A landscape in turmoil: characterizing the multi-decadal growth trajectory of brackishwater aquaculture in Medinipur Coastal Plain, India

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Abstract. The spatio-temporal growth trajectory of coastal brackishwater aquaculture (CBA) in the coastal tracts of Purba Medinipur, India and its impending repercussions on the immediate environs, was primarily assessed in this study through application of geostatistics, landscape metrics, and geospatial technologies. Three Community Development (CD) Blocks, namely, Contai-I, Deshapran, and Ramnagar-II were considered to analyze the growth pattern of the area under CBA. Landsat datasets of the assessment years (1991, 2001, 2011, 2021, and 2023) were used to prepare the land use/ land cover (LULC) maps and to derive pertinent landscape metrics of patch and class levels for this region. This brought forward a highly fragmented and dispersive spatial concentration of the CBA farms in the entire study area. Additionally, Census Village-wise growth pattern of CBA was analyzed by conducting a spatial autocorrelation analysis which depicted prominent clustering of villages with a higher concentration of CBA. Results showed that there has been an incessant growth of CBA in the last three decades, however, a sharp drop has been recorded owing to recurrent bouts of diseases, swelling production costs, and a sharp drop-in market rate. The nature of growth and/ or decay of the CBA was predicted for the year 2025 using Cellular Automata and Artificial Neural Network (CA-ANN) model. After careful calibration and validation, the model projected further lessening of the CBA area along with a continued expansion of abandoned aquaculture. Accordingly, ecologically viable livelihood alternatives and environmentally sustainable management measures were suggested for the efficient monitoring of these highly fragile tropical ecosystems.

Keywords: abandoned shrimp-farm, CA-ANN modelling, coastal aquafarming, hotspots, land engulfment, spatial clustering.

1. Introduction

Brackishwater aquaculture has been considered a reliable source of foreign exchange for the nations and income opportunity for the marginalized communities inhabiting coastal floodplains in the third world (Stonich & Bailey, 2000). Commercial brackishwater aquaculture, especially shrimp farming, therefore, rapidly pervaded throughout the coastal zones of tropical countries of Asia, Latin America, and Africa (Stonich & Bailey, 2000; Hall, 2003; Hossain et al., 2013) since the 1980s, largely replacing the traditional livelihoods and transforming the natural habitat over widespread areas (Cruz-Torres, 2000; Pradhan & Flaherty, 2007; Pokrant, 2009). Although brackishwater aquaculture began as a traditional economic practice in coastal districts of Indonesia dating back to the 1400s, the sector started to expand at a rapid pace in the mid-1980s and became a promising source of foreign exchange (Gowing et al., 2006). For instance, the exponential growth of demand in the global market and price hikes have lured the farmers of coastal Bangladesh to convert agricultural lands to shrimp farms since the 1970s and have become one of the thriving industries in Bangladesh (Pokrant, 2009; Hossain et al., 2013; Hoque et al., 2017). Similar scenarios have been found in Vietnam (Anh et al., 2010), Honduras (Dewalt et al., 1996), and the Philippines (Primavera, 1995).

In India, traditional brackishwater aquaculture has been widely practiced along the east coast, especially in Tamil Nadu, Andhra Pradesh, Orissa, and West Bengal for ages. However, since the 1980s aquaculture in India shifted from its traditional form and largely became an export-oriented commercial activity, and the area under coastal brackishwater aquaculture (CBA) grew incessantly throughout the coastal states including West Bengal, Orissa, Andhra Pradesh, and Tamil Nadu, in response to the huge demand of shellfishes in the global market (Rajitha et al., 2007; Pradhan & Flaherty, 2007; Ojha & Chakrabarty, 2018). Owing to high profitability, shrimp farming became the most important and widely cultured species in this sector and attracted huge investments from private companies (Pradhan & Flaherty, 2007). Since the 1980s, India has become one of the major shrimp exporters in the global market (Galappaththi & Nayak, 2017). As a result, wide tracts of land along the coastal plain having higher soil salinity and low productivity of rice were rapidly converted to CBA farms, causing considerable land use transformation (Dutta et al., 2016). In West Bengal, export-oriented shrimp production started in the late 1980s and has grown exponentially since 1995 (Ghoshal et al., 2017). The lucrative profit margin provided the initial impetus for the local farmers to adopt CBA over the traditional paddy culture. West Bengal in particular, contributed a major share of India's total brackishwater fish and shrimp production and export (Boyd et al., 2018; Ghoshal et al., 2019). CBA in West Bengal is mostly practiced in Purba Medinipur, South 24 Parganas, and North 24 Parganas (Datta et al., 2010; Roy, 2013; Datta & Ghosh, 2015; Ojha & Chakrabarty, 2018).

Despite the wide scope of research to address the dramatic changes brought about by the hasty growth of CBA in the regional landscape characteristics, most of the research so far has adopted the theoretical approach and focused on the production growth, technical issues, policy issues pertaining to the industry, and socio-economic and ecological implications.

However, there remains a noticeable dearth of empirical research and quantitative data to address the changes in the landscape and associated ecological and social impacts at the regional level (Bhattacharya, 2012; Roy, 2013). In India, brackishwater aquaculture has been an explored area of research till recent times, and most of the existing research regarding shrimp farming mainly involved discussions on various technical and economic issues (Bhattacharya, 2012). With regards to West Bengal, very little research was found in this field and they were mostly restricted to the Sundarban regions and concentrated on the benefits of the thriving shrimp culture (Roy, 2013). Accordingly, empirical research is needed to address the growth pattern of CBA and the consequent changes in the landscape characteristics as well as imminent socio-economic and environmental impacts. In this backdrop, the present study aims to pursue an empirical study on the spatio-temporal patterns of growth of CBA in the selected coastal CD Blocks of the Purba Medinipur district of West Bengal and its looming impacts on the surrounding landscape which can abridge the existing research gap.

2. Methods

2.1. Study area

The present study took into consideration three coastal CD Blocks namely, Ramnagar-II, Contai-I, and Deshapran of Purba Medinipur district of West Bengal. Geographically, the area is located within the Medinipur Coastal Plain along the Bay of Bengal which was formed due to the Quaternary fluvio-tidal deposition of alluvium. This area was drained by multiple rivers including Rasulpur, Champa, and Pichaboni inlets, and contained a notable number of inland water bodies (Chakrabarti, 1995; Mondal, 2012). The meso-tidal coastal plain of the study area contained successive rows of dunes and interdunal flat tracts which were formed due to continuous sediment deposition during the interrupted regression of the sea throughout the Holocene (Das & Dandapath, 2012). A perusal of scientific studies showed that the conducive physical settings such as wet-tropical climate, presence of wide flat coastal tract, easy access to saline water through various rivers, creeks, and canals, natural salinity of the soil, etc. provided an impetus for the expansion of CBA in the study area. In the study area, CBA has developed mainly based on the source of saline water which was available in the coastal region from the tidal rivers, creeks, and canals. Besides, low productivity of paddy and vegetables due to high soil salinity, lack of drainage, frequent incidence of flood, and invasion of tidal water resulted in backward economic conditions, prompting the marginal communities inhabiting the study area, to adopt brackishwater aquaculture as a lucrative source of income. Despite its economic significance, the rapid growth of CBA in the study area has become a debatable issue due to its obvious detrimental impacts on the environment and socioeconomic conditions. Rapid decrease in area and productivity of traditional agriculture, constant increase in soil and water salinity, and adverse effects on the sensitive coastal ecosystem were some of the direct consequences of the rampant growth of CBA in the area (Dutta et al. 2016; Ojha & Chakrabarty, 2018).

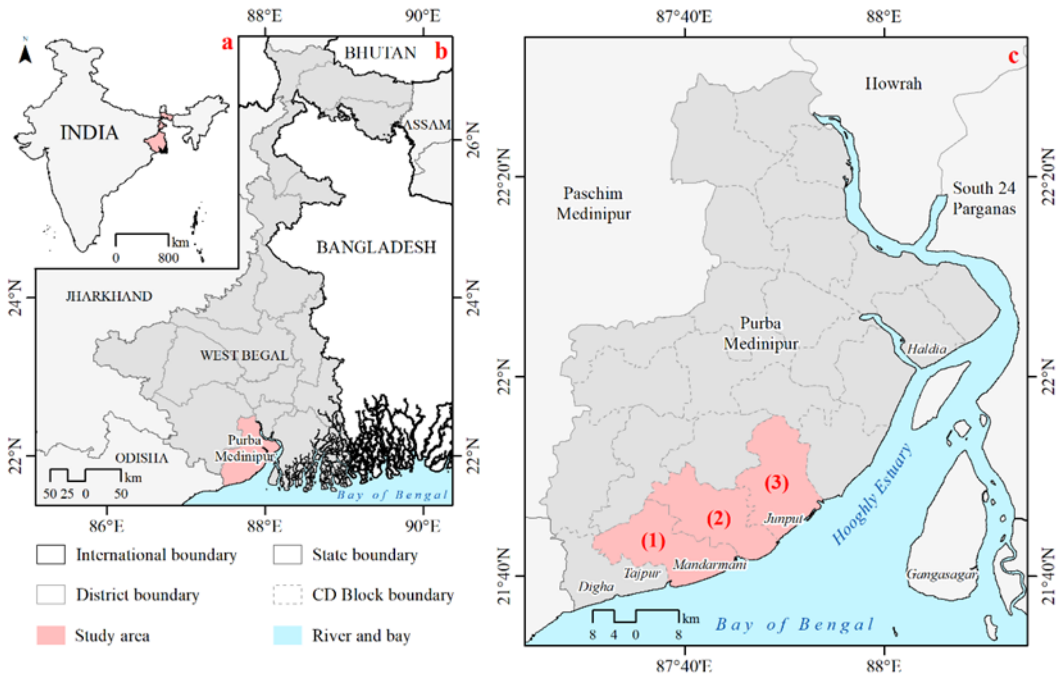

Figure 1. Location map of the selected study sites. Numeric digits in parenthesis indicate different CD Blocks of Purba Medinipur district, viz. (1): Ramnagar-II; (2): Contai-I; and (3): Deshapran

2.2. Data used

Six orthorectified, cloud-free multi-temporal satellite images of pre-monsoon months covering the study area were acquired from the open-source collection of the United States Geological Survey (USGS) Glovis (http://glovis.usgs.gov) website for the present study (Table 1) (Roy & Datta, 2018). These images, having Universal Transverse Mercator (UTM) projection and World Geodetic System 84 datum, included data of Landsat 5 Thematic Mapper (TM) (Path 139, Row 45; dated February 9, 1991, March 6, 1991, April 25, 2001, and February 16, 2011), Landsat 8 Operational Land Imager (OLI) (Path 139, Row 45; dated March 15, 2021), and Landsat 9 Operational Land Imager 2 (OLI–2) (Path 139, Row 45; dated April 14, 2023) (Roy et al., 2021b). Since the pre-monsoon months are regarded as the prime season for aquaculture cultivation, they were deliberately chosen for analysis. Alongside, a total of 200 ground control points (GCPs) were collected from different parts of the study area covering all the land use/ land cover (LULC) classes relying on GPS-based surveys (Handheld Garmin 12 channel device). During the satellite data collection, the only challenge we faced was that the used data be the only freely available data source and of moderate resolution (30 m). The results could be more precise if fine-resolution imagery could be used, especially for LULC classification.

Table 1. Details of satellite images used for LULC classification.

Date of Acquisition	**Sensor**	**Path/ Row**	**Spatial resolution (m)**
9th February 1991 6th March 1991 25th April 2001 16th February 2011	Landsat 5 Thematic Mapper (TM)	139/45	30
15th March 2021	Landsat 8 Operational Land Imagery (OLI)		
14th April 2023	Landsat 9 Operational Land Imager 2 (OLI–2), Thermal Infrared Sensor 2 (TIRS–2)		

2.3. Image processing and classification

Radiometric correction and atmospheric corrections were performed using ERDAS Imagine 2014 software to obtain improved accuracy of the satellite data for the image classifications (Roy & Datta, 2018). Afterward, the image of 2023 was geocoded with the help of GCPs collected from the field, and the other images were successively geo-referenced using the image-to-image georeferencing method. For the georeferencing of the successive images, a third-order polynomial geometrical model was selected and the root mean square error (RMSE) was retained less than 0.5 pixels (Bhattacharjee et al., 2022). The area of interest indicating the study area was clipped from the images using the same software.

Supervised image classification of the five images was carried out using the maximum likelihood parametric decision rule (Lillesand et al., 2008; Li et al., 2014). A total of eight LULC classes were taken into consideration for the image classification relying on the authors' a-priori knowledge regarding the present study area. The LULC classes were aquaculture, abandoned aquaculture, other waterbody, cropland, mangrove vegetation, other vegetation, built-up, and bare land and sand (Datta & Deb, 2012). It is noteworthy to mention that the aquaculture LULC class in this study denoted the CBA. To distinctively identify CBA, during the field survey CBA farms were identified in the field and the record was maintained separately which was used during the LULC classification. Besides, the spectral signature of the pixels, along with tones, patterns, shapes, and textures were taken into consideration to distinguish between CBA and other waterbodies (Mazumder et al., 2021). It is necessary to mention that other vegetation also included the under-canopy rural settlements. Accuracy assessment was performed for all five classified images with the help of 200 GCPs collected from all eight LULC classes during the ground truth survey. Alongside, overall accuracy and Kappa Coefficient were generated to validate the accuracy level. Following the image classification, LULC transformation matrices were generated to assess the inter-class LULC changes within the assessment period (Mazumder et al., 2021; Roy et al., 2021a).

2.4. Geo-statistical analysis

To detect the growth trajectory of CBA, the percentage of Census Village-wise aquaculture area was calculated for the assessment years, i.e., 1991, 2001, 2011, 2021, and 2023, and was predicted for the year 2025. Additionally, a hotspot analysis was carried out for similar years. Anselin (1995) stated that spatial data analysis techniques can identify spatial association and autocorrelation in ortho-referenced images. One such measure of spatial autocorrelation is Moran's I (Moran, 1950). The Local Influence of Spatial Autocorrelation (LISA) method is found to be useful in identifying the existence of local spatial clustering or 'hot spots' and, accordingly, has been applied here (McCullagh, 2006; Pérez-Peña et al., 2009; Ratcliffe, 2010; Yunus et al., 2015). The Hot Spot Analysis calculates the Getis-Ord Gi* (Gi) statistic for features in a weighted set of features. Given a set of weighted data points, the Gi statistic identifies the clusters of points with values higher in magnitude and tells whether features with high values or features with low values tend to cluster in a study area. In Gi statistics, if a feature's value is high, and the values for all its neighbouring features are also high, it is part of a hot spot. The Getis-Ord Gi* is defined as:

$$\text{Gi*} = \sum_{j} w_{ij}(d)x_j \div \sum_{j} x_j$$

where, $w_{ij}(d)$ are the elements of the contiguity matrix for distance d. The matrix assigns a spatial weight for each point pair within a distance d of i. The resultant Gi statistic is in the form of a statistically significant Z score. The larger the Z score is, the more intense the clustering of high values. These statistical analyses have been taken into account since they are proportionate to the global indicator of spatial correlation and they show the degree of significant geographical clustering of comparable values around the specific observation (Anselin, 1995).

2.5. Analysis of patch dynamics of CBA

Numerous extensively recognized spatial metrics were computed to assess the growth trajectory of CBA from 1991 – 2023 from the LULC raster datasets, using the spatial pattern analysis program, FRAGSTATS version 4.2 software (University of Massachusetts, Amherst, USA) (McGarigal, 1995; Tolessa et al., 2016; Nandi et al., 2020; Roy, et al., 2021b). Patch area (AREA), patch perimeter (PERIM), and shape index (SHAPE) were chosen for analysis at the patch level after construing pertinent research related to relevant spatial metrics (Li et al. 2004; Matsushita et al., 2006). Furthermore, ten traditional landscape indices were selected at the class level, covering three aspects of patch complexity, namely, area, shape, and degree of agglomeration (Supplementary Table 1).

(1) Area indices. In this study, class area (CA) was chosen as a measure of landscape composition; specifically, to identify how much of the landscape is comprised of a particular patch type (Li et al., 2004; Jia et al., 2019). To measure the proportional abundance of each patch type in the landscape, the percentage of the landscape (PLAND) was chosen. The number of patches (NP) of a particular patch type is a simple measure of the extent of subdivision or fragmentation of the patch type, thereby representing the class consisting of a single patch. The mean patch area (AREA_MN) measured the statistical distribution of land area. In addition, the largest patch index (LPI), a measure of dominance, that depicts the degree of landscape fragmentation, was selected to measure the proportion of the total area taken up by the largest patch in the study area (Lausch & Herzog, 2002; Li et al., 2004; Su et al., 2011).

(2) Shape indices. In this study, the mean perimeter-area ratio (PARA_MN) and the mean fractal dimension index (FRAC_MN) were used as two shape indices under a particular class (Southworth et al., 2004; Su et al., 2011). Between the two, PARA_MN is the simplest measure of patch shape. When the shape of a patch remains constant, PARA_MN changes with the patch area. FRAC_MN circumvents PARA_MN's primary shortcoming in gauging shape complexity, with a greater FRAC_MN indicating a more irregular shape.

(3) Degree of agglomeration indices. The degree of spatial agglomeration or separation of patches in a landscape is represented by agglomeration indices. The degree of agglomeration is low when a landscape is made up of numerous small, discrete patches; it is high when a landscape is made up of a few large patches or if the patches belonging to the same category are sufficiently connected. In this study, the indices assessing the degree of agglomeration were patch density (PD), landscape shape index (LSI), and percentage of similar adjacency (PLADJ). PD represents the degree of fragmentation in a landscape. Landscape patch indices,

LSI and PLADJ, both quantify the degree of class aggregation in terms of shape complexity (Southworth et al., 2004; Datta et al., 2021).

2.6. Projecting future CBA growth trajectory

After the preparation of LULC maps of 2011, 2021, and 2023, prediction for the year 2025 was done using a hybrid modelling approach, i.e., Cellular Automata and Artificial Neural Networks (CA-ANN) model with the help of the MOLUSCE (Modules of Landuse Change Evaluation) plugin in open-source QGIS software (Version 2.18.23). Several spatial variables, namely, digital elevation model (DEM), slope, rainfall, temperature, population density, and distance from roads and canals were considered as driving factors to run the projection. In this CA-ANN model, a hidden layer of 10, an iteration of 1000, a momentum value of 0.06, and a learning rate of 0.001 were used (Perovic et al., 2018; El-Tantawi et al., 2019). Area change and transition probability matrices were generated using the 2011 and 2021 LULC maps. Initially, the LULC scenario of 2023 was simulated using LULC data for the years 2011 and 2021. Further, it was validated with reference to the actual LULC map of 2023 as a measure of calibration. Finally, the LULC map for the year 2025 was developed by the calibrated system (by calculating the overall Kappa coefficient), using the actual classified maps of 2021 and 2023, respectively.

3. Results

3.1. Patterns of LULC transformation

During the span of the assessment period of 33 years (i.e., from 1991 to 2023), the landscape of the study area experienced a notable transformation of the landscape where the major noticeable aspect was the pattern of growth and decay of aquaculture in the region (Fig. 2). The classification accuracy of all the five LULC maps was generated in this regard. Here, the overall Kappa coefficient values were 0.75, 0.78, 0.77, 0.80, and 0.84 and overall classification accuracies were 79.50%, 81.31%, 80.90%, 83.33%, and 86.36 % for the years 1991, 2001, 2011, 2021, and 2023, respectively (Table 2).

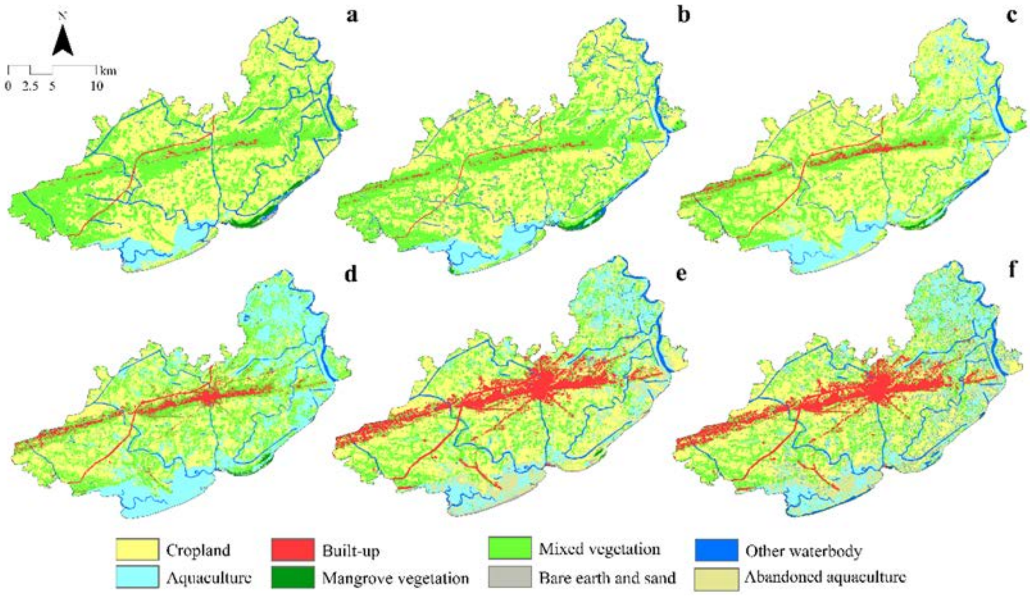

Figure 2. Spatial distribution of different LULCs for the year (a) 1991, (b) 2001, (c) 2011, (d) 2021, (e) 2023, and predicted for the year (f) 2025

In 1991, the area under CBA was 24.28 km^2 which increased by 73.35% and covered 42.09 km^2 in 2001 (Table 3A). 10.44 km^2 of land under agriculture was converted to CBA. Besides, 3.06 km^2 of other waterbody and 2.75 km^2 of other vegetation also got converted to CBA. Between 1991 and 2001, agricultural land had marginally increased from 266.09 km^2 to 270.81 km^2 whereas land under other vegetation decreased from 208.67 km^2 to 189.35 km^2. It was also noticeable that the patch of coastal mangroves also reduced in area, a considerable part of which got converted to CBA.

Following the trend of the previous decade, between 2001 and 2011 the land under CBA increased by 74.54%, and 73.47 km^2 area came under CBA (Table 3B). Specifically, 22.88 km^2, 5.72 km^2, and 2.57 km^2 of area under cropland, other waterbodies, and other vegetation respectively got converted to CBA. The patch of coastal mangroves was further reduced from 2.51 km^2 to 1.45 km^2 of which 0.77 km^2 was converted to CBA.

Between 2011 and 2021, CBA drastically grew from 73.97 km^2 to 155.97 km^2 which indicates 110.87% of growth (Table 3C). A considerable amount (i.e. 70.78 km^2) of agricultural land was converted to CBA. As a result, between 2011 and 2021, agricultural land was reduced from 284.41 km^2 to 217.17 km^2. Other vegetation had also reduced from 149.92 km^2 to 122 km^2 of which 8.63 km^2 of other vegetation was converted to CBA. Besides, to compensate for the conversion of agricultural land to CBA, 33 km^2 of other vegetation had been converted to agricultural land. Coastal mangrove covers were further reduced from 1.45 km^2 to 1.06 km^2, and 33 km^2 of mangrove was converted to CBA.

A drastic change in the landscape scenario was observed in 2023, especially in the case of CBA (Table 3D). Although, from 1991 to 2021, CBA increased incessantly, a drastic fall in land under CBA was observed in 2023 when the land under CBA reduced from 155.97 km^2 to 96.94 km^2 within only two years and 36.76 km^2 of land under CBA had become abandoned. Some amount of land under CBA also got converted to agricultural land, other vegetation, other water bodies, and barren land.

Table 2. Accuracy assessment report of classified images.

Year	Overall accuracy (%)	Overall Kappa (K^)
1991	79.50	0.76
2001	81.31	0.78
2011	80.90	0.77
2021	83.33	0.80
2023	86.36	0.84

Table 3A. LULC transformation matrix from 1991-2001.

LULC class	Area in 2001 (km^2)								
	Abandoned aquaculture	Cropland	Aquaculture	Bare earth and sand	Built-up	Mangrove vegetation	Mixed vegetation	Other waterbody	Total area (1991)
Area in 1991 (km^2)									
Abandoned aquaculture	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cropland	0.00	207.93	10.44	0.32	1.73	0.01	40.86	4.80	266.09
Aquaculture	0.00	0.01	24.21	0.03	0.00	0.01	0.01	0.01	24.28
Bare earth and sand	0.00	0.16	0.64	0.29	0.53	0.02	0.10	0.37	2.11
Built-up	0.00	0.00	0.01	0.01	4.32	0.00	0.01	0.01	4.36
Mangrove vegetation	0.00	0.16	0.98	0.08	0.00	2.31	0.27	0.40	4.20
Other vegetation	0.00	55.73	2.75	0.17	2.44	0.08	143.35	4.15	208.67
Other waterbody	0.00	6.82	3.06	0.08	0.23	0.08	4.75	17.78	32.80
Total area (2001)	0.00	270.81	42.09	0.98	9.25	2.51	189.35	27.52	542.51

Table 3B. LULC transformation matrix from 2001-2011.

LULC class	Area in 2011 (km^2)								
	Abandoned aquaculture	Cropland	Aquaculture	Bare earth and sand	Built-up	Mangrove vegetation	Mixed vegetation	Other waterbody	Total area (2001)
Area in 2001 (km^2)									
Abandoned aquaculture	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cropland	0.00	219.97	22.88	0.02	1.46	0.01	23.83	2.64	270.81
Aquaculture	0.00	0.22	41.81	0.02	0.01	0.00	0.01	0.02	42.09
Bare earth and sand	0.00	0.35	0.20	0.20	0.01	0.05	0.06	0.11	0.98
Built-up	0.00	0.01	0.02	0.01	9.17	0.00	0.01	0.03	9.25
Mangrove vegetation	0.00	0.15	0.77	0.20	0.00	1.30	0.06	0.03	2.51
Other vegetation	0.00	56.11	2.57	0.07	6.37	0.05	122.75	1.43	189.35

Other waterbody	0.00	7.60	5.72	0.11	0.08	0.04	3.20	10.77	27.52
Total area (2011)	0.00	284.41	73.97	0.63	17.10	1.45	149.92	15.03	542.51

Table 3C. LULC transformation matrix from 2011-2021.

LULC class	Area in 2021 (km^2)								
	Abandoned aquaculture	Cropland	Aquaculture	Bare earth and sand	Built-up	Mangrove vegetation	Mixed vegetation	Other waterbody	Total area (2011)
Area in 2011 (km^2)									
Abandoned aquaculture	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cropland	0.00	183.44	70.78	0.02	4.61	0.02	22.23	3.31	284.41
Aquaculture	0.03	0.02	73.49	0.07	0.03	0.04	0.05	0.24	73.97
Bare earth and sand	0.00	0.01	0.40	0.18	0.01	0.00	0.02	0.01	0.63
Built-up	0.00	0.02	0.01	0.00	17.02	0.00	0.03	0.02	17.10
Mangrove vegetation	0.00	0.09	0.33	0.00	0.00	0.98	0.03	0.02	1.45
Other vegetation	0.00	33.30	8.63	0.00	7.38	0..02	99.62	0.99	149.92
Other waterbody	0.00	0.29	2.33	0.07	0.10	0.02	0.02	12.20	15.03
Total area (2021)	0.03	217.17	155.97	0.34	29.15	1.06	122.00	16.79	542.51

Table 3D. LULC transformation matrix from 2021-2023.

LULC class	Area in 2023 (km^2)								
	Abandoned aquaculture	Cropland	Aquaculture	Bare earth and sand	Built-up	Mangrove vegetation	Mixed vegetation	Other waterbody	Total area (2021)
Area in 2021 (km^2)									
Abandoned aquaculture	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.03
Cropland	3.18	151.01	10.32	2.02	15.01	0.00	31.12	4.51	217.17
Aquaculture	36.76	13.79	84.82	2.43	1.23	0.01	11.79	5.14	155.97
Bare earth and sand	0.01	0.01	0.01	0.31	0.00	0.00	0.00	0.00	0.34
Built-up	0.00	0.04	0.00	0.00	29.09	0.00	0.01	0.01	29.15

Mangrove vegetation	0.01	0.48	0.01	0.02	0.00	0.51	0.02	0.01	1.06
Other vegetation	0.05	41.16	1.48	0.06	10.39	0.03	66.42	2.41	122.00
Other waterbody	0.01	1.50	0.30	0.05	0.00	0.00	0.58	14.35	16.79
Total area (2023)	40.04	208.00	96.94	4.89	55.72	0.55	109.94	26.43	542.51

Table 3E. Projected LULC transformation matrix from 2023-2025.

	Area in 2025 (km^2)								
LULC class	Abandoned aquaculture	Cropland	Aquaculture	Bare earth and sand	Built-up	Mangrove vegetation	Mixed vegetation	Other waterbody	Total area (2023)
Area in 2023 (km^2)									
Abandoned aquaculture	37.76	0.41	0.40	0.01	0.01	0.00	0.90	0.55	40.04
Cropland	1.42	194.14	0.80	0.01	2.16	0.00	1.01	8.46	208.00
Aquaculture	20.17	0.74	73.34	0.01	0.03	0.00	1.49	1.16	96.94
Bare earth and sand	0.03	0.02	0.01	3.80	0.00	0.00	0.05	0.98	4.89
Built-up	0.00	0.00	0.00	0.00	55.72	0.00	0.00	0.00	55.72
Mangrove vegetation	0.00	0.01	0.00	0.00	0.00	0.07	0.01	0.46	0.55
Other vegetation	0.20	2.00	0.50	0.40	0.03	0.00	105.56	1.25	109.94
Other waterbody	1.14	0.03	0.15	0.00	0.02	0.00	0.03	25.06	26.43
Total area (2025)	60.72	197.35	75.20	4.23	57.97	0.07	109.05	37.92	542.51

3.2. Census Village-wise growth pattern of CBA

In the study area, CBA was found to be growing incessantly from 1991 to 2021. It was observed that, at the initial phase, i.e., in 1991, CBA had developed nearly at all the coastal Census Villages of Ramnagar-II and the coastal Census Villages located at the southwestern part of Contai-I CD Blocks, respectively (Fig. 3). In the following decades, CBA spread in the other Census Villages located along the coast as well as in the Census Villages located at more inland parts mainly along the tidal rivers and canals. In 2001, CBA was initiated in those areas that were located away from the coastal region and had grown along the tidal rivers and canals. In 2011, the area under CBA grew in the Census Villages where the CBA had already been established. Furthermore, CBA grew in adjacent Census Villages and spread in the more inland parts with the highest spread in the Deshapran block, where CBA got initiated in almost all Census Villages located along the Rasulpur river and had even spread in more western part as far as Chhota Kukraaul Census Village. The massive growth of aquaculture had taken place between 2011 and 2021, and CBA had grown and initiated in all the Census Villages located along the coast. Following the trend of the previous decade, the areal growth was highest in the Census Villages of Deshapran Block, where CBA had initiated in the further western side in the inland part. CBA had also spread in the extreme northern part of the study area. A drastic change in the scenario was found in 2023 when the land under CBA had been considerably reduced and a notable portion of CBA farms became abandoned. The concentration of CBA had reduced in almost all villages. In 2023, a high concentration of CBA was mainly found in the villages along the coast and a few villages in the inland part. Coastal villages in Contai-I and Deshapran still had a higher concentration of CBA, though the percentage of land under CBA in these villages had reduced than 2021.

The hot spot analysis revealed the pattern of significant clustering of villages with higher concentrations of CBA. In 1991, hot spots (with 99% Confidence Interval) were mainly found in the all-coastal villages and a few near-coastal villages of Ramnagar-II, and in the coastal villages located at the southwestern part of the Contai-I Block. In 2001, hot spots propagated along the coast and in the near coastal villages in these two CD Blocks. Hot spots emerged in the eastern part of Deshapran Block mainly along the Rasulpur river and existing canals in 2011. Along with this, significant clustering of villages with low CBA, i.e., cold spots, were found in the middle portion of the study area where the amount of built-up was higher, which was developed over the dune ridges. In 2021, hot spots had spread across more villages, and the highest spread was found in the Deshapran Block. However, a more significant clustering of cold spots appeared in the middle portion of the study area. In 2023, the concentration of CBA reduced, and hot spots were found mainly in the coastal and near-coastal villages (Fig. 4). It is noteworthy to mention here that the Z score values were 11.20, 17.17, 23.44, and 27.97 for the years 1991, 2001, 2011, and 2021 respectively, which denoted that CBA continued to cluster more intensely up to 2021. However, the Z score value for the year 2023 decreased to 20.20 denoting a decrease in the clustering of CBA. Nonetheless, p values for all the cases were statistically significant (*p* <0.05) and Z scores were positive (Supplementary Table 2). This indicated more significant spatial clustering and fewer chances of spatial randomness (Badlowski et al., 2021).

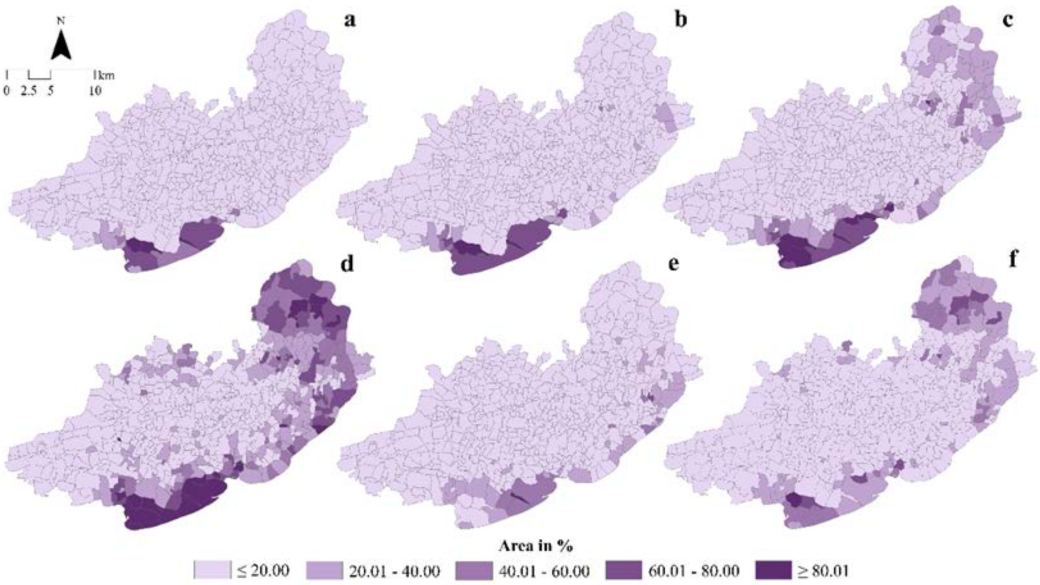

Figure 3. Census Village-wise percentage of area under aquaculture for the year (a) 1991, (b) 2001, (c) 2011, (d) 2021, (e) 2023, and predicted for the year (f) 2025

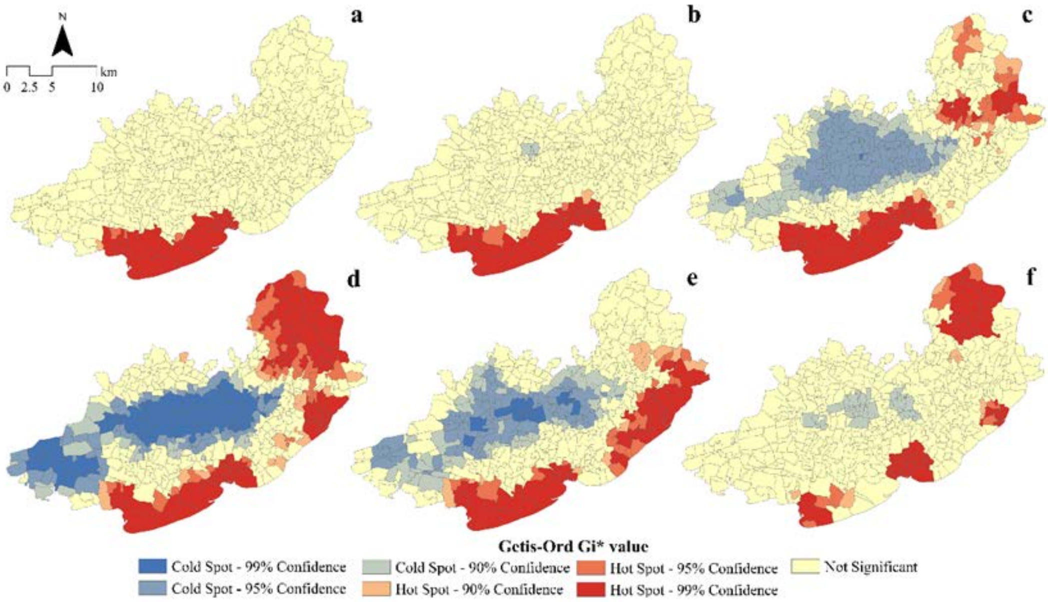

Figure 4. Spatial distribution of aquaculture hotspots for the year (a) 1991, (b) 2001, (c) 2011, (d) 2021, (e) 2023, and predicted for the year (f) 2025

3.3. Patch dynamics of CBA

To assess the growth pattern of CBA, the output of patch level and class level metrics of the three CD Blocks of the study site had been intensively analyzed. At the patch level, the mean AREA metric of Contai-I had decreased from 5.25 ha to 1.65 ha and it had again increased to 2.97 ha in 2023. Similarly, the largest patch AREA value (332.55 ha) came down to 40.05 ha only in a span of two years. The same trend can be noticed regarding maximum PERIM values, where there had been a constant increase (from 15060 m to 42600 m), followed by a huge fall to 8580 m. The mean values of the SHAPE metric depicted a drop in the first four decades (1.33 to 1.20), followed by a rise (1.30) in 2023. The same trend can be observed with regard to the SHAPE metric in Ramnagar-II. However, a steady notable rise in the SHAPE metric (1.16 to 1.40) can be noticed in Deshapran. Here, the mean AREA metric had constantly increased from 0.33 ha in 1991 to 4.68 ha in 2021, thereafter falling to 3.10 ha in 2023. The maximum PERIM values rose from 3660 m to 527820 m, thereby dropping to 397080 m. However, the mean PERIM values depicted a notable rise from 267.50 m to 1141.16 m. In Ramnagar-II, the mean AREA metric had sharply declined from 13.48 ha to 3.75 ha (Table 4A). Similarly, the largest patch AREA value (3708.45 ha) came down to 435.15 ha only. The mean PERIM values depicted a declining pattern (1082.71 m to 79537 m) followed by an upsurge (1052.62 m). In this CD Block, the maximum PERIM values increased gradually between 1991 and 2021 (112440 m to 151920 m) and then fell to 108720 m in 2023.

Regarding the class level metrics, results revealed that from 1991 to 2021, the changing patterns of the CBA and the entire study region were consistent, and became more fragmented and dispersed. However, the scenario got reversed for the year 2023. The absolute values of CA for CBA increased rapidly suggesting an increased area and landscape heterogeneity, with the changing decades (from 236.07 ha to 2741.49 ha in Contai-I; from 31.23 ha to 7622.10 ha in Deshapran; from 2235.96 ha to 4313.25 ha in Ramnagar-II), up until the year 2023, when it fell to 1336.50 ha, 4657.21 ha, and 2102.40 ha respectively. (Table 4B). From 1991 to 2021, large areas of CBA have appeared, evident in the increasing PLAND for all the CD Blocks. After 2021, the metric reduced notably, reaching 6.80% in Contai-I, 25.32% in Deshapran, and 12.95% in Ramnagar-II. Both NP and PD values (per 100 ha) have recorded a steep rise since 1991 in Contai-I and Deshapran, thereby indicating an augmented area and landscape heterogeneity. However, both the values for these two CD Blocks fell sharply in the year 2023 (NP: 813 and 1503; PD: 4.14 and 8.17, respectively). The scenario is different for Ramnagar-II where a constant rise in NP and PD values can be noticed. LPI values have constantly increased over time (1991-2021), pointing towards the development of larger and combined patches in all the CD Blocks, i.e., the CBA patches were broken first and then aggregated and again broke in 2023. However, AREA_MN in Deshapran has continuously increased since 1991, suggesting that although large areas of CBA patches are fragmented, they have not disappeared. An opposite condition has been noticed in the other two CD Blocks with a steady fall in CBA patches since 2001. FRAC_MN values have depicted a very minute growth which could possibly lead to the development of shape complexity over time. The patch complexity has also been analyzed with the PARA_MN metric and it showcased falling values for the three CD Blocks from 1991-2023 demonstrating the presence of less dispersive patches. Regarding the metrics of agglomeration, LSI statistics depicted the emergence of amorphous patches from 2001 to 2023 in Deshapran and Ramnagar-II. In the case of Contai-I, disaggregation was initiated in 1991 (7.17) and continued up to 2021 (41.13), post which there was a direction towards aggregation with values falling to 36.39 in 2023. High PLADJ values reveal maximum agglomeration, however decreasing values in Contai-I (85.93 in 1991 to 70.10 in 2023) and Ramnagar-II (92.77 in 1991 to 78.93 in 2023) reveal a discontinuous pattern of CBA development. Nevertheless, ever-increasing values in the last 30 years (1991-2021) from 38.33 to 83.73 indicate continuous CBA patches with the commencement of relative disaggregation in 2023. Overall, the changing trend of landscape indices mirrors the loss, fragmented, and complicated nature of CBA across the study area under consideration.

Table 4A. Comparison of landscape metrics at patch level from 1991 to 2023.

CD Block	Year	Patch metric								
		Area (ha)			PERIM (m)			SHAPE		
		Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Contai-I	1991	0.09	162.99	5.25	120	15060	984	1.00	5.19	1.33
	2001	0.09	202.23	2.22	120	20100	524.88	1.00	3.53	1.21
	2011	0.09	271.53	1.45	120	26340	430.79	1.00	3.99	1.17
	2021	0.09	332.55	1.65	120	42600	519.64	1.00	5.82	1.20
	2023	0.09	40.05	2.97	120	8580	840.00	1.00	3.33	1.30
Deshapran	1991	0.09	8.46	0.33	120	3660	267.50	1.00	3.05	1.16
	2001	0.09	99.99	1.47	120	22680	505.40	1.00	8.04	1.19
	2011	0.09	205.11	1.59	120	44520	570.76	1.00	8.73	1.24
	2021	0.09	3517.83	4.68	120	527820	1015.69	1.00	22.21	1.24
	2023	0.09	1528.29	3.10	120	397080	1141.16	1.00	25.36	1.40
Ramnagar-II	1991	0.09	1854.72	11.24	120	112440	1082.71	1.00	6.51	1.23
	2001	0.09	2522.43	13.48	120	139980	1056.31	1.00	6.96	1.21
	2011	0.09	2936.97	8.79	120	146100	870.53	1.00	6.73	1.26
	2021	0.09	3708.45	8.91	120	151920	795.37	1.00	6.24	1.19
	2023	0.09	435.15	3.75	120	108720	1052.62	1.00	12.76	1.34

AREA: patch area; PERIM: patch perimeter; SHAPE: shape index

Table 4B. Comparison of landscape metrics at class level from 1991 to 2023.

CD Block	Year	Class metric									
		CA	PLAND	NP	AREA_MN	LPI	FRAC_MN	PARA_MN	PD	LSI	PLADJ
Contai-I	1991	236.07	1.20	45.00	5.25	0.83	1.05	1045.72	0.23	7.17	85.93
	2001	536.04	2.73	242.00	2.22	1.03	1.04	1060.91	1.23	13.66	82.23
	2011	1021.23	5.19	706.00	1.45	1.38	1.04	1039.64	3.59	23.69	77.66
	2021	2741.49	13.94	1662.00	1.65	1.69	1.04	976.78	8.45	41.13	76.37
	2023	1336.50	6.80	813.00	1.64	1.00	1.05	941.70	4.14	36.39	70.10
Deshapran	1991	31.23	0.17	96.00	0.33	0.05	1.03	1166.14	0.52	11.26	38.33
	2001	928.08	5.04	633.00	1.47	0.54	1.04	1021.38	3.44	26.14	74.15
	2011	2893.95	15.73	1818.00	1.59	1.11	1.04	990.03	9.88	48.17	73.11
	2021	7622.10	41.43	1628.00	4.68	19.12	1.04	1021.22	8.85	47.27	83.73
	2023	4659.21	25.32	1503.00	3.10	8.31	1.06	996.88	8.17	62.69	72.39
Ramnagar-II	1991	2235.96	13.78	199.00	11.24	11.43	1.04	1105.12	1.23	11.36	92.77
	2001	2628.09	16.19	195.00	13.48	15.54	1.04	1030.89	1.20	10.04	94.12
	2011	3278.79	20.20	373.00	8.79	18.09	1.04	1014.73	2.30	14.17	92.57
	2021	4313.25	26.57	484.00	8.91	22.84	1.04	965.50	2.98	14.65	93.31
	2023	2102.40	12.95	561.00	3.75	2.79	1.05	981.84	3.46	32.16	78.93

CA: total class area; PLAND: percentage of landscape; NP: number of patches; AREA_MN: mean patch area; LPI: largest patch index; FRAC_MN: mean fractal dimension index; PARA_MN: mean perimeter-area ratio; PD: patch density; LSI: landscape shape index; PLADJ: percentage of similar adjacency

3.4. Modelled CBA spread pattern in 2025

The LULC scenario of the study region had been predicted using a multi-parameter-based model (Fig. 2f). The simulations have directed towards a steady growth in all the LULC classes barring aquaculture, cropland, and bare earth and sand. A notable loss of area in CBA has been projected at 75.20 km^2, representing a reduction of 4.01% (~ loss of 21.74 km^2 area) from the 2023 context. The greatest decline has been observed in the southern section of Ramnagar-II followed by the northeastern portion of Deshapran. This loss can be attributed to the predicted rise of abandoned aquaculture by 3.81% and other water bodies by 2.12% (Table 5). Furthermore, the model denotes that there has been a maximum conversion of CBA to abandoned aquaculture which could probably be due to a multitude of reasons, including recurrent bouts of diseases, swelling production costs, and a sharp drop-in market rate. Contai-I, on the other hand, also portrays plummeting in the CBA area, but not as much as the other two CD Blocks under consideration. This showcased that the diminution of the CBA area would be foreseeable in the long run; other waterbodies along with expansion in abandoned aquaculture would be expected to continue for the next few years at the expense of other LULC classes (cropland, mangroves, and other vegetation).

Table 5. LULC statistics for the predicted scenario of 2025.

LULC class	Area (km^2)	Area (%)
Abandoned aquaculture	60.72	11.19
Cropland	197.14	36.38
Aquaculture	75.20	13.86
Bare earth and sand	4.23	0.78
Built-up	57.97	10.69
Mangrove vegetation	0.07	0.01
Other vegetation	109.05	20.10
Other waterbody	37.92	6.99

4. Discussion

4.1. Consequences of CBA growth

The global demand for shrimp, especially in the USA, Japan, and the EU, has led to a surge in cultured shrimp aquaculture in tropical coastal areas (Stonich & Bailey, 2000; Hossain et al., 2013; Galappaththi & Nayak, 2017). This has resulted in a 34% increase in global production between 2002 and 2008, benefiting marginal farmers in infertile coastal lands with high salinity (Hossain et al., 2013; Salunke et al, 2020). CBA growth in developing countries attracted national and international investors (Béné, 2005).

Despite its commendable contribution to social and economic well-being, the development of CBA in the coastal areas of the tropics remained fraught with controversies owing to the perpetual degradation it has wrought on the environment and society (Béné, 2005). Coastal brackishwater aquaculture, particularly commercial shrimp farms, has caused water and soil contamination due to excessive use of chemical pesticides and poor feed quality. Effluents released from these farms also cause high pollutant and silt loads in estuaries, causing severe damage to ecosystems. The expansion of CBA has led to the annihilation of mangroves in countries like Thailand, the Philippines, Indonesia, Honduras, Bangladesh, and India (Hall, 2003; Pokrant, 2009; Hossain et al., 2013). Lax management, including high stocking density, overuse of chemical fertilizers, and pesticides, and irrational use of antibiotics, makes commercial shrimp farming susceptible to frequent disease outbreaks. The shrimp cultured in Third World countries were aimed at exporting to the developed world, unable to address the food security issue of native dwellers (Stonich and Bailey, 2000; Hall, 2003; Hossain et al., 2013). Most of the revenue from the farms was added to urban capital, depriving rural areas. The practice has also challenged the availability of common property resources, introduced food insecurity, exposed the rural community to global market fluctuation, altered social structures, and propagated marginalization of the native rural community (Stonich and Bailey, 2000; Hall, 2003; Hossain et al., 2013; Bush & Marschke, 2017). Similar environmental and social threats have been found in the states of South and South East coastal regions of India including the study area (Pradhan & Flaherty, 2007; Dutta et al., 2016; Rajesh et al., 2016). Major landscape transformation had taken place in the coastal areas of Purba Medinipur district owing to the brisk growth of CBA (Dutta et al., 2016; Ojha & Chakrabarty, 2018). In the study area, between 1991 and 2021 the proportion of land under CBA had grown at an exponential rate at the cost of cropland, coastal mangroves, other vegetation, waterbodies, and fallow lands.

This rampant growth has also brought about considerable damage to the existing natural resources and the ecology of the surrounding region in general. A notable increase in soil salinity and soil pH in the areas encompassing the CBA ponds had a debilitating impact on rice productivity (Ojha & Chakrabarty, 2018; Roy et al., 2020) which has further provoked the crop farmers either convert their lands to CBA farms or to lease out their lands to the CBA farmers. This has adversely impacted the food security of the otherwise crop-culture-based marginal rural community. Since pond management was a major challenge for the shrimp farmers, small ponds were preferred over larger ones instead of high demand. To reap higher profits from the small ponds, farmers preferred high stocking density (Islam et al., 2005). However, this trend of highly intensive culture and unhygienic practice of culture has led to water pollution Direct disposal of this polluted water without treatment to the rivers, creeks, and canals has induced water pollution in natural waterbodies (Salunke et al., 2020). The same scenario has been observed in the present study region as well (Roy et al., 2021a).

4.2. Recent trend of decline in CBA practice

Various global surveys indicated that the commercial shrimp production in 2023 was 0.04 percent less than the normal production. In southeast Asia, there was a 3 percent reduction (Jory, 2023). In India, the considerable decrease of land under CBA and their transformation to abandoned land in 2023 can be validated by the 3% reduction in the national shrimp production rate between 2022 and 2023. This had happened due to multiple causes including climate vagaries eliciting multiple virus infestations like white spot syndrome virus (WSSV), Enterocytozoon hepatopenaei (EHP), white feces syndrome (WFS), infectious myonecrosis virus (IMNV), etc., the increasing cost of production, and a sharp decline in market rate in 2022 (Aqua Culture Asia Pacific, 2023). Since 2021 (post Covid-19 pandemic), a sharp decline in market rate has been caused due to lower demand from the United States, and European Union as well as China which were the three major shrimp exporting countries of India. Furthermore, Ecuador has become a major competitor for India in China's shrimp import market which flooded the international market with shrimp at a much cheaper rate than India. Thus, India's seafood export market has been facing a dual crisis of a 20-30 % decline in international market demand and a 20-25% fall in global price rate. Additionally, global inflation and multiple economic aftermaths of the Russia-Ukraine war including a sharp increase in energy prices caused an increase in production costs and a decrease in market price (Dao, 2022; Pijl, 2022; Cliff White, 2023, Rajani & Balasubramanian, 2023). As a result, a huge number of farmers faced massive economic loss which made them get into the vicious cycle of indebtedness, which has waned the eagerness of the farmers to initiate the production cycle in 2023 (Salunke et al., 2020). This has resulted in the abandonment of a considerable amount of CBA farms in India (Dao, 2022; Datta et al., 2022). India's leading shrimp-producing states, Andhra Pradesh and West Bengal, have experienced a sharp decrease in area under CBA and production since 2021 (Dao, 2022; Chu Se Pepper, 2022; Rajani & Balasubramanian, 2022; Rajani & Balasubramanian, 2023). This is mainly due to a decrease in market demand, lower prices, and increased production costs, leading to crop failures and abandonment of CBA farms (Murali, 2023; Rajani & Balasubramanian, 2023). About 50% of farmers stopped stocking their farms in anticipation of loss and fear of indebtedness. To make CBA economically more viable and ecologically sustainable, policy guidelines need to be developed, addressing place-specific uncertainty and regulatory barriers. This includes fostering policies at the state level to address water pollution, habitat degradation, biodiversity loss, and climate mitigation. Policy mandates for restorative aquafarming should be facilitated, and green licensing systems should be implemented. Additionally, emission reduction, treatment management, and locally-led adaptations are recommended.

5. Conclusions

This study was chiefly based on the assessment of the growth trajectory of the CBA in the Purba Medinipur coastal plain, India. The novelty of the research lies in the fact that the work was conducted by the integration of geostatistics and landscape metrics along with geospatial technology in the Indian context which in turn provided a comprehensive and systematic approach to understanding the spatial patterns and dynamics of CBA expansion and/or reduction. The incorporation of this landscape metric approach furnished the analysis with a spatial perspective, going beyond the simple area-based assessments. The major finding was that the area under CBA was continuously growing throughout the entire region in the last three decades. However, an extreme alteration in the scenario could be noticed in the present year, wherein the land under CBA was reduced substantially and a notable portion of CBA farms became abandoned. Significant clusters with greater CBA concentrations along shorelines gradually shifted to built-up areas, demonstrating the havoc landscape modification caused by farm fragmentation. Farmers and the nearby towns that depend on this industry have suffered financial losses as a result of the amplified degree of landscape alteration and subsequent drop in the CBA area. Farmers' incomes have declined as a result of this deterioration, and the overall economic growth of the region has slowed down. The mammoth conversion of the CBA farms to abandoned aquaculture farms has led to an upsurge of unproductive land. Owing to the already existing high saline conditions, these lands can also not be converted to croplands, thereby affecting the food security of the local populace. In this context, it was apprehended that realistic paths need to be explored to make CBA farming both ecologically sustainable and economically feasible. Aquaponics (coupling of aquaculture and hydroponic farming) can be introduced which in turn could contribute to food security, diversification, and resource efficiency. Additionally, the initiation of crab fattening in abandoned aquaculture farms could offer opportunities for income generation and diversification in the aquaculture sector. The local government should encourage the residents of coastal areas to manage resources sustainably. In a nutshell, to follow the path of sustainable land management in this vulnerable coastal environment, both stakeholders and governing bodies need to be more aware of the environmental carrying capacity by maintaining anthropogenic modification up to its optimal limit and by introducing holistic management strategies. In this regard, the present study tried to abridge the persisting research gap in empirical data availability, especially regarding changing coastal landscapes and related socio-economic and environmental impacts which will be crucial in national to regional level policy planning and sustainable coastal management. However, it needs to be validated across contrasting socio-ecology in a global perspective to understand the dimensions of problems through comprehensive research.

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