally higher than the former in both types of harvests: tiger prawns and white-legged shrimps. Nonetheless, the total annual revenues from the intensive model being 57,288 USD/ha.year^{-1} are still substantially higher than those from the artisanal/semi-intensive model being 37,393 USD/ha.year^{-1} (Fig. 3D). Applying Formula (1), the ES economic values or RR were estimated as summarized in Fig. 3E. The intensive model yields comparatively higher RR than the artisanal/semi-intensive model in line with the total revenues. In particular, the average RR of the former is 30,855 USD/ha.year^{-1}, while that of the latter is 29,911 USD/ha.year^{-1}. The spatial distribution of the RR and the total revenues are illustrated in Fig. 4.

It is remarkable that 37 out of 140 respondents have negative values of ES, implying substantial economic losses. Among these farmers, 26 were associated with intensive rearing.

A χ^2 (Chi-squared) test was performed, which resulted in $p = 1.42e\text{-}8$ ($<< 0.0.5$), hence verifying the statistically significant association between the rearing practices and the negativity of the ES economic values. Averaged by the hamlets, 20% or 5/26 hamlets practicing intensive farming have the negative RR, of which four are located in My Xuyen district, and the other is located in Vinh Chau district. The respective figures of the artisanal/semi-intensive model are 40% and 7/18 hamlets, respectively. The majority of these semi-intensive hamlets having negative RR are located in My Xuyen district (3), Tran De (2), and Vinh Chau (2). It should be re-emphasized herewith that the semi-intensive farms have a substantially smaller sample size (32 vs 108) yet have more negative values of ES. Even though the sample size is distorted to an extent, we speculate that artisanal/semi-intensive farming is more likely to generate negative values for ES.

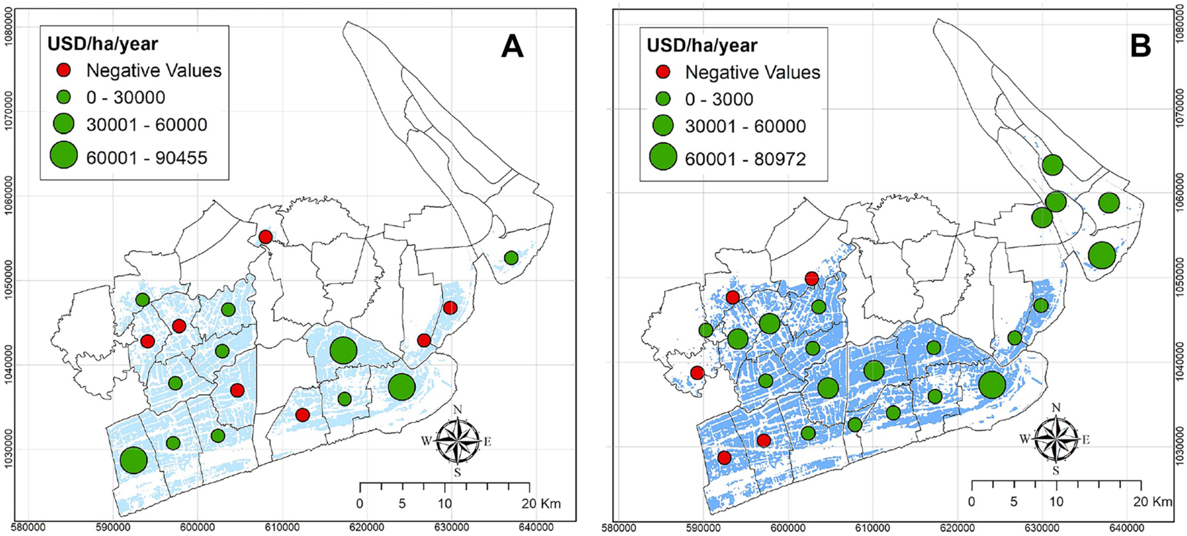

Fig. 4 Economic values of ecosystem services averaged by communes. **A** Artisanal/semi-intensive model, **B** intensive model. The blue shades in the figures represent the aquaculture areas as classified using remote sensing

Multivariate analyses

Principal components

Bartlett's test resulted in the *p* value of 7×10^{-4} verifying the applicability of the PCA method for the collected data. Figure 5 summarizes the results from the first exploratory multivariate analysis, PCA (Bartlett, 1937). In general, with two principal components extracted, the results could have explained the total number of 43.9% of the variances (PC1: 28.8% and PC2: 15.1%). This amount of extracted variances is acceptable considering the number of latent variables originally considered in the analysis.

In general, PC1 is the most associated with *crop yields*, *total revenues* (TR), and stocking intensity, whereas PC2 is the most associated with *farm areas*, *OC*, *and VC*. The other variables are less correlated with either PC1 or PC2, hence having less contributions to the construction of these two principal components (Fig. 5A). Even though "Prices" contributes a substantial role in the RR, this factor has the least contribution because of the small variance. Compared with other quantitative variables, the selling prices are considerably more homogenous than the other quantitative variables across the collected responses. During our survey, we observe that neighboring farmers are more collaborators than competitors, sharing crucial information, including, of course, market-related intel among themselves. In doing so, the farmers can protect themselves from the prices being lowered down by the vendors, as reflected by the relatively uniform selling prices in our study.

Figure 5B–E depict the associations of the primary variables (quantitative) with the supplementary variables (qualitative and categorical). More specifically, regarding the geographical locations (Fig. 5B), My Xuyen and Vinh Chau have the most extensive farm areas and also the largest OC. However, the other two districts are substantially higher in the remaining aspects, e.g., total revenues and yields. With respect to the stocking alternatives (Fig. 5C), the tiger prawn requires substantially larger farms, hence higher OC, yet could not generate as much income as the white-legged shrimp. The *combined* individuals, on the other hand, stretches on both ends, implying the intermediate attribute. Regarding the number of annual harvests (Fig. 5D), from the factor map plotted, it can be recommendable that the optimum choice would be 2–3 crops to balance between the costs and benefits. More specifically, having only 1 crop (mostly semi-artisanal/semi-intensive) will make it harder to justify the investments, hence the highest opportunity costs. On the other hand, 3–4 crops (mostly intensive model) will incur substantially larger fixed costs and variable costs, making it harder for small-scale

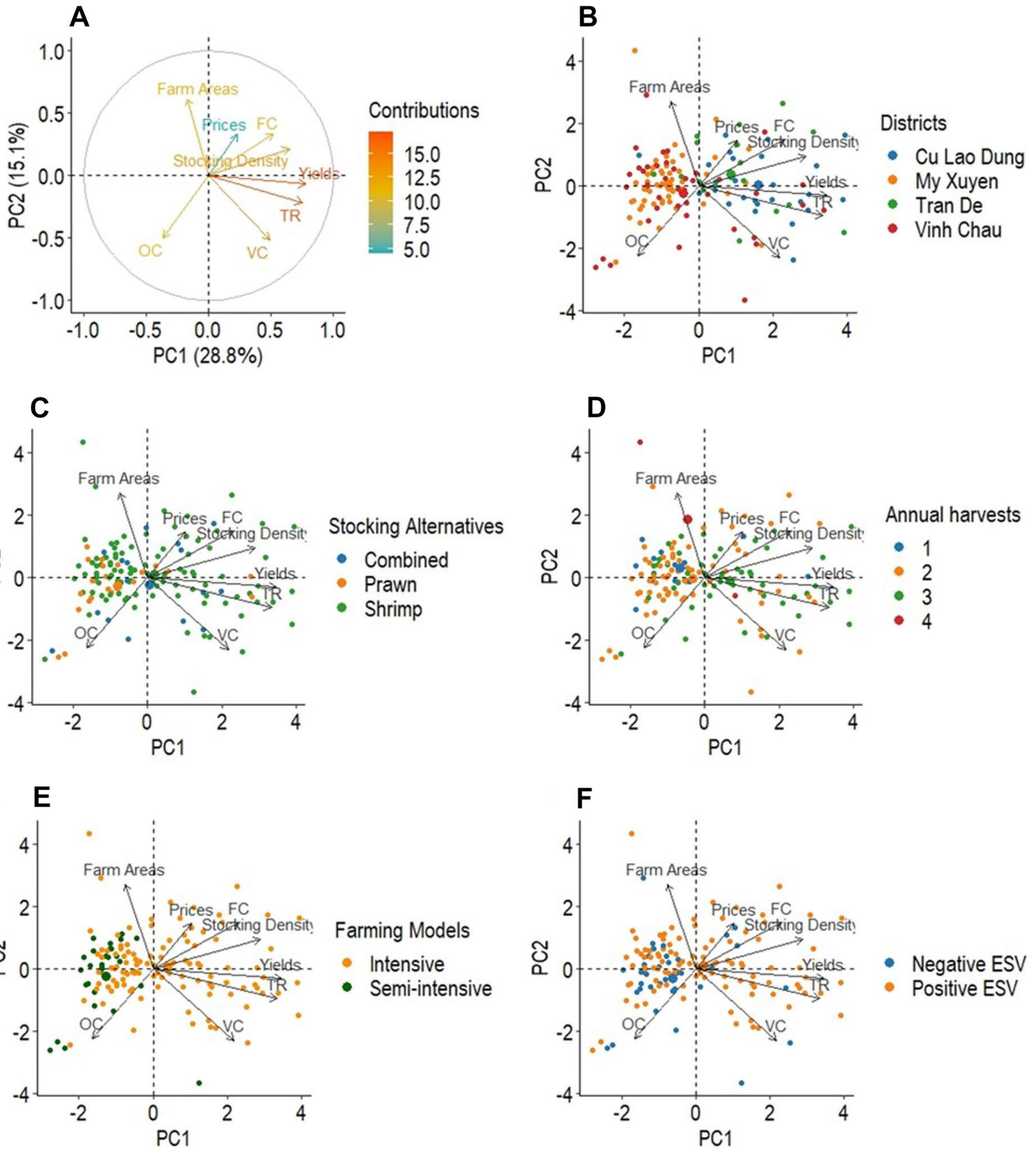

Fig. 5 Principal component analysis. **A** Contributions of the latent variables into the construction of the first two principal components. **B–E** Biplot integrating the supplementary qualitative variables: geographical locations, or districts (**B**); stocking alternatives (**C**); annual harvests, i.e., how many crops harvested per year (**D**); and farming models (**E**). **F** Biplot integrating the negativity of the ES economic values

farmers to adopt. Plus, too many crops for 1 year will essentially exhaust the ecosystem services essential to sustain any agriculture/aquaculture production (Tran et al., 2021). Finally, a substantial relevance between the two binomial variables—farming models and the negativity of the ES values—is clearly illustrated in Fig. 5E–F. More specifically, the intensive models are substantially less likely to generate negative ESV than the artisanal/intensive models. It is also notable that most artisanal, semi-intensive farms have larger areas, meaning higher opportunity costs yet lower in investments (fixed costs and variable costs) and returns (total revenues). These adverse conditions have collectively offset the financial benefits of the artisanal/semi-intensive farming models, thus resulting in the negativity of the ES economic values

Hierarchical clustering

We integrated the descriptive findings from the PCA into the HCA to identify the potential bundles within the collected dataset. The results of the hierarchical clustering of the responses are summarized in Fig. 6.

For this study, we relied on Ward's agglomerative methods to decide on the optimum number of clusters from the original data set. As suggested by the statistical mode (Fig. 6A), two is the optimum number of clusters for our data set (the vertical blue dotted line). We argue that since our data set already has a subtle bivariate, i.e., the two rearing models, hence re-classifying into only two groups would entail a substantial loss of information and could not facilitate any in-depth explorations. Hence, for this study, we opted for the next best option is six clusters (the vertical red dashed line). The biplot of the variables vs observations is developed and presented in Fig. 6B, reflecting the clear separation among the developed clusters.

All eight primary variables have statistically significant links with the development of the clusters, and only five supplementary variables do. The list of the significant variables and the results of their significant tests are summarized in Table 2.

Based on the significant variables identified, distinguishing characteristics of each cluster are realized as presented in Table 3. More specifically, the first two clusters are the most favorable ones in terms of both economic returns and investments. In particular, cluster 1 is the highest in terms of FC, stocking density, and selling prices while the second-highest in yields. Similarly, cluster 2 is the highest in total revenues and VC while the second-highest in stocking density. Regarding the categorical variables, both clusters are intensive model predominant. Geographically, cluster 1 is the representative for farmers from Cu Lao Dung with 1–5 years of experience, while cluster 2 comprises both Cu Lao Dung and Tran De farmers who prefer the white-legged shrimps or combined models rather than pure tiger prawn farming.

The artisanal/semi-intensive farms constitute the third cluster, with the second-highest in selling prices, only marginally lower than the cluster 1. In addition,

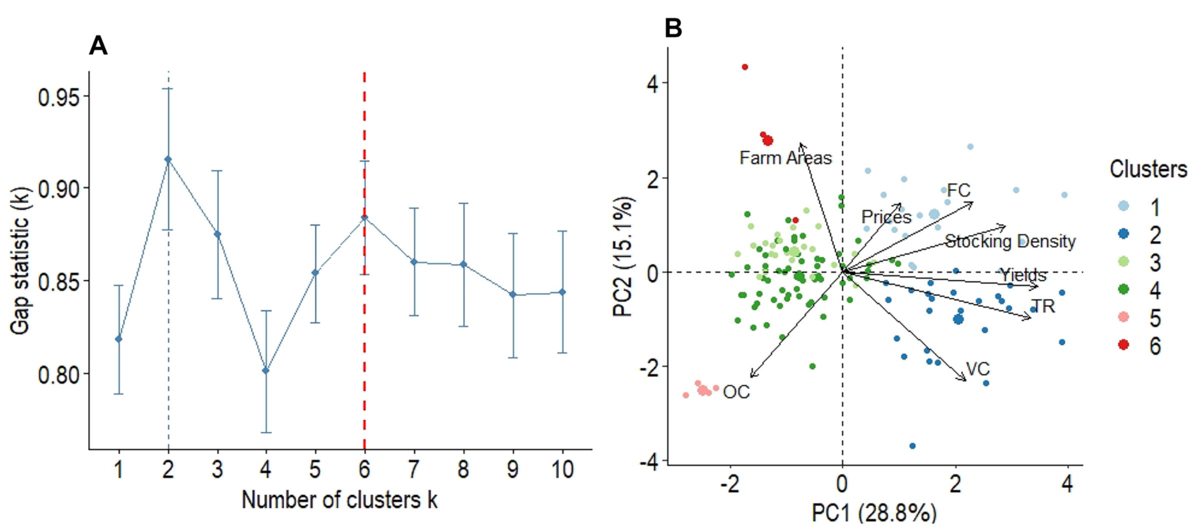

Fig. 6 **A** Identification of optimal number of hierarchical clusters based on the Ward's agglomerative methods. Blue dotted line, number suggested by the statistical model; red dashed line—ultimate selection for this study considering the characteristics of the data set. **B** Map of the constructed clusters versus the quantitative variables

Table 2 Links between the latent variables and the development of the clusters

Types of variables	No	Variables	*P* value (< 0.05)
Primary (continuous)	1	Opportunity costs	$3.59\ e^{-32}$
	2	Farm areas	$7.74\ e^{-24}$
	3	Prices	$7.01\ e^{-23}$
	4	Yields	$1.60\ e^{-20}$
	5	Total revenues (TR)	$1.23\ e^{-18}$
	6	Fixed costs (FC)	$1.62\ e^{-18}$
	7	Variable costs (VC)	$2.96\ e^{-12}$
	8	Stocking density	$1.26\ e^{-11}$
Supplementary (categorical)	9	Districts	$3.65\ e^{-6}$
	10	Model	$1.77\ e^{-5}$
	11	Experience	$7.06\ e^{-5}$
	12	Annual harvests	$2.04\ e^{-3}$
	13	Stocking alternatives	$1.51e^{-2}$

this cluster has substantially lower-than-average statistics in terms of FC, total revenues, VC, stocking intensity, and yields, reflecting the small-scale and household practices of the artisanal/semi-intensive farming model. Regarding the supplementary variable, cluster 3 consists mostly of farmers from Vinh Chau district with 11–20 years of experience. These farmers substantially favor rearing the tiger prawn over the white-legged shrimp. Of equal association is cluster 4; however, it is essentially unfavorably distinguished. This cluster is highlighted as the semi-intensive farmers that suffer the most from the negativity of the economic values of ES. Based on the latent variables, this cluster comprises farmers with the most disadvantaged attributes in key measurements, i.e., stocking density, VC, FC, yields, total revenues, and prices. These imply that savings on costs do not always result in better economic returns. Most of the individuals within cluster 4 are farmers from My Xuyen district.

Finally, respectively distinguished by the largest farm areas and opportunity costs are cluster 5 and cluster 6. Regarding the supplementary characteristics, cluster 5 is the most experienced group, consisting mostly of farmers with 11–20 years of experience, which are associated with the artisanal/semi-intensive rearing practice. Cluster 6, on the other hand, is those farmers with the most intensified farming practice, up to 4 crops per year. Paradoxically, they are not the most, if not among the least, beneficial of all the clusters developed and investigated. This could have been due to the highest opportunity costs of the lands, hence pushing the farmers to more exhaustive farming practices.

Discussions

Challenges and future outlooks

Intensive model

The intensive model, in general, has the major edge in generating substantially more total revenues compared to the artisanal/semi-intensive model. This study expands the knowledge by also highlighting potential areas that can be further improved to enhance the sustainable development of the intensive shrimp farming model not only in Soc Trang but across the VMD alike. More specifically, being more industry-induced of the two, the economic edge of the intensive model evidently relates to more significant investments as reflected in the associations of the operations cost-related vectors (FC, VC) with the economic outcome vectors, including the livestock yields and the total revenues. However, there are also other factors that correlate otherwise, i.e., the stocking intensity and the annual harvests. For the stocking intensity, we observe that from 100 to 120 larvae/ha could have been the optimum choice while both lesser or higher can hurt the ultimate total revenues. Even though this is not an aquaculture science paper, we speculate that lesser density would entail inefficient costs, while higher stocking densities imply more risks of livestock fatality during their lifespan due to the in-farm/in-pond competition of the limited resources. Similarly, 2–3 crops per year are the optimum practice. In contrast, a single crop is only associated with the artisanal/semi-intensive model,

Table 3 Descriptions of the six clusters developed*

Clusters	Primary (continuous)		Supplementary (categorical)	
1	**Highest Fixed costs**	$7.60\ e^{-16}$	Intensive Model	0.004
	Highest Stocking Density	$2.71\ e^{-9}$	*Districts*:	
	2nd highest Prices	$4.60\ e^{-3}$	• Tran De	0.039
	2nd highest Yields	$2.25\ e^{-2}$	• Cu Lao dung	0.044
2	**Highest Total revenues**	$3.54\ e^{-15}$	Intensive Model	$6.33\ e^{-3}$
	Highest Yields	$3.11\ e^{-14}$	1-5 Years of experience	$1.04\ e^{-3}$
	Highest Variable costs	$1.34\ e^{-12}$	3 crops/year	$4.84\ e^{-3}$
	2nd Highest Density	$4.36\ e^{-2}$	*Districts*	
	Smallest farms	$2.54\ e^{0-2}$	• Cu Lao dung	$4.33\ e^{-5}$
3	**Highest in Prices**	$1.02\ e^{-12}$	Artisanal/semi-intensive	$2.52\ e^{-3}$
	Lowest Fixed Costs	$4.26\ e^{-2}$	Tiger Prawn stocking	0.005
	2nd Lowest Total Revenues	$2.31\ e^{-2}$	11-20 YOE	0.029
	Lowest Variable Costs	$1.26\ e^{-2}$	*Districts*	
	Lowest Stocking Density	$1.55\ e^{-2}$	• Vinh Chau	0.032
	Lowest Yields	$6.94\ e^{-4}$		
4	2nd Lowest Stocking Density	$2.08\ e^{-2}$	Negative ES economic values	$7.31\ e^{-4}$
	2nd Lowest Variable Costs	$4.34\ e^{-3}$	*Districts*	
	2nd Lowest Fixed Costs	$1.79\ e^{-4}$	• My Xuyen	0.007
	2nd Lowest Yields	$1.83\ e^{-5}$		
	Lowest Total Revenus	$3.39\ e^{-6}$		
	Lowest Prices	$3.34\ e^{-13}$		
5	**Highest Farm Areas**	$1.83\ e^{-18}$	4 crops/year	0.043
6	**Highest Opportunity Costs**	$5.40\ e^{-22}$	Artisanal/semi-intensive	0.012
			> 20 Years of experience	0.039

*The shading colors for the clusters are the same in Fig. 6B for convenient reference whereas those having four crops per year are actually having substantially less total economic returns, even with substantially larger-than-average farm areas. The performance of intensive farming models varies considerably across the study area. More specifically, Tran De and Cu Lao Dung have the highest total revenues and ES economic values as compared to the other two districts, i.e. Vinh Chau and My Xuyen (see Fig. 5B). This could have been due to various geographical factors, i.e., water quality and accessibility to roads, that are beyond this study.

Artisanal and semi-intensive model

Even though being disadvantaged in terms of revenue generation, the existence of artisanal/semi-intensive models has their roles in Soc Trang's aquaculture landscape and for the VMD, in a broader sense. Combining the findings from this study and the previous literature (Loc et al., 2020; Nguyen et al., 2015), we remark that these non-industrial farming models are still relevant for at least two main reasons. Firstly, the delta-wide transition from rice-focused agriculture to aquaculture was triggered by the need to help the farmers better adapt to the intensification of salinity intrusion in recent years. The artisanal/semi-intensive models, henceforth, emerged as one of the most promising adaptive models that the farmers could have taken up, in part, due to its non-demanding requirement in technical and financial investments. Second, these artisanal/semi-intensive farming models can provide multiple environmental benefits on top of generating income for the farmers, among which protection of the coastal mangrove forests is the most important.

Nevertheless, artisanal/semi-intensive shrimp farming is among the most important livelihood options for the VMD's farmers. Therefore, if it is not economically viable, they will ultimately shift to other better alternatives (Trang & Loc, 2021; Hui et al., 2022). In this study, we were able to identify the potential causes that could have compromised the economic benefits of certain artisanal/semi-intensive shrimp farms, i.e., unappropriated stocking density, low yields, high production costs, and low selling prices. Related to the first three reasons, we speculate that the interventions of the local government can substantially alleviate via training programs. For the last reason, we consider this could have underlined the overlooked opportunity to re-position the artisanal/semi-intensive shrimp products. More specifically, instead of competing with the products from the intensive farms, farmers of non-industrial models can focus more on cultivating their products as non-chemical, organic, purely natural products. Thereupon, they can gain a unique marketing edge, thus being able to sell with much higher prices and even reach out to the much higher demanding international markets such as Japan or Korea. Additional investments will evidently necessary, but the sustainability of organic produces could justify in the long run. Although beyond the scope of this study, we remark that thorough assessments should be conducted, including market demand research and cost–benefit analysis to enhance the feasibility of organic models.

Methodological implications

Remote sensing and GIS

Remote sensing, GIS, and earth observation techniques have been utilized in ES-related studies (Cetin, 2015; Loc et al., 2018c; Kuenzer et al., 2013; Loc et al., 2018a, b, 2021a, b, c; Plieninger et al., 2013). In this study, we contributed novel evidence of how these two methods are of particular relevance to ES studies. More specifically, inland aquaculture is a LULC type that is relatively difficult to identify based on conventional image analyses accurately. Users frequently face misclassification between other water surfaces (e.g., seasonal flooding areas, permanent wetland, river, and lake) and aquaculture areas. These LULC types are similar in nature, and even utilization of enhanced water index (e.g., modified normalized difference water index) cannot improve the classification at a specific period. Time-series image analysis considers pixel alternation through a time frame before labeling a pixel. It is able to discriminate seasonal flooding areas based on flooding time. Yet, obtaining an optical time-series image in the coastal area for aquaculture detection is often not easy due to high cloud cover (Diep et al., 2019). S1-SAR is able to overcome all these barriers when it is unaffected by weather with high spatial–temporal resolution and completely free among other satellites. It is extremely beneficial to consider backscatter values in the case of inland aquaculture detection. The backscatter values are dissimilar between aquaculture and river because deeper water absorbs more incoming pulse, e.g., the mean VV polarization value range for deep-water surface (lake) is approximately −17 to −18 and lower; in contrast, it is higher for shallow water of around − 15 (Gulácsi & Kovács, 2020). It is a critical basis to separate inland aquaculture and river on S1, while conventional analyses cannot differentiate it. Yet, noise affecting image analysis obviously exists on SAR imagery that requires applying spatial filters to limit misclassification, especially for urban neighboring areas. This study only defined aquaculture areas, while the clear separation of semi-intensive and intensive aquaculture was not done. The primary difference between these two models belongs to the management method and rearing scale rather than land cover differences. Hence, intensive farming is able to be detected using fusion data of S1, Sentinel-2, and very-high-resolution images to determine them with the contribution of geometrical traits in object-oriented classification.

Expanding the application of ecosystem services evaluation

Via this paper, we showcase the merits of using ES evaluation to investigate the sustainability of adaptive agriculture/aquaculture models against adverse environmental conditions. First, using the ES economic evaluation has the edge over conventional economic assessments for explicitly accounting for the human-nature interactions via an integrated market-based methodological approach. Even though seemingly similar, each method takes a very different analytical approach. While the traditional economic analysis methods, e.g., cost–benefit analysis, do not separate between the two components, handling nature's contributions as one of the integral costs, the ES evaluation accounts for each party's role, thus being able to reveal multiple overlooked yet interconnected features. This study was able to provide a case in point in this regard via the investigations of the correlations between the socio-demographic variables (age, experience) with the production-related variables (costs, revenues, farm areas). Plus, the incorporation of opportunity costs also acts as a proxy to reveal the people's awareness of the ES available on their lands. The second advantage of our approach relates to the use of the two-step multivariate analysis to explore the underlying associations and bundles of the variables and individuals of the sampled populations. In this study, the former relates to the relatively different roles of the production costs on the total revenues, i.e., FC and VC are positively correlated while that of the OC is a negative relationship. Another important finding is the development of 6 clusters among the collected responses, hence revealing the sufferings of certain artisanal/semi-intensive farmers that could have been overlooked otherwise.

This study adopts and essentially expands the exploratory application of ES evaluation in evaluating the ecosystem-based agricultural production in the VMD against the adverse environmental pressures, firstly contributed by Loc et al. (2017). The findings presented herewith, therefore, are of particular relevance not only as an empirical reference for sustainable agriculture/aquaculture management in the VMD, but also as an important methodological addition to the ES-related studies in Vietnam and Southeast Asia. While the former relates to the identification and investigation of economic insecurity that certain artisanal/semi-intensive household farms had been suffering, the latter substantially widens the application horizon of the ES concept beyond the traditional fields of applications, including biodiversity conservation or payment for ES (Suhardiman et al., 2013; To et al., 2012). In essence, we are hopeful that our studies could have been a stimulus for other scholars to continue to explore the applicability of ES in agriculture management related, not only in the VMD but also other world's major river deltas confronting the menace of salinity intrusion.

Policy relevance

With the ever-intensification intrusion of saline water in recent years, the VMD is facing an urgent need to gradually move away from rice-intensive agriculture heritage and to strategically diversify crops and livestock, especially adopting those that are more salinity tolerant (Loc et al., 2021a, b, c; Park et al., 2020). Within this major transformation of an agricultural landscape, soft measures such as rearing high-value brackish livestock, e.g., such as prawn and shrimp, are of equal, if not more important than the complex structural interventions, such as dikes, sluice gates, or irrigation development (Loc et al., 2017; Nguyen et al., 2015; Pham et al., 2020). Across the VMD, Soc Trang was among the first provinces to switch to aquaculture-pivotal agriculture, with a specific focus on prawn and shrimp production. Our findings henceforth could have provided a timely and in-depth investigation for the province's two most important shrimp rearing models: intensive and artisanal/semi-intensive. Our analysis remarks that each model has a distinctive role in that the former prioritizes revenue generation the most, whereas the latter leans more towards livelihood adaptation for small-scale farmers. This is also in line with the provincial and delta-wide strategic planning. Even so, the fact that certain semi-intensive farmers suffer from economic losses as reflected in the negative values of ES implies a dawning situation. Not only have we recognized these groups from the collected data set, but also revealed potential causes as discussed in the previous section. See also the description of cluster 4 in Table 3.

It should be noted that compared to large-scale intensive shrimp farms, small-scale household farms are less resilient to unfavorable economic conditions, hence incapable of tolerating the economic losses for long. This would translate into a consequence whereby these farmers would ultimately give up on their regulated farming models (artisanal/semi-intensive) and shift to other livelihood strategies to support their families. While some could have successfully transitioned to other farming models, including the intensive model, the others fell over the cracks and were forced to sell their lands and move to the bigger cities to find industrial jobs. Such a domestic migration from rural to urban areas, in turn, creates pressures for both areas. While the latter will be forced to absorb additional laborers, the former will gradually transform into neo-colonies, in which mid-sized family farms are gradually sabotaged by large-scaled corporations (Dun, 2011; Huy, 2009; Tran et al., 2021). Therefore, it is recommendable that the policy planners thoroughly investigate the potential causes highlighted in this study and find ways to better support the most disadvantaged farmers to sustain their livelihoods. As such, the intangible benefits of these ecosystem-based farming models can be further realized.

Summary and conclusions

This study employs the concept of ES to investigate the efficiency of two major shrimp aquaculture models of the VMD: intensive and artisanal/semi-intensive. A mixed-method approach was presented, combining remote sensing, social survey, and multivariate statistical analyses. Notable findings of this research are summarized as follows:

- The intensive model has the edge over the artisanal/semi-intensive option, in part, due to the large investments reflected in both initial investments and operational/seasonal costs. There are, however, factors that can compromise the efficiency of this model, including the stocking density and the number of the annual crops. We remark that 100–120 larvae/ha and 2–3 crops per year could have been the optimum figures for the intensive shrimp farming model to generate the highest economic values of ES.
- The artisanal/semi-intensive model, although being less economically competitive, is still relevant for the VMD. First, this farming model is more suitable for small-scale agricultural households because it requires substantially less investment. Second, the model could have offered more environmental and ecological benefits, such as protecting the coastal mangrove forests.
- We remark that inappropriate stocking density, low yields, high production costs, and low selling prices are major challenges for artisanal/semi-intensive shrimp farmers. While for the first three reasons, the interventions of the local government could have been relevant, and the last problem could have required a strategic repositioning. More specifically, instead of competing with the products from the intensive farms, farmers of non-industrial models can focus more on cultivating their products as non-chemical, organic, purely natural products, thus being able to sell with much higher prices at international export markets.

In addition to these knowledge contributions, this study also showcases the merits of the methods employed. First, we showcased the advantages of using S1-SAR to obtain cloud-free multitemporal images, fundamental to detect the inland aquaculture areas. Second, the strong points of using ES as compared to conventional economic analysis were highlighted related to the explicit accounts of the human-nature nexuses. Finally, the findings presented in this paper are of particular relevance to advancing ES-related studies in Vietnam and Southeast Asia. More specifically, our study essentially widens the application horizon of the ES concept beyond the traditional fields of applications, including biodiversity conservation or payment for ES. We therefore believe that our studies could have encouraged other scholars to continue to explore the applicability of ES in agriculture management related to the VMD, and other world's major river deltas confronting the threat of salinity intrusion.

Moving forward, several recommendations have been drawn from the research findings. With respect to the intensive model, which is more income-generating advantage of the two models investigated. However, there are also underlying risks, i.e., the stocking intensity and the annual harvests. Therefore, follow-up studies focusing more on these aquaculture science-related aspects are urgently needed. Regarding the artisanal/semi-intensive models, it is remarkable that these non-industrial farming models are still relevant, first, to help the farmers, especially the marginalized ones to adapt to salinity intrusion, and second, to achieve multiple environmental benefits such as protection of the coastal mangrove. Also, it is recommended that shrimp yields from artisanal/semi-intensive can enjoy added values from integrating organic farming settings even though comprehensive re-evaluations will be necessary.

With respect to the policy relevance, our study has provided a timely and in-depth investigation of two of the most important salinity intrusion adaptive livelihood models: intensive and artisanal/semi-intensive shrimp farming. We have revealed unique merits and limitations of each model, highlighting their distinctive role in supporting the VMD in adapting to the ever-intensifying intrusion of seawater. More specifically, the intensive model is more suitable for revenue generating while the artisanal/semi-intensive is important to support for small-scale farmers. This is also in line with the provincial and delta-wide strategic planning. However, we were able to take a critical note that certain semi-intensive farmers suffer from economic losses and revealed the underlying causes. Therefore, it is recommendable that the policy planners thoroughly investigate the potential causes highlighted in this study and find ways to better support the most disadvantaged farmers to sustain their livelihoods against the salinity intrusion.

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Declarations

Conflict of interest The authors declare no competing interests.

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