Integrated Environmental Assessment and Management — Volume 16, Number 5—pp. 773–787
Received: 27 February 2020 | Returned for Revision: 13 April 2020 | Accepted: 4 May 2020

Ecosystem Services

Identification of Conservation Priority Zones Using Spatially Explicit Valued Ecosystem Services: A Case from the Indian Sundarbans

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ABSTRACT

Demarcation of conservation priority zones (CPZs) using spatially explicit models is the new challenge in ecosystem services (ESs) research. This study identifies the CPZs of the Indian Sundarbans by integrating 2 different approaches, that is, ESs and ecosystem health (EH). Five successive steps were followed to conduct the analysis: First, the ESs were estimated using biophysical and economic methods and a hybrid method (that combines biophysical and economic methods); second, the vigor–organization–resilience (VOR) model was used for estimating EH; third, the risk characterization value (RCV) of ESs was measured using the function of EH and ESs; fourth, Pearson correlation test was performed to analyze the interaction between ESs and EH components; and fifth, the CPZs were defined by considering 7 relevant components: ecosystem vigor, ecosystem organization, ecosystem resilience, RCV, EH, ESs, and the correlation between EH and ESs. Among the major ecoregions of the Sundarbans, the highest ESs value in economic terms is provided by the mangrove ecosystem (US$19 144.9 million per year). The highest conservation priority score was projected for the Gosaba block, which is dominated by dense mangrove forests. The estimated CPZs were found to be highly consistent with the existing biodiversity zonations. The outcome of this study could be a reference for environmentalists, land administrators, researchers, and decision makers to design relevant policies to protect the high values of the Sundarbans ecosystem. *Integr Environ Assess Manag* 2020;16:773–787. © 2020 SETAC

Keywords: Conservation priority zones   Ecosystem services   InVEST   Ecosystem health   Nature's value

INTRODUCTION

Ecosystem services (ESs) are the bundle of ecosystem goods and services that provide benefits to human subsistence and welfare (Costanza et al. 1997). In order to understand and communicate why ESs are so important, we need to understand and provide a measure for their impacts on local livelihoods (Wang et al. 2018; Zhang, Song et al. 2018). Ecosystem service values (ESVs), through proper evaluation and quantification, could be a useful tool for land administrators and policy makers to design and support suitable land resource conservation and management plans to strengthen and protect ecosystems and natural capital and to improve the socioecological status of an ecological priority zone (Costanza et al. 2014; Sannigrahi, Zhang, Joshi et al. 2020).

Demarcation of conservation priority zones (CPZs) using spatially explicit modeling has been the new challenge in ESs research (Lin et al. 2017; Hou et al. 2018; Qin et al. 2019). In most cases, traditional conservation strategies have focused solely on species diversity, richness, and habitat conservation (Brooks et al. 2006). Several studies have considered the ESs approach to spatially define CPZs (Lin et al. 2017; Hou et al. 2018; Qin et al. 2019). Accurate quantification of ESs

This article contains online-only Supplemental Data.
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Published 14 May 2020 on wileyonlinelibrary.com/journal/ieam.

DOI: 10.1002/ieam.4287

could be relevant for integrating ESs into the decision making for natural conservation policies (Burkhard et al. 2013; Crossman et al. 2013). Challenges still remain in order to include ESs values in decision making (Ruckelshaus et al. 2015). Therefore, it is essential to explore methods for integrating ESs and ESVs approaches into effective conservation practices to offer cost-effective solutions to decision makers and environmental practitioners.

Several studies have evaluated the effectiveness of ESs for demarcating spatially explicit CPZs. Baral et al. (2014) suggested that mapping and spatial quantification of ESVs are highly effective in identifying ecologically sensitive regions. The Baral et al. (2014) study also reported that conservation assessment that relied solely on habitat conservation might not be effective for conservation planning. Manea et al. (2019) evaluated the usability of ESs-based conservation priority assessment for demarcating Marine Spatial Planning (MSP) zones, which highlights the importance of spatially explicit quantification of ESs in the planning and conservation of marine protected regions. Zhang, Xu et al. (2018) found that both biodiversity and ESs valuation are instrumental for the conservation of protected regions. The authors had examined the collective effects of these 2 components for identifying the suitable conservation areas for giant panda in China and found that the regions with higher habitat suitability for giant panda are positively associated with the distribution of ESs. Scolozzi et al. (2014) performed a Strengths Weaknesses Opportunities and Threats (SWOT) analysis for evaluating the effectiveness of ESs-based conservation prioritization. Three biogeographical regions, that is, Alpine, Continental, and the Mediterranean, were considered for this evaluation, and the Alpine site was found to exhibit higher opportunities and strengths compared to Continental and Mediterranean experimental sites (Scolozzi et al. 2014). Turner et al. (2012) evaluated the flow of ESs and its association with the global distributions of biodiversity, physical, and socioeconomic causative factors and observed that the top 25% CPZs could provide 56% to 57% of benefits in terms of necessary ESs. The integrated cost–benefit analysis of the Turner et al. (2012) study suggests that the aggregate benefits derived from biodiversity conservation are 3 times the estimated opportunity costs. Verhagen et al. (2017) mapped the ESs demand and capacity of C sequestration, flood regulation, air quality, pollination, and urban leisure services at multiple spatial scales in the European region and suggested that flow of ESs capacity or demand should be the key factor for identification of ESs priority areas. Several other studies have evaluated the effectiveness of ESs-based conservation zonation for water resources management (Fan and Shibata 2014), environmental policy and decision making (Izquierdo and Clark 2012; Qu and Lu 2018), ecosystem health (EH) and habitat quality assessment (Duarte et al. 2016), and soil conservation and land degradation (Li et al. 2017).

Several methods have been developed in the last 2 decades to evaluate and quantify the spatially (in)explicit ESVs at many ecosystem scales. Of these methods, the benefits transfer approach proposed by Costanza et al. (1997, 2014) has become the most popular due to its simple adaptability and straightforward calculation. However, this approach has proven to be ineffective in many cases while explaining the spatial variation of ESVs because it is based on spatially homogenous benefit transfer from source site to experimental site (Sannigrahi et al. 2018). Broadly, the quantification of ESs can be categorized into 2 types: 1) unit price–based evaluation and 2) area-based valuation. The unit price method is suitable for the regional- and local-level ESs valuation. This method is based on a simple linear association between ESs and several ecological components, whereas the area value method is based on direct benefit transfer approach and suitable for large-scale assessments (Fang et al. 2018). Furthermore, Kumar (2010) categorized 3 major groups of approaches for the valuation of ESs. These include 1) direct market valuation approaches, for example, market price approach, cost-based approach (damage cost, avoided cost, replacement cost, restoration or mitigation cost), and production-based approach (production function and factor income); 2) revealed preference approaches, for example, travel cost method and hedonic pricing; and 3) stated preference approaches, for example, contingent valuation method (willingness to pay, willingness to accept), and payment for ecosystem services (Zhang et al. 2019), choice modeling and conjoint analysis, and group valuation. However, none of these valuation approaches are free from the expected uncertainties (information failure, market failure, institutional failure) that exist in the valuation process (Turner and Daily 2008; Tallis and Polasky 2009).

The main research question of the present study is this: What is the relevance and potential for implementation of ESs valuation approaches in identifying spatially explicit CPZs of a natural reserve region with limited data availability? To address the research question, we defined 4 main research objectives: 1) to estimate the biophysical and economic values of relevant ESs of the Sundarbans, 2) to evaluate the status and health of the ecosystem using the spatially explicit vigor–organization–resilience (VOR) model, 3) to evaluate synergies and trade-offs between EH and ESs, and 4) to identify the CPZs of the Indian Sundarbans. In the present study, a substantial difference between the biophysical and economic valuation approaches was observed. This means that the 2 valuation methods tend to provide divergent perspectives for ecosystem service valuation, each of which should be associated with uncertainties and biases. This could be a reason for considering a variety of approaches and methods for evaluating and quantifying spatially explicit ESs.

MATERIAL AND METHODS

Study area

The Sundarbans is known for its biodiversity and ecological richness, which makes it one of the world's biodiversity hot spots. The Sundarbans mangrove is the world's largest single intact mangrove forest (Mitra et al. 2012). Due

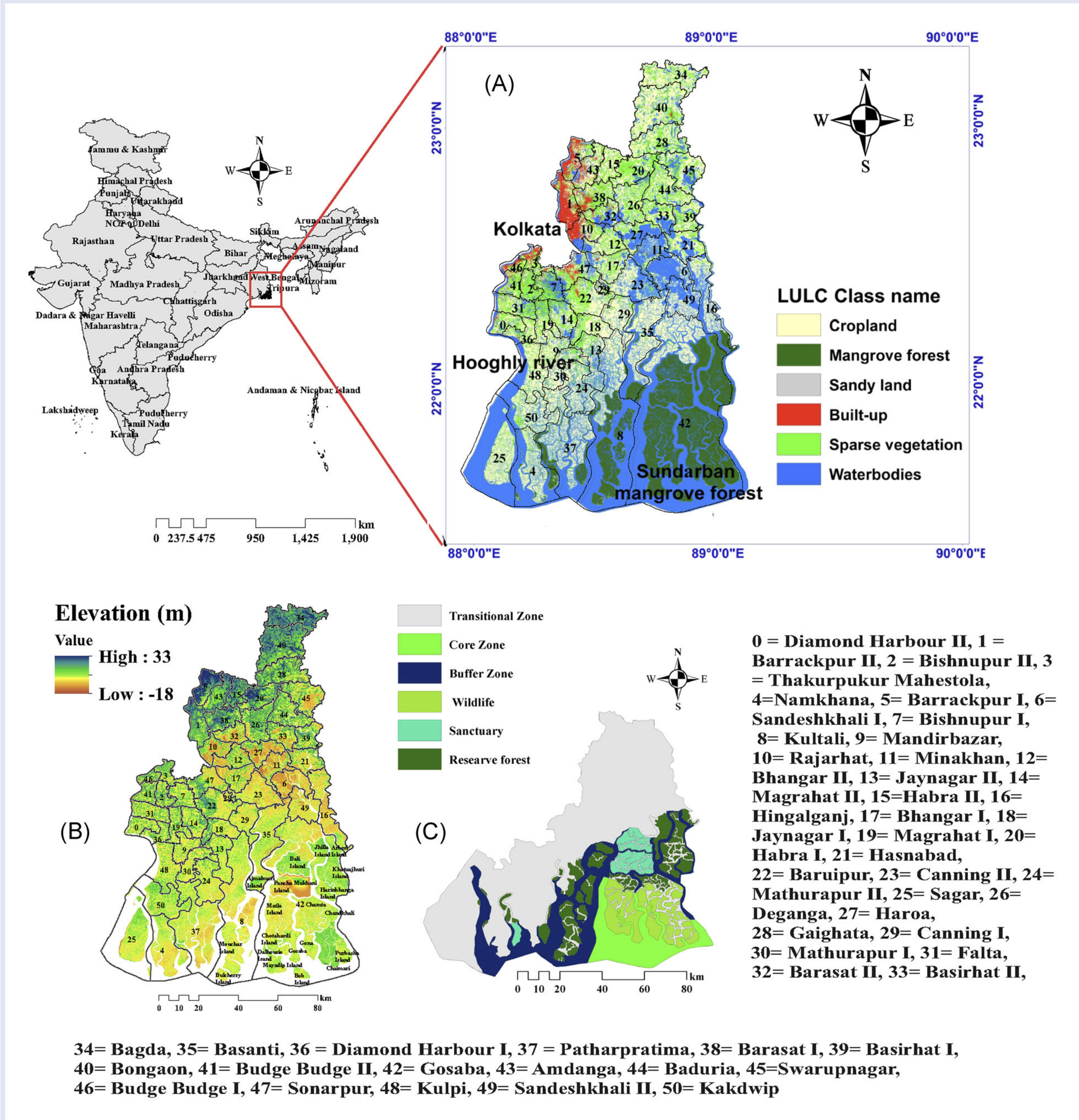

Figure 1. Study area map shows the land use land cover (LULC) (A); elevation (m) (B); and major ecoregions of the Indian Sundarbans (C).

to its ecological and environmental importance, this vibrant ecosystem is designated as a Ramsar site by labeling this ecosystem a "Wetland of International Importance" (https://rsis.ramsar.org/ris/2370), and it was declared a United Nations Educational, Scientific and Cultural Organization (UNESCO) World Heritage Site in 1987 (https://whc.unesco.org/en/list/798/). Additionally, the Sundarbans mangroves are the world's largest coastal wetland ecosystem, which lies in the convergence of the Ganga, Brahmaputra, and Meghna rivers and covers nearly 10 000 km^2 (62% in Bangladesh and 38% in India). This ecosystem comprises various physiographic features, including sand beaches, tidal creeks and inlets, sand flats, mudflats, dunes, estuaries, salt marshes, and mangrove littoral swamps (Figure 1). The elevation of the Sundarbans ranges from 3 to 8 m from sea level (Ray et al. 2014). The dominant mangrove species are *Avicennia alba*, *Avicennia marina*, and *Avicennia officinalis*. The Indian Sundarbans comprised of 102 islands, of which 54 are suitable for human habitation, 48 are not inhabited (Mitra et al. 2012).

Data source and preprocessing

The open-accessed Landsat archived remote sensing data have been widely used for land use and land cover analyses

(Woodcock et al. 2008; Liu et al. 2019). The geometrically and radiometrically adjusted Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper (ETM), and Landsat Operational Land Imager (OLI), and Thermal Infrared Sensor (TIRS) data products were used for classifying the region into several ecoregions. For land-use land-cover (LULC) classification and subsequent analysis, we adopted supervised machine learning models including artificial neural network (ANN), Bayes, decision tree (DT), gradient boosted tree (GBT), linear discriminant analysis (LDA), k-nearest neighbor (KNN), maximum likelihood classifier (MLC), random forest (RF), and support vector machine (SVM). The classification of LULC, postprocessing, and accuracy assessment of thematic layers are discussed in detail in Sannigrahi, Chakraborti et al. (2019). The entire region was classified into cropland, mangrove, water bodies (inland wetland and coastal estuary), urban land, mixed vegetation, and sand beach. The boundary clean and majority filter were applied to remove isolated pixels from the classification outputs. Time series Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) estimates for 2000 to 2017 were approximated from MOD13Q1 16-d composites, which were retrieved from the University of Natural Resources and Life Sciences, Vienna, Austria (http://ivfl-info.boku.ac.at/). The initial 16-d MOD13Q1 NDVI/EVI scenes were converted to annual units using the ArcPy python package module. The climatic variables, including maximum temperature (°C), minimum temperature (°C), average temperature (°C), precipitation (mm), latent heat ($W \cdot m^{-2} \cdot s^{-1}$), sensible heat ($W \cdot m^{-2} \cdot s^{-1}$), incoming solar radiation (W/m^2), actual and potential evapotranspiration (mm), surface runoff (mm), soil moisture (mm), vapor pressure (kPa), vapor pressure deficit (kPa), and climate water deficit (mm), were collected from TerraClimate (http://www.climatologylab.org/terraclimate.html). The real values of these climatic variables were retrieved based on their corresponding biophysical conversion factors. A spatially explicit Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model (Sharp et al. 2020), developed by Stanford University, was used in the present study for biophysical quantification of ESs. The InVEST model uses maps as an input variable and produces spatially explicit maps as the outcome of the model. This model has been used extensively in mapping and valuation of natural goods and services at multiple scales. The InVEST model generally produces the estimate in both biophysical (e.g., tons of C sequestered) and economic (e.g., monetary value of that sequestered C) terms (Sharp et al. 2016). The input variables for the InVEST model, including C pool, root depth, plant available water content, soil texture, soil organic C, elevation, and slope, were retrieved from the Food and Agriculture Organization (FAO) Harmonized World Soil Database v 1.2 (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/), National Bureau of Soil Survey and Land Use Planning (NBSS&LUP) (https://nbsslup.in/), and Shuttle Radar Topography Mission (SRTM) (http://srtm.csi.cgiar.org/).

Methodology

Quantification of ESs. In the present study, 3 groups of approaches, including biophysical, economic, and hybrid, were adopted to quantify the biophysical and monetary values of key ESs in the Sundarbans region. The hybrid ESs valuation method proposed in the present study is an integration of the biophysical and economic methods. Additionally, diverse quantification approaches (e.g., spatially explicit biophysical models, equivalent weight and value coefficient methods, benefits transfer method, InVEST model) have been considered for quantification and valuation of ESs (Figure 2). Several ESs, including biological control (BC), climate regulation (CR), cultural (CUL), disturbance regulation (DR), genetic services (GEN), gas regulation (GR), habitat service (HA), nutrient cycling (NC), raw material production (RM), water supply (WS), and waste treatment (WT), were considered for evaluation. Additionally, using the InVEST module, the biophysical values of C storage (CS), N export (N_Exp), P export (P_Exp), sediment export (SED_Exp), and sediment retention (SDR) services were calculated.

Estimating biophysical values of ESs. The biophysical values of multiple ESs were calculated based on the modeling of Net Primary Productivity (NPP). The NPP is the C biogeochemical process, and it denotes the amount of gaseous C sequestered by green vegetation (Sannigrahi 2017). The spatiotemporal NPP was estimated at the pixel level using 5 ecosystem models, including Carnegie-Ames-Stanford Approach (CASA) (Potter et al. 1993), Eddy Co-variance Light Use Efficiency (EC-LUE) (Yuan et al. 2007), Global Production and Efficiency Model (GLO-PEM) (Prince and Goward 1995), Moderate Resolution Imaging Spectroradiometer Model (MOD17) (Zhao et al. 2006), and Vegetation Photosynthesis Model (VPM) (Xiao et al. 2004). The biophysical values of BC, CR, DR, GR, NC, RM, WS, and WT were quantified from the results of NPP as well as other biophysical inputs (e.g., precipitation, evapotranspiration, runoff, elevation, slope, water body occupancy ratio) (Barral and Oscar 2012). The performances of the 5 NPP models were assessed to identify the best model for the calculation of the biophysical values of ESs. Proxies, such as C tax (Ricke et al. 2018), social cost of C (Song et al. 2015; Song and Deng 2017; Ricke et al. 2018), price of C (Song et al. 2015; Song and Deng 2017), price of O (Song et al. 2015; Song and Deng 2017), cost for dam construction (Barral and Oscar 2012; Kibria et al. 2017; Zhang et al. 2017), price of nutrients (Ray et al. 2014; Kibria et al. 2017; Ray and Jana 2017; ICAR-IISS 2020), were used to quantify the biophysical values of ESs. The biophysical estimate of CS, N_Exp, and P_Exp, SED_Exp, and SDR services were calculated using the InVEST model.

Estimating economic values of ESs. The economic values of ESs were quantified using 5 successive steps: 1) determining equivalent weight coefficient, 2) parameter adjustment and rectification, 3) determining standard invariant equivalent value factor, 4) dynamic correction and comparable

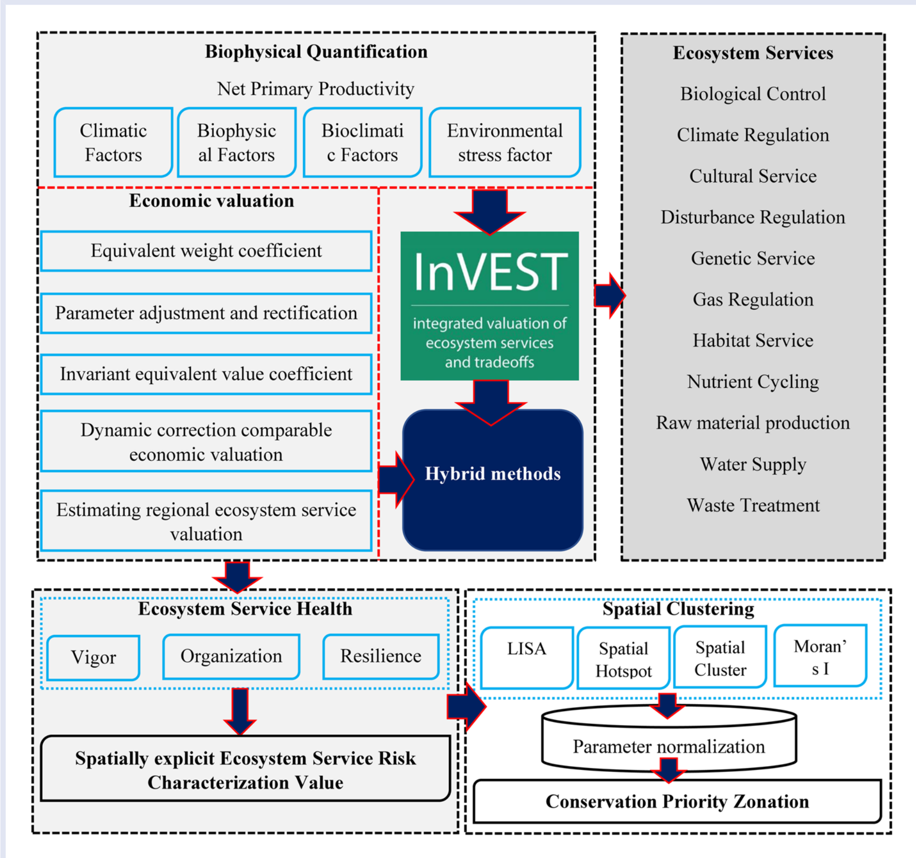

Figure 2. Methodological flowchart showing the linkages of components used in this research for delineating conservation priority zones of the Indian Sundarbans.

economic valuation, and finally 5) estimating regional economic service (ES) values using adjusted coefficients, which have been discussed in detail in an earlier study (Sannigrahi, Chakraborti et al. 2019). The global equivalent weights developed by Costanza et al. (1997, 2014) were adopted to measure the adjusted equivalent weight coefficient of each ES. Among all of the ESs, the food production service of cropland is the most direct ES. Hence, the weight coefficient of food production service of cropland was used as the base for estimating the weight coefficients of the other ESs. Several biophysical and climatic dynamic correction factors (NPP, NDVI, crop yield, precipitation, fractional vegetation cover [FVC], and NPP/NDVI) were used for adjusting the global weight coefficients and estimating local- or regional-level ESs. The historical crop production and yield statistics values of the Sundarbans were retrieved from district statistical handbook, provided by the Department of Planning & Statistics, Government of West Bengal (https://www.wbpspm.gov.in/). Subsequently, the per-unit economic value of the food production service of cropland was quantified, assuming that the projected monetary value of food production service is one-seventh of the real food production (Xie et al. 2008). The monetary values of the other ESs were projected based on the per-unit values of food production services of cropland. Additionally, several economic dynamic factors, including Pearl's S-shaped growth curve (PGC) model (Fu et al. 2016), Engel coefficient (En), inflation rate (IR), and Consumer Price Index (CPI), were also used for adjusting price fluctuations and estimating the economic values of ESs (Fei et al. 2016).

Estimation of ES values using a hybrid method. To address and minimize the uncertainties in the valuation of ESs, the present study proposes a hybrid valuation method, which is an integration of existing biophysical and economic valuation methods. Both normalized and absolute values of the biophysical and economic ES values were considered for the hybrid ESs valuation. The spatially explicit biophysical and economic valuation methods are not free from predictable biases and uncertainties. The biophysical valuation approach, which entirely depends on the quality of biophysical (NPP, EVI, NDVI) and climatic (precipitation, temperature, evapotranspiration) variables, is likely to be highly uncertain because it depends on highly dynamic natural variables. Without proper preprocessing, the measures would produce substantial biases in the calculation of ESs. Meanwhile, the associated direct and indirect methods for the economic valuation of ESs, such as contingent valuation, willingness to pay, willingness to accept, hedonic pricing, travel cost, damage cost, benefits transfer method, and statistical value transfer model, are highly sensitive to price fluctuations, socioeconomic status, and demographic characteristics of the region.

Estimation of EH. In the present study, EH was evaluated based on 3 criteria: vigor (V), organization (O), and resilience (R). Finally, the risk characterization values (RCVs) of ESs were estimated using a function of EH and ESs (Costanza 2012; Peng et al. 2015; Yan et al. 2016). In the VOR model, V characterizes the ecosystem and biomass richness and productivity, O refers to the landscape diversity and connectivity, and R refers to the capacity of an ecosystem in maintaining the structure and function in the presence of external disturbances (Costanza 2012; Peng et al. 2015; Yan et al. 2016). The formula of EH is

$$\mathrm{EH} = \sqrt[3]{\mathrm{V} \times \mathrm{O} \times \mathrm{R}}, \tag{1}$$

where V = NPP (used as a proxy in the present study); the O was calculated as

$$\begin{aligned}\mathrm{O} = 0.35 \times \mathrm{LC} + 0.35 \times \mathrm{LH} + 0.3 \times \mathrm{IC} = 0.1 \\ \times \mathrm{AWMPFD} + 0.25 \times \mathrm{FN1} + 0.15 \times \mathrm{SHDI} \\ + 0.1 \times \mathrm{MSIDI} + 0.1 \times \mathrm{CONT} + 0.1 \\ \times \mathrm{FN2} + 0.05 \times \mathrm{CONNECT1} + 0.1 \\ \times \mathrm{FN3} + 0.05 \times \mathrm{CONNECT2}\end{aligned}, \tag{2}$$

where LC = landscape connectivity; LH = landscape heterogeneity; IC = patch connectivity of ecologically important landscape (forest, water, grassland); AWMPFD = area-weighted mean patch fractal dimension; FN1 = landscape fragmentation; SHDI = Shannon's Diversity Index; MSIDI = Modified Simpson's Diversity Index; CONT = landscape contagion index; FN2 = fragmentation index of forest land; CONNECT1 = patch connectivity of forest land; FN3 = fragmentation index of water; and CONNECT2 = patch connectivity of water (Peng et al. 2015; Yan et al. 2016).

Resilience was calculated as follows:

$$\mathrm{R} = \left(1 + \left(\frac{\mathrm{CS_{norm}} + \mathrm{CN_{norm}} + \mathrm{EVI_{norm}}}{3}\right)\right) \times \sum_{1=1}^{n} f_i \times \mathrm{RC}_i, \tag{3}$$

where $\mathrm{CS_{norm}}$, $\mathrm{CN_{norm}}$, and $\mathrm{EVI_{norm}}$ are C sequestration, curve number, and enhanced vegetation index; f_i is the area ratio of the major ecosystem type i; and RC_i refers to the ecosystem resilience coefficient (Kang et al. 2018).

Next, the RCV was calculated as

$$\mathrm{RCV} = \sqrt{\mathrm{EH} \times \mathrm{ESs}}. \tag{4}$$

After that, using VOR estimates, EH, ESs (derived from the hybrid method), and RCV, the CPZs for the Sundarbans region were estimated. For this purpose, the spatial cluster and hot spots of the variables were estimated using local indicators of spatial association (LISA) statistics.

Evaluation of synergies, trade-offs, and spatial distribution of ESs and EH components

Estimating synergies and trade-offs. The spatial and non-spatial synergies and trade-offs among ESs and EH components were evaluated using the Pearson correlation test at the administrative scale (the 51 administrative blocks, represented by numbers 0–50). The PerformanceAnalytics package for R statistical software was used to calculate the Pearson correlation matrix (Peterson et al. 2018). Both trade-offs (negative association, characterized by negative *r*-value) and synergies (positive association, characterized by positive *r*-value) among the variables were evaluated at $P \leq 0.001$, 0.01, and 0.05 significance levels. The trade-off refers to a win–lose condition when increases of 1 ES component decrease the provision of another ES component and vice versa. The synergy refers to the positive correlation between 2 components, that is, when increasing 1 ES component would be effective for the increment of another ES component, and thereby yield a win–win situation. A total of 51 sample points was generated for each ESs and EH component.

Estimating spatial distribution of ESs. Global Moran's I quantify the spatial autocorrelation of distributed features as a whole, whereas the LISA assess location-specific spatial autocorrelation using local Moran's I (Anselin 1995; Fu et al. 2014). Local Moran's I is mostly used to identify the distribution of spatial clusters and spatial outliers (Harries 2006):

$$I_i = \frac{z_i - \bar{z}}{\sigma^2} \sum_{j=1, j \neq i}^{n} [w_{ij}(z_j - \bar{z})], \tag{5}$$

$$\sigma^2 = \frac{\sum_{j=1, j \neq i}^{n} (x_j - \bar{X})^2}{n - 1}, \tag{6}$$

where $\bar{z}$ is the mean value of z; z_i is the value of the variable at location i; z_j is the value at location j ($j \neq i$); σ^2 is the variance of z; and w_{ij} is the weight between z_i and z_j, which can be defined as the inverse of distance. Weights can also be determined using a distance band: Samples within a distance band are given the same weights, whereas those outside a distance band will get a weight of 0; n is the sample number (Fu et al. 2014).

Identification of CPZs. In the present study, the CPZs of the Sundarbans were identified using 2 approaches: ESs and EH. Additionally, a hybrid method based on biophysical and economic valuations of ESs was also proposed, which minimizes the valuation biases that exist in different valuation methods. Afterward, using the ES values estimated through this hybrid method, EH components (V, O, R, EH, RCVs), the Pearson correlation coefficients, and the cluster and outliers and hot and cold spot estimates derived from Moran's I, and Getis-Ord Gi*, CPZs were incorporated for demarcating spatially explicit CPZs. All the 7 relevant components (ESs, correlation estimates, RCV, EH, O, R, and V) were then normalized, and the final CPZs score was calculated by summing up the normalized values of all the 7 components. Based on the final score, CPZs were categorized into very high, high, moderate, low, and very low CPZs. The calculation was carried out at the administrative scale to validate the findings with the established reports and scholarly works.

RESULTS AND DISCUSSION

Distribution and spatiotemporal changes of ESs

The spatial and nonspatial distribution of different ESs is shown in Figure 3 and Supplemental Data Figure S1. The monetary values of the ESs were evaluated using the biophysical, economic, and hybrid valuation methods (Figures 3A and 3B). Figures 3C, 3D, 3E, and 3F show the values of ESs for the 6 major ecoregions, and the combined results of the ESs and 6 LULC. For biophysical methods, the mangrove regions have produced the maximum amount of ESs, followed by cropland, mixed vegetation, coastal estuary, inland wetland, and urban region (Table 1). The HA, NC, and CR are the main ESs of mangrove, cropland, and mixed vegetation regions, whereas the coastal estuary region is most important for its DR and GEN. Additionally, the inland wetland ecosystem is primarily significant for producing NC, CR, GEN, and DR services (Tables 1 and 2). For all the major ecosystem types reported in the present study, the maximum amount of ESVs is provided by the mangrove ecosystem, illustrating the significance of natural reserve ecosystems that could support a wide range of landscapes and natural capitals, (such as forest and water bodies) which have a substantial importance in order to produce the marketable and nonmarketable natural goods and services that are essential for subsistence and human well-being

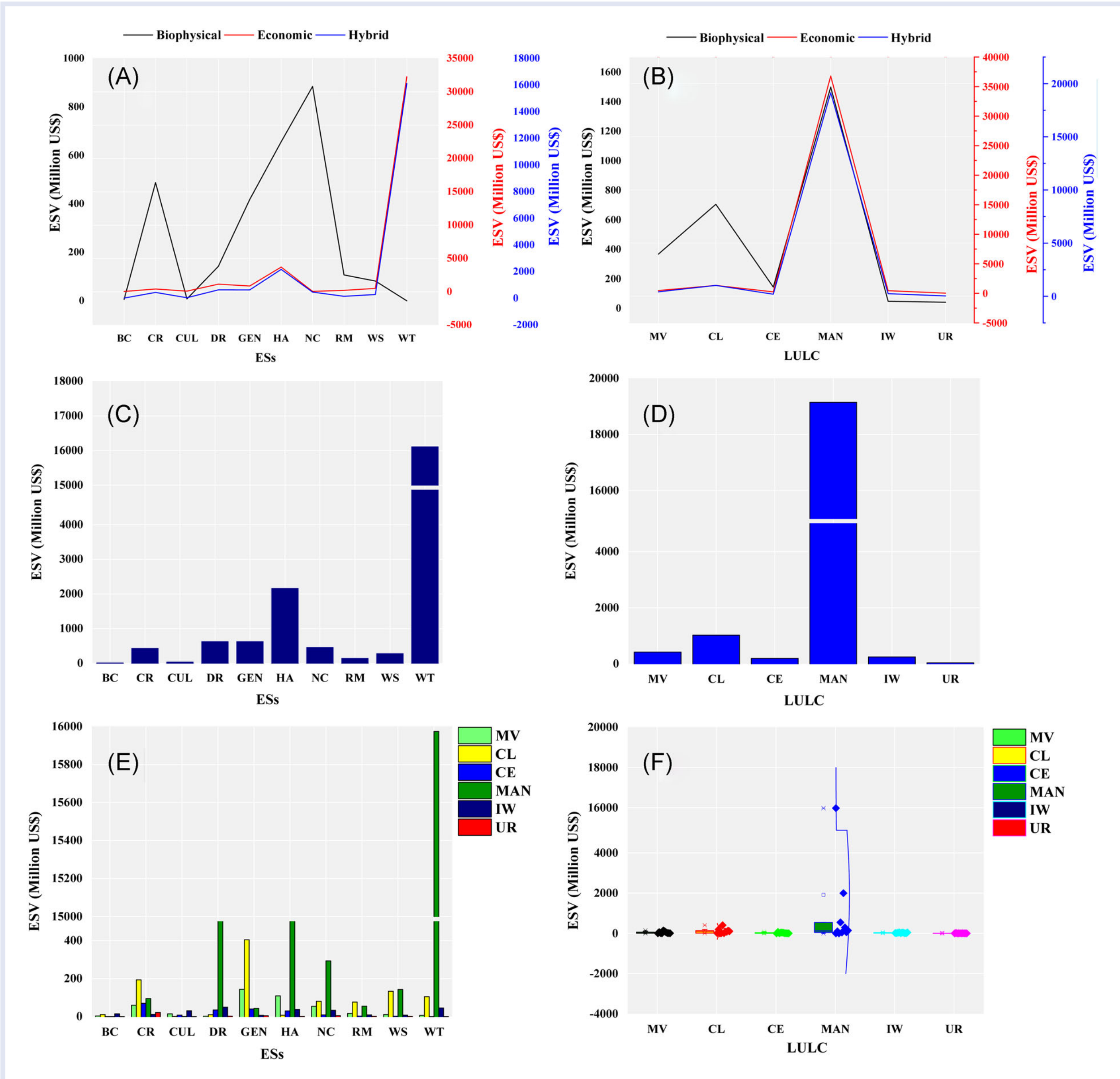

Figure 3. Ecosystem service values of ESs (A), LULC (B) derived from biophysical, economic, and hybrid methods, (C) represent the ESV of different ESs, (D) denotes the ESV of different ecosystem types, (E) shows the contribution of different ecosystem types to provide ESV, and (F) shows the range of ESV of each LULC. BC = biological control; CE = coastal estuary; CL = crop land; CR = climate regulation; CUL = cultural; DR = disaster regulation; ESs = ecosystem services; ESV = ecosystem service value; GEN = genetic service; HA = habitat service; IW = inland wetland; LULC = land use land cover; MAN = mangrove; MV = mixed vegetation; NC = nutrient control; RM = raw material production; UR = urban; WS = water supply; WT = waste treatment.

 DOI: 10.1002/ieam.4287

Table 1. Biophysical ESVs estimated for 6 ecosystem units

ESs	Mixed vegetation	Cropland	Coastal estuary	Mangrove	Inland wetland	Urban
BC	1.29	3.68	0.11	0.10	0.48	0.14
CR	112.89	169.60	8.35	177.21	8.07	12.05
CUL	1.33	1.22	4.40	0.27	0.79	0.08
DR	3.78	19.81	70.03	35.18	9.03	4.42
GEN	85.33	257.61	30.08	25.75	10.81	8.87
HA	16.80	14.39	6.60	615.69	2.19	0.94
NC	108.36	161.19	17.99	577.18	10.86	9.29
RM	24.78	37.23	1.83	38.90	1.77	2.64
WS	10.95	38.24	3.04	26.38	2.07	1.27
WT	0.00	0.01	0.00	0.25	0.00	0.00
Total	365.52	702.97	142.43	1496.91	46.08	39.70

BC = biological control; CR = climate regulation; CUL = cultural; DR = disturbance regulation; ES = ecosystem service; ESV = ecosystem service value; GEN = genetic services; HA = habitat service; NC = nutrient control; RM = raw material; WS = water supply; WT = waste treatment.

(Costanza et al. 2014; Keesstra et al. 2018; Sannigrahi, Joshi et al. 2019). The present study has also shown that the mangrove-rich Sundarbans ecosystem is extremely important for the provision of key regulating services like DR, CR, CS, WS, and WT. Ray et al. (2011) had quantified the CO_2 emission of the Indian Sundarban as 33 620 Gg C per year, which is equivalent to 123 385 Gg CO_2 per year and is produced mainly from the community plant respiration of coastal blue ecosystem of the Indian Sundarbans per year. Ray et al. (2011) also observed that the net C storage of this ecosystem is about 36 670 Gg C per year, which is equal to 134 579 Gg CO_2. Therefore, approximately 11 194 Gg CO_2 is sequestered by the Indian Sundarbans every year and acts as a net sink for CO_2 that can have a significant impact on regional C balance of the Bay of Bengal region (Akhand et al. 2016; Rodda et al. 2016). However, the valuation approaches adopted in the present study considered only tangible and realized benefits of the ecosystems but did not include intangible benefits provided by the ecosystems; if it had been so, the real values of such ESs would have changed significantly (Kubiszewski et al. 2013). Additionally, the Sundarbans is one of the most dynamic ecosystems in the world, where several climatic and anthropogenic extremities, including floods, cyclones, coastal erosion, destruction of mangroves, and depletion of coastal and maritime resources, are posing severe environmental and socioeconomic threats to coastal communities of the Sundarbans (Giri et al. 2011; Sannigrahi, Zhang, Pilla et al. 2020).

Table 2. Ecosystem service values estimated after aggregating biophysical and economic values for 6 ecosystem units

ESs	Mixed vegetation	Cropland	Coastal estuary	Mangrove	Inland wetland	Urban
BC	3.24	10.56	0.05	0.05	14.49	0.07
CR	59.76	193.49	69.84	95.01	11.37	21.72
CUL	14.48	0.61	8.10	0.13	30.34	0.04
DR	1.89	9.91	35.01	544.82	49.40	2.21
GEN	143.30	404.31	39.71	43.52	6.89	4.44
HA	109.03	7.19	29.90	1996.45	38.00	0.47
NC	54.18	80.60	9.00	293.37	33.05	4.65
RM	16.88	76.52	2.56	54.72	8.99	1.32
WS	10.81	133.49	1.52	142.55	7.61	0.63
WT	6.24	104.89	0.00	15974.27	45.32	0.00
Total	419.81	1021.56	195.69	19144.90	245.45	35.55

BC = biological control; CR = climate regulation; CUL = cultural; DR = disturbance regulation; ES = ecosystem service; GEN = genetic services; HA = habitat service; NC = nutrient control; RM = raw material; WS = water supply; WT = waste treatment.

Using the economic valuation methods, we have estimated the ESs value of different natural capitals of the Sundarbans (Figure 3, Supplemental Data Figure S1). The mangrove regions have produced the maximum amount ESs, followed by cropland, mixed vegetation, inland wetland, coastal estuary, and urban region (Figure 3, Supplemental Data Figure S1). The WT, HA, DR, and WS are the major ESs of mangrove region. However, due to the increasing level of physical and anthropogenic disturbances, the natural dynamics and ecological stability of this ecosystem have been severely affected. Raha et al. (2012) evaluated the impact of climate change on the Indian Sundarbans and found that both the coastal erosion and accretion processes accelerated during the research period (1924–2008). This could be due to the deficiency of sediment influx in the downstream channel prompted by the construction of Farakka barrage in the upstream channel. The decreases of freshwater inputs into this estuarine river system and the resulting increase in water salinity are causing a reduction of phytoplankton and fish communities in the Indian Sundarbans (Raha et al. 2012). In addition, due to the anthropogenic intervention, especially in the fringe region of the Sundarbans (Sagar Island and Lothian Island), the concentration of dissolved inorganic N is significantly higher than the other part of the deltaic lobe (Mandal et al. 2013). Mondal et al. (2013) estimated that if the mangrove litter biomass is reduced to 50%, the amount of detritus will be decreased by 44% and 55% in Sagar Island and Lothian Island. For the cropland region, GEN, WS, CR, and WT functions are producing the maximum ESs in the Sundarbans. The mixed vegetation region is most significant for the provision of HA and GEN services. The CR, HA, and GEN services are the key ES functions of the coastal estuary ecosystem. Additionally, the WT and DR services are the key ESs of inland wetland ecosystem in the Sundarbans (Figure 3, Supplemental Data Figures S1 to S7).

The present study has adopted both biophysical and economic methods to quantify the values of ESs, and substantial difference between these 2 valuation methods was found (Figure 3A). The estimated differences were minimal for CR, RM, GEN, BC, and CUL services, whereas substantial difference was observed for WT, DR, HA, NC services (Figure 3E). The spatial distributions of different ESs estimated using hybrid, biophysical, and economic valuation methods are described in Supplemental Data Figures S1, S6, and S7. Among the selected ESs, the CR, DR, HA, NC, RM, WS, and WT services were found to be at a maximum over the mangrove forested region (Supplemental Data Figure S1), whereas the BC, CUL, and GEN services were found very high over the inland wetland and mixed vegetation region. Among the major ecoregions of the Sundarbans, the mangrove ecosystem was providing the maximum amount of ESVs in terms of economic units (US$19 144.9 million per year), followed by cropland (1021.56 million per year), mixed vegetation (419.81 million per year), inland wetland (245.45 million per year), coastal estuary (195.69 million per year), and urban region (35.55 million per year). Supplemental Data Figure S8 shows the normalized ESVs of different key ESs at administrative scale. The highest concentration of ESs was observed at Gosaba (code 42), Patharpratima (code 37), Namkhana (code 4), Sagar (code 25), and Kultali (code 8) blocks. These administrative units are mostly covered by mangrove forests and water bodies.

Association between the biophysical and economic ESs

To evaluate the association between biophysical and economic valuation methods, we performed a linear regression analysis, and the results were represented by a 2D kernel density plot (Figure 4). Among the 10 pairs of ESs, the highest coefficient of determination values was observed for HA service ($R^2 = 0.75$), followed by CUL and GEN services ($R^2 = 0.70$), CR ($R^2 = 0.57$), WT ($R^2 = 0.50$), WS ($R^2 = 0.46$), DR ($R^2 = 0.40$), BC ($R^2 = 0.18$), RM ($R^2 = 0.15$), and NC ($R^2 = 0.08$) services, respectively (Figure 4). However, in the present study, we observed a substantial difference between the biophysical and economic valuation approaches. This means that the 2 valuation methods tend to provide divergent perspectives for ES valuation, each of which should be associated with uncertainties and biases. Therefore, the proposed approach would provide an alternative view of estimating ESVs.

The biophysical method is based on spatially explicit modeling, including InVEST, Artificial Intelligence of Ecosystem Service (ARIES) (Villa et al. 2014), and quantification of ESs using the market values of different proxies (C tax, social cost of C, price of O, price of C, price of food production, cost of dam construction). This high level of dependencies on proxy-based valuation makes the biophysical estimation highly sensitive to the selection of appropriate proxies. Accordingly, the effective uses of most of the biophysical models and approaches are often limited for estimating the biophysical values of ESs, including CS (t/ha), WT (g/m^3), and SDR (t/ha) services, whereas the economic valuation methods, including simple benefit transfer, expert-derived value transfer, statistically modeled value transfer, and spatially explicit value transfer, have been used extensively for the estimation of monetary values of ESs.

Distribution of EH components

The distributions of the studied EH components, that is, V, O, and R, and EH, were analyzed spatially, which are shown in Supplemental Data Figure S9. Ecosystem V was mostly concentrated over the Gosaba (code 42) and Kultali (code 8) blocks, and partly in the northern part of the study region (Basirhat, code 39; Haora, code 27; Minakhan, code 11). The ecosystem O values were found to be at a maximum over the central and northern region (Canning, code 29; Bhangar, code 12; Sandeshkhali, code 6; Sonarpur, code 47; Rajarhat, code 10; Minakhan, code 11). The ecosystem R and EH values were found very high over the southern region (Gosaba, code 42; Kultali, code 8; Namkhana, code 4; Patharpratima, code 37; Sagar, code 25; Mathurapur, code 24; Kakdwip, code 50; Basanti, code 35), whereas comparatively lower values were found over the northern and western part

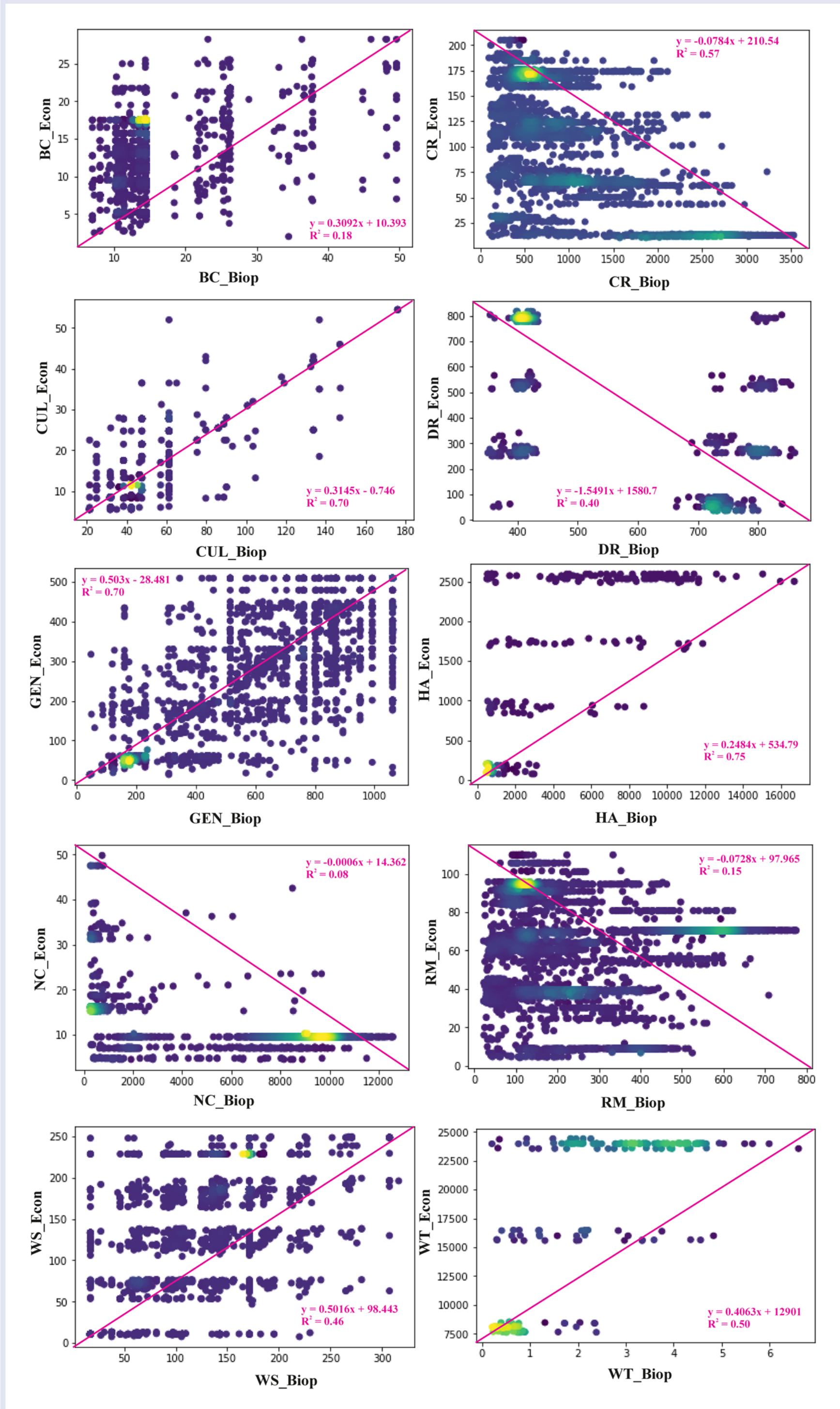

Figure 4. Association between the biophysical and economic ESs. BC = biological control; Biop = ecosystem services calculated using biophysical method; CR = climate regulation; CUL = cultural; DR = disaster regulation; Econ = ecosystem services calculated using economic method; ESs = ecosystem services; GEN = genetic service; HA = habitat service; NC = nutrient control; RM = raw material production; WS = water supply; WT = waste treatment.

of the region. The southern part of the study region is mostly covered by dense mangrove forests and estuarine land.

Synergies and trade-offs between EH components and ESs

The RCV and EH components have shown a very strong synergy with CS, CR GR, RM services, whereas a moderate to weak synergy was observed between RCV and biodiversity management (BDM), NC, SDR services. A trade-off association was also observed between RCV and BC, DR, N_Exp, P_Exp, and water yield (WY) services (Figure 5). However, the ecosystem O component showed a different association with the ESs. A strong to moderate synergetic

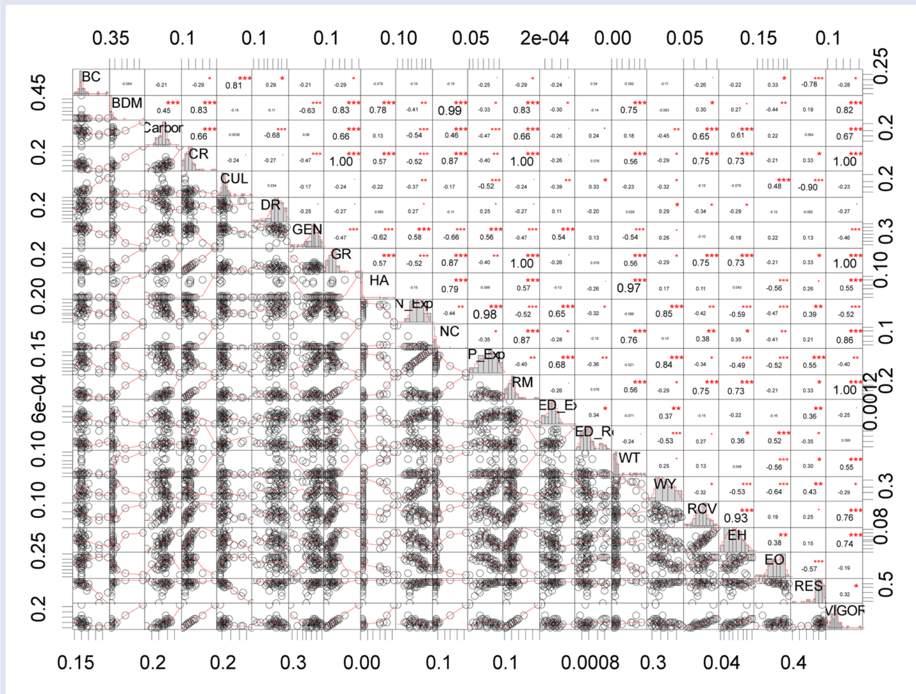

Figure 5. Pearson correlation matrix depicts the directional interaction among the ESs and ecosystem health components. BC = biological control; BDM = biodiversity management; CR = climate regulation; CUL = cultural; DR = disaster regulation; EH = ecosystem health; EO = ecosystem organization; GEN = genetic service; GR = gas regulation; HA = habitat service; N_Exp = nitrogen export; NC = nutrient control; P_Exp = phosphorous export; RCV = risk characterization value; RES = resilience; RM = raw material production; SED_E = sediment export; SED_R = sediment retention; WT = waste treatment; WY = water yield.

association was observed between O and BC, CUL, and SDR services, whereas ecosystem O is found negatively associated with the BDM, HA, N_Exp, NC, P_Exp, WT, and WY services. Furthermore, the association between ecosystem R and ESs was also analyzed. The R component has exhibited a strong to moderate synergetic association with P_Exp, N_Exp, WY, SDR, WT, RM, GR, HA, and CR services (Figure 5). In continuation, the association between V and ESs were evaluated at different significance levels. The positive correlation was found between the V and CR, GR, RM, BDM, CS, HA, NC, and WT services (Figure 5).

Among the 5 EH components, the RCV has produced a very strong synergetic association with EH and V. In contrast, a weak correlation was detected between the RCV and R, and no correlation was found between RCV and O. The EH factor was strongly associated with RCV, V, and O, and it had no statistically significant association with the R factor. Regarding the O factor, it has a moderate synergy with the EH factor and a strong trade-off with the R factor. The V factor is positively associated with all other EH factors, except the O factor (Figure 5).

Spatial distribution of CPZs

The very high CPZs were projected for the Gosaba block (code 42), which is mostly covered by dense mangrove forest (Figure 6). The Sundarbans natural reserve region, along with several wildlife sanctuaries, natural reserve forests, and national parks, is also located in this administrative block. Our spatially explicit CPZs are, therefore, perfectly matched with the existing literature and highlight the administrative zones and landscape that should be protected. Earlier studies (Sannigrahi, Chakraborti et al. 2019; Sannigrahi, Joshi et al. 2019; Sannigrahi, Zhang, Joshi et al. 2020; Sannigrahi, Zhang, Pilla et al. 2020) in this region have revealed that the mangrove and water bodies (coastal estuary and inland wetland) are the most sensitive ecosystems among the major ecosystem types of the Indian Sundarbans. To preserve the ecological stability of this ecosystem, several conservation and protection initiatives have been adopted by local stakeholders (forest protection committees [FPCs] and forest directories [FDs]). However, due to unawareness and methodological uncertainties, the importance of this ecosystem for the provision of valuable ESs and how these valuation estimates can be effectively utilized for delineating the CPZs are seemingly untouched or have not been substantially explored.

The high conservation priority scores have been estimated for Patharpratima (code 37), Kultali (code 8), Mathurapur I (code 30), Mathurapur II (code 24), Jaynagar I (code 18), Jaynagar II (code 13), Basanti (code 35), Hingalganj (code 16), Baduria (code 44), and Basirhat (code 38) administrative blocks. The moderate priority score is accounted for in Namkhana (code 4), Kakdwip (code 50), Kulpi (code 48), Mandirbazar (code 9), Diamond Harbour (code 0), Falta (code 31), Canning I (code 29), Bhangar I (code 17), Bhangar II (code 12), Hasnabad (code 21), Deganga (code 26), Basirhat II (code 33), Habra I (code 20), Gaighata

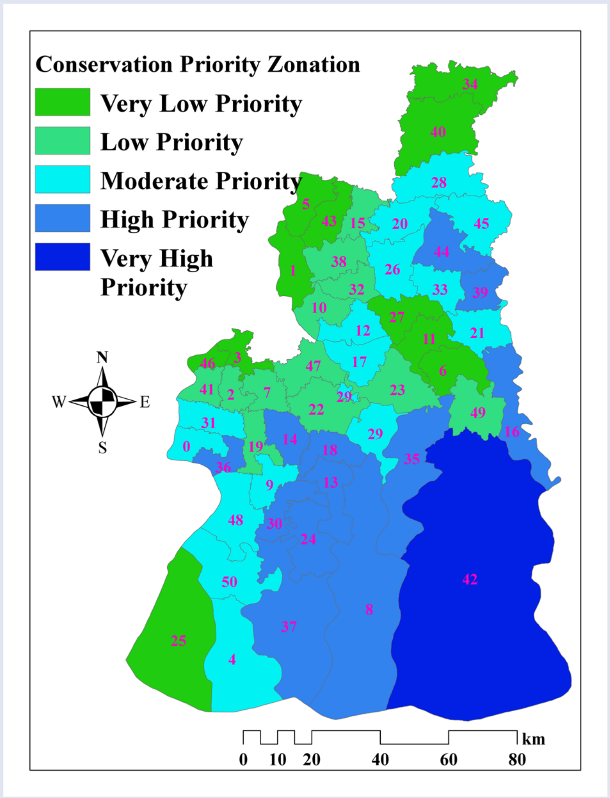

Figure 6. Conservation priority zonation of the Indian Sundarbans.

(code 28), and Swarupnagar (code 45) blocks (Figure 6). Most of the administrative blocks that exhibited less green cover and more urbanized areas have been categorized as low priority zones. Such blocks are Magrahat I (code 19), Budge Budge II (code 41), Bisnupur I (code 7), Bisnupur II (code 2), Baruipur (code 22), Sonarpur (code 47), Canning II (code 23), Sandeshkhali II (code 49), Rajarhat (code 10), Barasat I (code 38), Barasat II (code 32), and Habra II (code 15) (Figure 6). The remaining administrative blocks (Sagar, code 25; Bagda, code 34; Bongaon, code 40; Barrackpore I, code 5; Barrackpore II, code 1; Amdanga, code 43; Budge Budge I, code 46; Thakurpukur, code 3; Haora, code 27; Minakhan, code 11; and Sandeshkhali I, code 6) have exhibited a very low priority zonation score (Figure 6).

The Sundarbans region has gone through a series of discourses for conservation and management of ESs, which in due course, merits thoughtful attention for scientific engagement and discussion. It is important to realize the challenges faced by environmentalists and decision makers for strengthening and protecting the natural capitals of this ecosystem. Costanza (2012) discussed the need for modern ecological engineering solutions in addressing socio-ecological problems of natural reserve regions. In addition, the author (Costanza et al. 2012) has stated that "The design of healthy ecosystems, which may be novel assemblages of species that perform desired functions and produce a range of valuable ecosystem services sustainably." This perhaps implies that modern problems need a modern solution, especially when designing the proper action plan for conservation of natural resources.

Globally, mangroves are disappearing at an alarming rate of 1% to 2% per year, which is much faster than other terrestrial and marine ecosystems such as tropical rainforests and coral reefs (Alongi 2002, 2008; DasGupta and Shaw 2013). For the Indian Sundarbans, nearly 150 000 ha of mangrove forest cover has been converted to agricultural land during the past 100 y (Giri et al. 2008, 2011, 2015; Kathiresan 2010). Additionally, land conversion due to shrimp cultivation is the second most important anthropogenic factor of mangrove degradation in South and Southeast Asia, including the Indian Sundarbans (DasGupta and Shaw 2013). The growth of shrimp cultivation and associated activities are becoming economically lucrative and viable livelihood options in the Indian Sundarbans as people can get direct benefits from them. This trend is evident in and around Patharpratima (code 37), Sandeshkhali (codes 6 and 49), Namkhana (code 4), and Kultali (code 8).

The current research has made a sincere effort to demarcate the ecosensitive zones of the Indian Sundarbans. Many key components, including connectivity of the ecological network, land-use intensity, and flora or fauna diversity, which should have been considered while delineating the conservation priority areas, could be a direction for future research. Also, the modeling approaches and ESs valuation methods adopted in the present study are not free from uncertainty and biases. Therefore, a proper discussion is much needed for exploring the caveats that exist in ESs quantification and modeling and also for its broader implications to inspire future relevant studies.

CONCLUSION

The present study proposes a new integrated approach to demarcate the spatially explicit CPZs of the Indian Sundarbans. The spatially explicit ESs value was quantified using biophysical, economic, and hybrid valuation approaches. Several ESs valuation approaches, including InVEST, equivalent weight and value coefficient method, and benefits transfer method, were utilized for quantification of ESs. The main findings of the present study are reported as follows:

1) Among the major ecoregions of the Sundarbans, the mangrove ecosystem is providing the maximum amount of ESs value in terms of economic units ($19 144.9 million per year), followed by cropland ($1021.56 million per year), mixed vegetation ($419.81 million per year), inland wetland ($245.45 million per year), coastal estuary ($195.69 million per year), and urban region ($35.55 million per year).
2) The very high conservation priority score is being projected for the Gosaba block (code 42), which is mostly covered by dense mangrove forest. The Sundarbans natural reserve region, along with several wildlife sanctuaries, natural reserve forests, national parks, tiger reserve, et cetera, are also located in this administrative block, thereby justifying the accuracy and effectiveness

of the ESs-based conservation method proposed in the present study.

3) Additionally, our spatially explicit conservation priority score thus, to a large extent, matches with the current knowledge and highlights the administrative zones and landscape that should be protected to maintain the geodiversity of the Indian Sundarbans.
4) The ESs-based CPZs are thoroughly examined in the present study and found to be highly effective in demarcating the ecosensitive zones of the Sundarbans. The generic approach and methods proposed in the present study can easily be replicated at any related ecosystem across the world, especially for regions with limited ground data availability. Additionally, all the models and data used in the present study are open access and freely available; therefore, the financial burden should not be a case for scientific replication and reevaluation.
5) In the present study, we have observed a substantial difference between the biophysical and economic valuation approaches. This means that the 2 valuation methods tend to provide divergent perspectives for ES valuation, each of which should be associated with uncertainties and biases. Therefore, the proposed approach would provide an alternative view of estimating ESVs.

In the present study, we have made a sincere effort to demarcate the ecosensitive zones of the Indian Sundarbans. We hope the outcome of the present study could be a reference for designing the relevant policies to protect the biodiversity values of this vibrant ecosystem and many others in the world.

Acknowledgment—The authors are also thankful to the anonymous reviewers and editor-in-chief for their constructive feedback and suggestions to enhance the quality of the manuscript. L Coscieme is funded by an IRC/Marie Skłodowska-Curie CAROLINE Postdoctoral Fellowship (IRCCLNE/2017/567).

Data Availability Statement—Readers should contact corresponding author Srikanta Sannigrahi (srikanta.sannigrahi@ucd.ie) for data and other details of this study.

SUPPLEMENTAL DATA

Abbreviations

Highlights

Figure S1. Spatial distribution of major ESs of Sundarbans.

Figure S2. ESVs of different LULC derived from biophysical and economic methods.

Figure S3. ESVs of different ESs derived from biophysical and economic methods.

Figure S4. ESVs of different LULC/ESs derived from biophysical and economic methods.

Figure S5. ESVs of different LULC.

Figure S6. ESs estimate using biophysical method.

Figure S7. ESs estimate using economic method.

Figure S8. Normalized values of ESs.

Figure S9. Spatial distribution of the ecosystem health components.

Figure S10. Local Moran's I hot spot and cluster of ESs.

Figure S11. Cold spot and hot spot of ESs distribution derived from Local Geary C.

Figure S12. Spatial distribution of risk characterization value (RCV).

Figure S13. Spatial distribution of correlation estimates between ecosystem services and ecosystem health.

Figure S14. Spatial arrangement and cluster/outlier of the ecosystem health factors.

Figure S15. Spatial distribution of the cold spot/hot spot of ecosystem health factors.

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