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Research article

Examining the effects of green revolution led agricultural expansion on net ecosystem service values in India using multiple valuation approaches

Srikanta Sannigrahi [a,*], Francesco Pilla [a], Qi Zhang [b], Suman Chakraborti [c], Ying Wang [d], Bidroha Basu [a], Arunima Sarkar Basu [a], P.K. Joshi [e], Saskia Keesstra [f,g], P.S. Roy [h], Paul C. Sutton [i], Sandeep Bhatt [j], Shahid Rahmat [k], Shouvik Jha [l], Laishram Kanta Singh [m]

[a] School of Architecture, Planning and Environmental Policy, University College Dublin, Richview, Clonskeagh, Dublin, D14 E099, Ireland
[b] Frederick S. Pardee Center for the Study of the Longer-Range Future, Frederick S. Pardee School of Global Studies, Boston University, Boston, MA 02215, USA
[c] Center for the Study of Regional Development (CSRD), Jawaharlal Nehru University, New Delhi, 110067, India
[d] School of Public Administration, China University of Geosciences, Wuhan, 430074, China
[e] Spatial Analysis and Informatics Lab (SAIL), School of Environmental Sciences (SES), Jawaharlal Nehru University (JNU), New Delhi 110 067, India
[f] Soil, Water and Land-use Team, Wageningen University and Research, Droevendaalsesteeg3, 6708PB, Wageningen, the Netherlands
[g] Civil, Surveying and Environmental Engineering, The University of Newcastle, Callaghan, 2308, Australia
[h] Innovation Systems for the Drylands (ISD), ICRISAT, Pathancheru, Hyderabad, 502 324, India
[i] Department of Geography and the Environment, University of Denver, 2050 East Iliff Avenue, Denver, CO, 80208-0710, USA
[j] Department of Earth Sciences, Indian Institute of Technology, Roorkee, 247667, India
[k] Department of Architecture and Regional Planning, Indian Institute of Technology Kharagpur, India
[l] Indian Centre for Climate and Societal Impacts Research (ICCSIR), Kachchh, Gujarat, 370465, India
[m] Agriculture and Food Engineering Department, Indian Institute of Technology Kharagpur, Kharagpur, 721 302, India

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ABSTRACT

Ecosystem Services (ESs) are bundles of natural processes and functions that are essential for human well-being, subsistence, and livelihoods. The 'Green Revolution' (GR) has substantial impact on the agricultural landscape and ESs in India. However, the effects of GR on ESs have not been adequately documented and analyzed. This leads to the main hypothesis of this work – '*the incremental trend of ESs in India is mainly prompted by GR led agricultural innovations that took place during 1960 - 1970*'. The analysis was carried out through five successive steps. First, the spatiotemporal Ecosystem Service Values (ESVs) in Billion US$ for 1985, 1995, and 2005 were estimated using several value transfer approaches. Second, the sensitivity and elasticity of different ESs to land conversion were carried out using coefficient of sensitivity and coefficient of elasticity. Third, the Geographically Weighted Regression model was performed using five explanatory factors, i.e., total crop area, crop production, crop yield, net irrigated area, and cropping intensity, to explore the cumulative and individual effects of these driving factors on ESVs. Fourth, Multi-Layer Perceptron based Artificial Neural Network was employed to estimate the normalized importance of these explanatory factors. Fifth, simple and multiple linear regression modeling was done to assess the linear associations between the driving factors and the ESs. During the observation periods, cropland, forestland and water bodies contributed to 80%–90% of ESVs, followed by grassland, mangrove, wetland and urban built-up. In all three evaluation years, the highest estimated ESVs among the nine ES categories was provided by water regulation, followed by soil formation and soil-water retention, biodiversity maintenance, waste treatment, climate regulation, and greenhouse gas regulation. Among the five explanatory factors, total crop area, crop production, and net irrigated area showed strong positive associations with ESVs, while cropping intensity exhibited a negative association. Therefore, the study reveals a strong association between GR led agricultural expansion and ESVs in India. This study suggests that there should be an urgent need for formulation of rigorous ecosystem management strategies and policies to preserve ecological integrity and flow of uninterrupted ESs and to sustain human well-being.

* Corresponding author.
E-mail address: srikanta.sannigrahi@ucd.ie (S. Sannigrahi).

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1. Introduction

Ecosystem Services (ESs) refer to benefits that humans freely gain from natural environment and ecosystems, and these add to the human well-being (Fisher et al., 2009; Costanza et al., 1997; Braat and Groot, 2012; MEA, 2005). Whereas the term ecosystem function denotes a bundle of ecological processes operating within an ecosystem that may or may not contribute to human well-being (Odum, 1956; Braat and Groot, 2012). Ecosystem Service Values (ESVs) are the values assigned to goods and services derived from ecological processes and can be used to assess the impact of anthropogenic activities on different ecosystems (e.g., MEA, 2005; Adekola et al., 2015). The estimation of ESVs aims to comprehensively appraise environmental-human development interactions to enhance sustainable natural resource management (Braat and de Groot, 2012; Potschin and Haines-Young, 2013; Pandeya et al., 2016; Sannigrahi et al., 2020a; Adekola et al., 2015). The focus on ESs has grown in importance as it can help improve cost-benefit analyses by incorporating both negative and positive effects of human development activities, such as Land Use and Land Cover (LULC) change, on diverse ecosystems (Sannigrahi et al., 2020b; Wang et al., 2018, 2019, Zhang et al., 2018, 2019; Yi et al., 2017).

Abbreviation description

ANN	Artificial Neural Network
CI	Cropping Intensity
CP	Crop Production
CY	Crop Yield
ESs	Ecosystem Services
ESVs	Ecosystem Service Values
GR	Green Revolution
GWR	Geographically Weighted Regression
LULC	Land Use and Land Cover
LCI	LULC change intensity
NIA	Net Irrigated Area
TCA	Total Crop Area

Table 1
The original and modified land use/land cover classification in India.

Final code	Modified LULC	Value	Original LULC	Value
1	Forestland	1,4,15,16,19	Deciduous Broadleaf Forest (DBF)	1
			Mixed Forest (MF)	4
			Evergreen Broadleaf Forest (EBF)	15
			Deciduous Needleleaf Forest (DNF)	16
			Evergreen Needleleaf Forest (ENF)	19
2	Cropland	2,10,11	Cropland	2
			Plantations	10
			Aquaculture	11
3	Urban built-up	3	Built-up Land	3
4	Grassland	5,14	Shrubland	5
			Grassland	14
5	Fallow land	6,7,8,13,18	Barren Land	6
			Fallow Land	7
			Wasteland	8
			Salt Pan	13
			Snow & Ice	18
6	Waterbodies	9	Water bodies	9
7	Mangrove	12	Mangrove Forest	12
8	Wetland	17	Permanent Wetlands	17

In India, agricultural ecosystems provide enormous valuable goods and services that are essential for human well-being and livelihoods (Power, 2010; Swinton et al., 2007). Through the introduction of modern agricultural technologies, including high yielding variety seeds, irrigation facilities, farm machinery, chemical fertilizers and plant protection measures, the ‘Green Revolution’ (GR) has helped farmers become financially stable by increasing their farm production (David and Otsuka, 1994). The GR has not only raised many people out of deprivation but has also increased economic growth and prevented many forested areas, wetlands, and other fragile ecosystems from being converted into agricultural land (Spielman and Pandya-Lorch, 2010). As a result of the GR, the entire cropping system in India changed during 1967–1977. This led to a tripling of agricultural production from 1965 to 1966 to 1998–1999. At the same time, the cultivated land area for food grain crops increased from 115.1×10^6 in 1965–1966 to 127.84×10^6 in 1990–1991 (Singh, 2000), which has positively impacted India's economy and changed the way of life in rural areas (David and Otsuka, 1994).

The GR led cultivation system has transformed India from a food-deficient country to one of the leading agricultural countries in the world (Pingali, 2012). However, the impact of the GR on multiple ESs in India has not been adequately documented and analyzed. Few studies have focused on creating agricultural-based sustainability indicators (Rao et al., 2018). Additionally, no prior study has attempted to analyze ESVs dynamics in a predominantly agricultural country, like India, where the GR has significantly changed the country's production. To fill these knowledge gaps, this paper quantified the impact that the successful agricultural expansion has had on the delivery of critical ESs in India. Specifically, India's changes in ESVs (Billion US$) during 30 years from 1985 to 2005 were estimated using multiple value transfer approaches (Costanza et al., 1997, 2014; de Groot et al., 2012; Xie et al., 2008). The specific objectives of this study were to (1) estimate the ESVs of different ecoregions of India, and (2) assess the impact of agricultural expansion on the nation's ESVs.

2. Materials and methods

2.1. Calculation of LULC dynamics

Time series LULC data were used to estimate per unit ESVs of each ecosystem type for the three reference years. The LULC data were derived from the study of Roy et al. (2015), which has produced detailed LULC information for India with the finest spatial resolution available for a national database and a temporal interval of 10 years (1985, 1995 and 2005). Overall classification accuracy of 94.4% was achieved for all LULC categories for 2005 (evaluated using ~12606 sample points). In this study, the original 17 LULC classes were reclassified into eight major biomes, i.e., forest land, cropland, urban built-up, grassland, fallow land, water bodies, mangrove and wetland, that correlated with some of Costanza et al. (2014) equivalent biomes (Table 1). Since some miscalculations (only in 2005 LULC) were detected for the Sundarbans mangrove region, a further adjustment was made in this study using the author's estimates (Sannigrahi et al., 2019a). Afterward, the spatio-temporal dynamics and conversion of LULC categories were quantified for two decadal periods (i.e., 1985–1995 and 1995–2005), and the entire 20-year period (i.e., 1985–2005). The following analyses were performed corresponding to these three periods. The reason for adding the whole period is that it can provide complementary information on the overall long-term trend that may not be directly revealed by the two sub-periods. The spatiotemporal LULC change dynamics were assessed as follows:

$$CP\_LULC_k = \frac{LULC_{end} - LULC_{start}}{LULC_{start}} \times 100 \quad (1)$$

Table 2
Equivalent weight of different ecosystem services per area (ha).

Ecosystem Service Functions	Ecosystem Service Value coefficient for different biomes													
	Forest land		Cropland		Urban built- up		Grassland		Fallow land		Water bodies		Wetlands	
	C97b	X08	C97b	X08	C97b	X08	C97b	X08	C97b	X08	C97b	X08	C97b	X08
Gas regulation	0	4.32	0	0.72	0	0	0.13	1.5	0	0.06	0	0.51	2.46	2.41
Climate regulation	2.65	4.07	0	0.97	0	0	0	1.56	0	0.13	0	2.06	0.08	13.55
Water regulation	0.09	4.09	0	0.77	0	0	0.06	1.52	0	0.07	0.14	18.77	0.35	13.44
Soil formation and retention	8.65	4.02	0	1.47	0	0	0.56	2.24	0	0.17	0	0.41	0	1.99
Waste treatment	1.61	1.72	0	1.39	0	0	1.61	1.32	0	0.26	12.31	14.85	0.08	14.4
Biodiversity maintenance	0.33	4.51	0.89	1.02	0	0	0.89	1.87	0	0.4	0	3.43	5.63	3.69
Food production	0.8	0.33	1	1	0	0	1.24	0.43	0	0.02	0.76	0.53	4.74	0.36
Raw material provision	2.56	2.98	0	0.39	0	0	0	0.36	0	0.04	0	0.35	1.96	0.24
Recreation and cultural, and aesthetics	1.26	2.08	0	0.17	0	0	0.04	0.87	0	0.24	4.26	4.44	26.94	4.69
Total	**17.95**	**28.12**	**1.7**	**7.9**	**0**	**0**	**4.53**	**11.67**	**0**	**1.39**	**17.47**	**45.35**	**42.24**	**54.77**

C97b = Costanza et al. (1997), X08 = Xie et al. (2008).

Table 3
ESV (US$ ha^{-1} $year^{-1}$) per area (ha) in India, according to five units of valuation.

Ecosystem Service Functions	Forest land		Cropland		Urban built-up		Grassland		Fallow land		Water		Wetlands	
	C97b	X08	C97b	X08	C97b	X08	C97b	X08	C97b	X08	C97b	X08	C97b	X08
Gas regulation	0.00	245.79	0.00	40.97	0.00	0.00	7.40	85.34	0.00	3.41	0.00	29.02	139.96	137.12
Climate regulation	150.77	231.57	0.00	55.19	0.00	0.00	0.00	88.76	0.00	7.40	0.00	117.21	4.55	770.94
Water regulation	5.12	232.70	0.00	43.81	0.00	0.00	3.41	86.48	0.00	3.98	7.97	1067.94	19.91	764.68
Soil formation and retention	492.15	228.72	0.00	83.64	0.00	0.00	31.86	127.45	0.00	9.67	0.00	23.33	0.00	113.22
Waste treatment	91.60	97.86	0.00	79.09	0.00	0.00	91.60	75.10	0.00	14.79	700.39	844.91	4.55	819.30
Biodiversity Maintenance	18.78	256.60	50.64	58.03	0.00	0.00	50.64	106.40	0.00	22.76	0.00	195.15	320.32	209.95
Food production	45.52	18.78	56.90	56.90	0.00	0.00	70.55	24.47	0.00	1.14	43.24	30.15	269.69	20.48
Raw material Provision	145.65	169.55	0.00	22.19	0.00	0.00	0.00	20.48	0.00	2.28	0.00	19.91	111.52	13.66
Recreation and cultural, and aesthetics	71.69	118.34	0.00	9.67	0.00	0.00	2.28	49.50	0.00	13.66	242.38	252.62	1532.78	266.84
Total	**1021.3**	**1599.92**	**96.72**	**449.48**	**0**	**0**	**257.74**	**663.98**	**0**	**79.09**	**993.97**	**2580.23**	**2403.29**	**3116.19**
Costanza (2014) 1997 Unit value (**C97a**)	**2769**		**126**		**0**		**321**		**0**		**11727**		**20404**	
Costanza (2014) 2011 Unit value (**C11**)	**5382**		**5567**		**6661**		**‘4166**		**0**		**12512**		**140174**	
de Groot (2012) 2007 Unit value (**D12**)	**5264**		**5567**[a]		**0**		**2871**		**0**		**4267**		**25682**	

[a] Chosen Costanza et al. (2011) unit values for cropland. C97b = Costanza et al. (1997), X08 = Xie et al. (2008).

where CP_LULC_k is the change in the area of LULC type k; $LULC_{end}$ and $LULC_{start}$ are the area of LULC type k at the past and current years, respectively. A transpose matrix was developed to quantify spatiotemporal changes of different LULC categories. The LULC categories for the start and end years were assigned a specific code to calculate the area transferred among classes between the two reference years.

2.2. Calculation of ecosystem service value (ESV)

The benefit transfer approach by Costanza et al. (1997, 2014) was employed in this study to estimate ESVs of each LULC category as follows:

$$ESV_k = \sum_f A_k \times VC_{kf} \tag{2}$$

$$ESV_f = \sum_k A_k \times VC_{kf} \tag{3}$$

$$ESV = \sum_f \sum_k A_k \times VC_{kf} \tag{4}$$

where ESV_k is ESVs of each LULC category$_k$; ESV_f is ESVs of each ecosystem function f, and ESV indicates the total estimated ESVs; $A_k$refers to the area (ha) of each LULC type$_k$; $VC_{kf}$is the equivalent value coefficient (US \$ ha^{-1} $year^{-1}$) of each LULC type $_k$ and ecosystem function f, respectively (Richmond et al., 2007; Kindu et al., 2016; Sannigrahi et al., 2018, 2019b). The changes in ESVs were calculated as follows:

$$\Delta ESV = \frac{ESV_{end} - ESV_{start}}{ESV_{start}} \times \frac{1}{t} \times 100 \tag{5}$$

where ΔESVrefers to the change of ESVs of a particular LULC type k;ESV_{end} and ESV_{start} exhibit ESVs of the past and current years, respectively, and t represents the time period.

Additionally, the Equivalent Value factor approach proposed by Xie et al. (2008) was used to estimate the ESVs of the key ESs of India (Tables 2 and 3). A preliminary study was conducted to select the most suitable ESs for Indian ecosystems. Hence, to address the uncertainties and biases involved in the valuation process, multiple valuation methods (Costanza et al., 1997; Xie et al., 2008; De Groot et al., 2012) were adopted in this study. Thereafter, the selected ESs were grouped and categorized to obtain the biome/LULC specific ESVs of India. Ultimately, a total of nine ESs were selected and grouped in four broad categories as follows: food production and production of raw materials are included in the *provisioning services*; greenhouse gas regulation, climate regulation, water regulation, and waste treatment are included in the *regulating services*; soil formation, conservation and retention, and biodiversity maintenance are included in the supporting *services*;

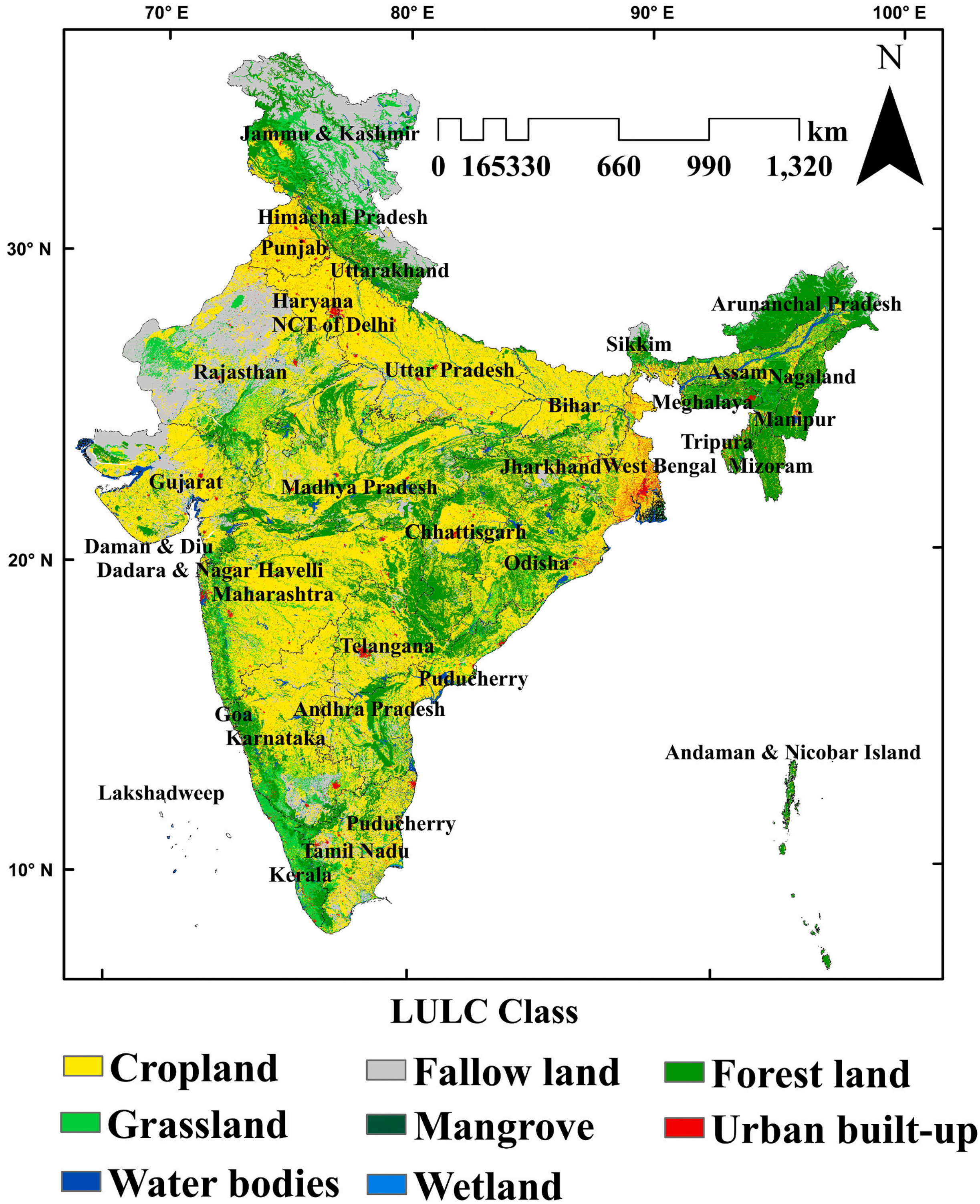

Fig. 1. The spatial distribution of different land use/land cover categories in 2005 in India.

aesthetic, cultural and recreation are included in the *cultural services*. The food production Equivalent Value for cropland ecoregions was first estimated using the valuation approaches from Costanza et al. (1997) and Xie et al. (2008). Consequently, the equivalent values of the other ESs were retrieved from the cropland equivalent factor. In the cropland valuation process, Liu et al. (2012) and Xie et al. (2008) have proposed that the projected food production service could be 1/7th of the real food production. This approximation was used to estimate equivalent value for multiple key ESs in India. Information on crop production, crop price, crop yield, net irrigated area, and cropping intensity of the major crops of India were extracted from Directorate of Economics and Statistics, Department of Agriculture, Cooperation, and Farmers Welfare, Govt. of India,[1] Open Government Data Platform, Govt. of India,[2] and

[1] http://eands.dacnet.nic.in/latest_20011.htm.
[2] https://data.gov.in.

Table 4
Summary statistics of temporal LULC dynamics from 1985 to 2005.

LULC	1985		1995		2005		1985–1995		1995–2005		1985–2005	
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Changes (ha)	Changes (%)	Changes (ha)	Changes (%)	Changes (ha)	Changes (%)
Forest land	75933445	**23.02**	74118935	**22.47**	72495713	**21.98**	−1814510	−2.39	−1607822	−2.17	−3422332	−4.51
Cropland	164880992	**50.00**	164532601	**49.89**	170477103	**51.69**	−348391	−0.21	5944502	3.61	5596111	3.39
Urban built-up	3429106	1.04	4038952	1.22	4719281	1.43	609846	17.78	680329	16.84	1290175	37.62
Grassland	23738211	7.20	23812022	7.22	24247304	7.35	73811	0.31	435282	1.83	509093	2.14
Fallow land	50049972	15.18	51004593	15.47	46200639	14.01	954621	1.91	−4803954	−9.42	−3849333	−7.69
Water bodies	11064694	3.36	11568986	3.51	10860343	3.29	504292	4.56	−708643	−6.13	−204351	−1.85
Mangrove	380895	0.12	378669	0.11	403422	0.12	−2226	−0.58	9353	2.47	7127	1.87
Wetlands	313315	0.10	335872	0.10	386825	0.12	22557	7.20	50953	15.17	73510	23.46
Total	**329790630**	**100.00**	**329790630**	**100.00**	**329790630**	**100.00**						

Ministry of Statistics and Programme Implementation.[3] The average food production and crop price in India during 1985–2005 were valued as 1495.21 kg ha^{-1} and 0.27 US$$kg^{-1}$ (1 US$ = 44.3 INR in 2005), respectively, and subsequently, the ESV of cropland food production service was estimated (1 × 1495.21 × 0.266/7 US$/ha).

2.3. Elasticity of ESV to LULC change

The coefficient of elasticity (C_{ES}) measures the sensitivity of the outcome variable to the change of a explanatory variable (Song and Deng, 2017). The specified weights of resistance and resilience depend on the probability of external forces (land use modification and associated alternation) surpassing the self-adjustment capability of any given ecosystem (Liu et al., 2017a,b). In this study, the spatiotemporal elasticity of ESVs to LULC changes is evaluated to identify the most sensitive and disturbing ecosystems of the country. This is estimated as follows:

$$C_{ES} = \left(\frac{(ESV_j - ESV_i)}{ESV_i} \times 100\right) \Big/ LCI \tag{6}$$

$$LCI = \frac{\sum_{k=1}^{n} \left|(LULC_{jk} - LULC_{ik})\right|}{\sum_{k=1}^{n} A_k} \times \frac{1}{t} \times 100 \tag{7}$$

where C_{ES} is the coefficient of elasticity; ESV_j and ESV_i are the ESVs of the current and past years, respectively; LCI is the LULC change intensity; $LULC_{jk}$ and $LULC_{ik}$ is the area of land use type k at the current and past years, respectively; t is the length of the research period; A_k is the area of land use type k.

2.4. Estimating relationship between ESV and cropping pattern

2.4.1. Geographically weighted regression (GWR)

The geographically weighted regression (GWR) approach, an extension of conventional ordinary least square method, was used in this study for its capability to capture the spatial variation that helps assess the spatial association, spatial non-stationarity, and coefficient of determination (local R^2) between explanatory and response variables (Fotheringham et al., 2002). We fitted the GWR model to show how spatial variation of cropping pattern determines the ESV pattern. Therefore, the spatial weight was described based on its proximity to the location of observation (Su et al., 2014). However, the weight estimate of GWR is always sensitive to the selection of the kernel size and bandwidth parameterization. In addition, the observation with higher proximity to the location of neighbouring features exhibits more significant influence than that of the distant elements on parameter estimation (Fotheringham et al., 2002; Su et al., 2014). Additionally, the improper (coarser) parameterization of bandwidth and kernel selection would generate a global relationship and spatial stationarity, while a local estimate of spatial association and spatial non-stationarity is produced when bandwidth was set too small (Zou et al., 2016; Su et al., 2014; Sannigrahi et al., 2020c). In this study, an adaptive kernel type was chosen for model parameterization (Mollalo et al., 2020; Song et al., 2020). The basic GWR equation is:

$$y(u_i, v_i) = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)x + \varepsilon(u_i, v_i) \tag{8}$$

where y is the dependent variable (ESVs); β is the intercept; β_1 is the coefficient; v_i, u_i are the coordinates of sample i; x is the independent variable, including Total Crop Area (TCA), Crop Production (CP), Crop Yield (CY), Net Irrigated Area (NIA), and Cropping Intensity (CI); $\varepsilon$is the error.

The required weight matrix can be retrieved as follows:

$$w_{ij} = \exp\left(\frac{-D^2{}_{ij}}{B^2}\right) \tag{9}$$

where $w_{ij}$is the weight of sample j for sample$i$; B is the kernel bandwidth; $D_{ij}$is the distance between the samples i and$j$. The bandwidth specification generally controls the degree of smoothness of local regression estimates (Fang et al., 2015). If the specified distance exceeds the specified bandwidth, the spatially varying weight reduced to zero. Therefore, the cross-validation method, Akaike Information Criterion, was performed for the selection of optimal bandwidth by minimizing the Akaike Information Criterion value (Fang et al., 2015).

2.4.2. Artificial Neural Network (ANN) for estimating relative effects of cropping factors on ESVs

Artificial Neural Network (ANN) was used as a machine learning algorithm that enables a system to predict human learning processes through establishing and strengthening of the internal self-adjustment linkage system (Were et al., 2015; Wen et al., 2014; Qiang and Lam, 2015)). The ANN algorithm can efficiently predict, classify, make a decision, and solve new problems through the trained parameters when the information is limited. An ANN architecture is comprised of an input layer, a set of hidden nodes, and an output layer, which are connected by a number of neurons (Chakraborti et al., 2018). In this study, we have adopted multilayer perceptron neural networks with a backpropagation algorithm to predict and simulate the ESVs pattern based on the aforementioned cropping factors. In this network, 30 hidden layers were chosen to generate optimum weights for predicting ESVs, wherein 70%, 15%, and 15% samples were approximated for training, testing, and validating the model estimates. Additionally, we have performed simple and multiple linear regression analysis to examine the single and joint

[3] http://www.mospi.gov.in.

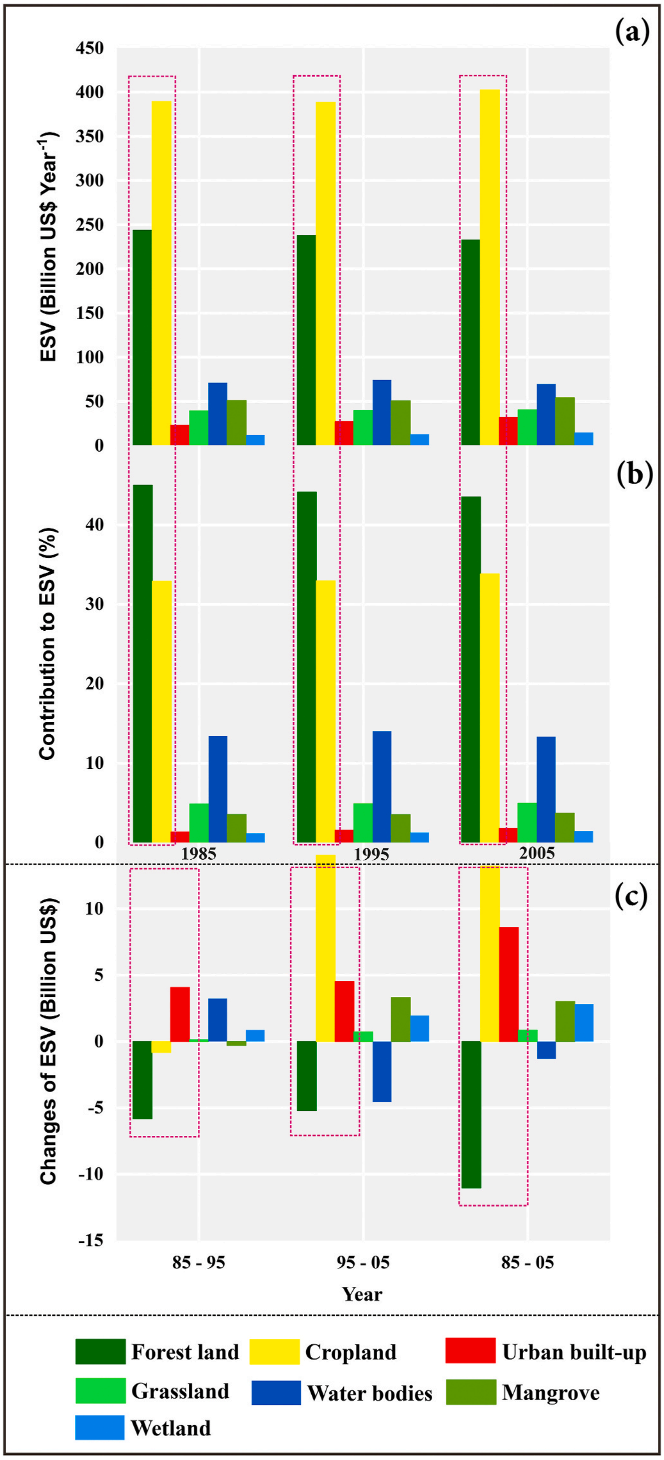

Fig. 2. (a) The mean ESV (Billion US$ year) derived from the five unit values, (b) percentage contribution to total ESVs by seven LULC categories, and (c) changes in ESVs (Billion US$) during the research period (1985–2005).

effects of the explanatory factors on ESVs.

3. Results and discussion

3.1. LULC changes in India during 1985–2005

The spatial distribution of different LULCs for 2005 is presented in Fig. 1. Cropland areas are mainly distributed along the Indo-Gangetic Plain (Uttar Pradesh, Bihar), Godavari (Maharashtra, Telangana, Andhra Pradesh, Chhattisgarh) Krishna (Karnataka, Telangana, Andhra Pradesh, Maharashtra) and Cauvery basins (Tamil Nadu, Karnataka, Kerala) and part of Narmada (Madhya Pradesh, Maharashtra), Tapi (Maharashtra, Madhya Pradesh, Gujarat), and Mahanadi basins (Chhattisgarh and Odisha) (Fig. 1). The highest proportion of forest cover is found in Central India, Eastern Himalayan region and part of Gujarat, and is scattered in Western Himalayan states (Uttarakhand and Himachal Pradesh).

The conversions of LULC were reported for the three research periods, i.e., 1985–1995, 1995–2005, and 1985–2005 (Fig. S1). Between 1985 and 1995, the increasing trend of cropland areas at the expense of fallow land and forest land was documented predominantly in the western parts (Rajasthan, Gujarat) of India. The incentives for comprehensive watershed management and sustainable irrigation management practices for this arid region had stimulated agricultural productivity, and hence the cultivated agricultural areas increased dramatically (Davidar et al., 2010). The destruction of evergreen pine and deciduous broadleaf forest areas, especially in the parts of Odisha, Eastern Himalayan region, and over the Western Himalayan states, have also been documented in this period. These damages can be attributed to natural causes (landslide, wildfire, climatic anomalies) and human appropriations (deforestation, shifting cultivation, grazing, and human-made fire). In addition, the following activities are listed as being responsible for forest degradation in India: (1) extraction of fuelwood, forest residual, and biomass products including wooden furniture, and timber products; (2) livestock cultivation including cattle, dairy, and leather products; (3) villagers involving mining and quarrying activities; and (4) industrial set-up and development of nearby forest landscapes (Meiyappan et al., 2017). During 1995–2005, substantial areas of cropland were reclaimed from fallow land, especially in the western parts of the country (comprising the dry regions of Gujarat, Rajasthan), and from forested and grassland regions in the southern (Tamil Nadu) part of India (FSI, 2003). Additionally, the exponential growth of urban built-up areas is documented in this period. Research results have shown that during this period, significant areas of grassland were converted to forest cover in the Western Himalayan (Himachal Pradesh, Uttarakhand, Jammu, and Kashmir), Eastern Himalayan (Arunachal Pradesh, Assam, Meghalaya, Mizoram), Central (part of Madhya Pradesh), and South-Eastern (in a scattered way in Odisha) parts of India (Fig. S1). However, over the entire research periods (1985–2005), a net expansion of cropland and urban areas was documented at the expense of forest land, grassland, and fallow land, respectively (Fig. S1, Table 4).

3.2. Impact of LULC on spatially explicit ESVs during 1985–2005

Using the five unit values (Costanza et al., 1997a, Costanza et al., 1997b, Costanza et al., 2014; de Groot, 2012, and Xie, 2008), the mean ESVs (Billion US$ year^{-1}) of India was estimated for 1985, 1995 and 2005 (Fig. 2a and b). Forest and cropland ecosystems provided the maximum (200–400 Billion US$ Year $^{-1}$) ESVs for all three reference years, with the maximum share (30–50%). Grassland, wetland, and water bodies shared 5–15% of total ESVs. The magnitude of ESVs changes during the first period (1985–1995), and the second period (1995–2005) was found markedly different for most of the LULC categories. This advocates the reason for performing a separate change analysis, considering the entire period (1985–2005), to add complementary information to the two sub-periods instead of overlapping with them. Except for the first reference period (1985–1995), cropland ESVs have increased throughout the research period (Fig. 2c). The maximum increase was observed during 1995–2005, followed by the 1985–2005 period. Whereas the forest ESVs has decreased substantially during the study period (Table. S1, S2).

The coefficients of elasticity of ESVs to LULC changes are documented for three different time periods, i.e., 1985–1995, 1995–2005, and 1985–2005 (Fig. 3). During 1985–1995, negative elasticities were documented for cropland, forestland, and mangrove eco-regions,

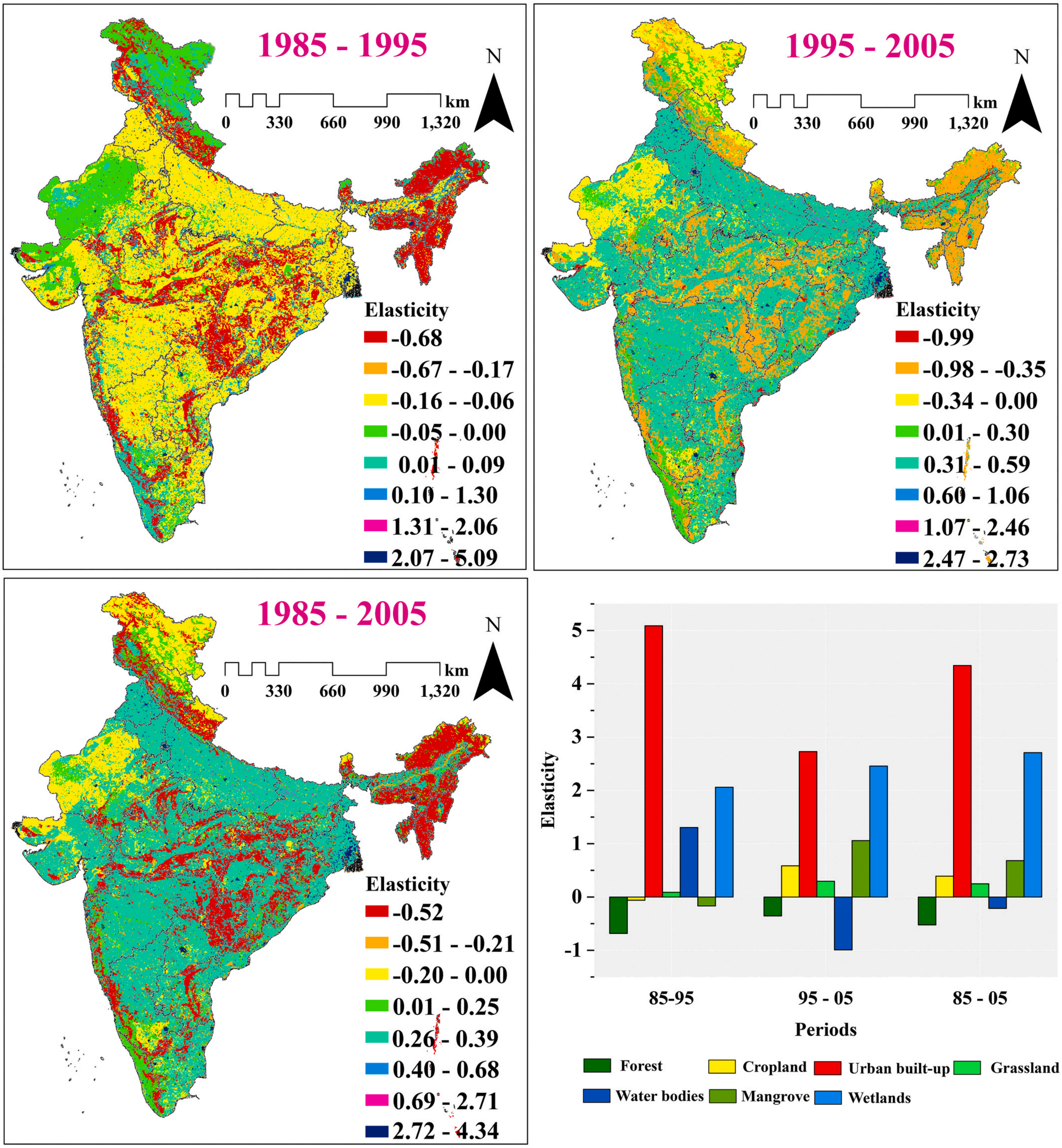

Fig. 3. Coefficient of elasticity of ESVs to LULC changes in India during 1985–1995, 1995–2005, and 1985–2005, respectively.

indicating a negative impact of LULC changes on ESVs. During 1985–1995, the highest negative elasticity was observed for the forest eco-region, indicating a negative impact of forest degradation and deforestation on the country-level natural capital formation (Fig. 3). The negative elasticity resulted from any unwanted changes reflects the decreasing status of a particular ecosystem, calling for special attention and consideration for the improvement of natural resource management and preservation (Song, 2018; Sannigrahi et al., 2018, 2019a). Considering the last half (1995–2005) and the whole research period (1985–2005), the cropland eco-region exhibits moderate to high elasticity to LULC changes (Fig. 3). The outcomes reveal a cumulative impact of agricultural expansion on the total ESVs in India. The value of positive elasticity of cropland was found significantly lower than that of the negative elasticity of forest land. This indicates a higher capacity of natural forest ecosystems to produce green capital than any anthropogenic inputs (Costanza et al., 1997, 2014). Water bodies exhibited the second largest negative elasticity of ESVs to the LULC changes, which is higher than the cropland elasticity.

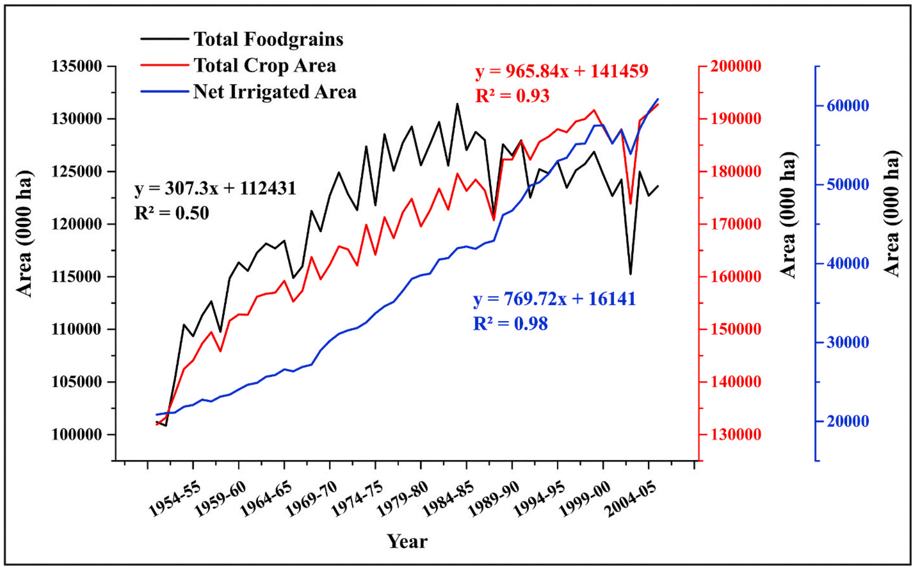

Fig. 4. Temporal changes of total food grains, total crop area, and the net irrigated area in India during 1950–51 to 2005–06.

3.3. Impact of GR on changing ESV patterns in India

During the research period (1985–2005), the total estimated ESVs have increased mainly due to a substantial expansion of cropland and wetland areas in India. Considering the total estimated ESVs in India, the cropland shares the major amount of mean ESVs (30–40%) during the observation period. This shows an enormous impact of agricultural productivity and subsequent food production on green economy of India. India has a predominantly agriculture-based economy, which contributes almost 20–50% to the total national Gross Domestic Product (GDP). However, the contribution of agriculture-based economies to the formation of national GDP gradually decreased, as it accounted for 39% in 1983 and only 24% in 2000–2001 (Mall et al., 2006). However, its contribution to the total employment generation during the same period reduced only slightly (63–57%) (Mall et al., 2006). While the global ESVs show a decremental trend (Costanza et al., 2014; Sannigrahi et al., 2018), the total estimated ESVs of India show an incremental tendency. The fast-tracked expansion of cropland areas in India, particularly during the period of 1995–2005 had happened due to the following: (1) climatic favourability, normal to excess monsoon rainfall received during 1995 and 2005, as till now the national average of 40% of the total cropped area in India is under the coverage of major and minor irrigation programmes, but almost 60% of the cultivated land is still rainfed and depends on seasonal monsoon rainfall (Mall et al., 2006; Guiteras, 2008; Roy et al., 2015). The two major cropping seasons of India, i.e., Kharif (June–September, monsoon or autumn crops) and Rabi (October–November, winter crops), provide the major productions of food grains and oilseeds of the country. The increasing trend of net primary production of the country has also been documented during this period, aligned with the rainfall anomalies and resulting cropping patterns of India (Nayak et al., 2013); (2) Several major and minor irrigation projects such as Indira Gandhi Canal System, Narmada Project and Accelerated Irrigation Benefit Programme were initiated in this period for boosting the crop production and resulting in an increase of net irrigated area. Additionally, this initiative has significantly increased the total cropped area at the expense of fallow land and forest land, especially in the western parts of India (Roy et al., 2015, Fig. 4). These programmes collectively increased the national irrigation potential of 5.44 million hectares under various major/medium irrigation projects and also generated 0.45 million hectares of potential irrigation land under the multiple minor/small irrigation schemes up to 2009.[4] Furthermore, the Ministry of Land Resource and the Ministry of Rural Development jointly adopted several area-specific watershed management programmes: the 'Drought Prone Areas Programme,' the 'Desert Development Programme,' and the 'Integrated Wasteland Development Programme' to eradicate land degradation that successfully epitomizes the ecosystem as well as agricultural productivity[5]; (3) The area under plantation and aquaculture has increased substantially during the research periods (these LULC categories were merged into cropland types in this study, see Table 1), especially in Southern India (Kerala, Tamil Nadu), and Western Himalayan region is also responsible for increasing observed cropland area in India (Roy et al., 2015). A significant amount of forest ESV (9–19 Billion US\$ year^{-1}) was lost during this period. This can be attributed to the substantial decrease in forest cover, specifically in the Central and Eastern Himalayan part of India (Roy et al., 2015). Different anthropogenic activities (biomass collections, including fuelwood, fodder, and green leaves harvesting by local communities), mining (including coal, iron, and aluminium ores), extensive shifting cultivation (especially in Eastern Himalayan region), population pressure and associated demand for agricultural land, construction of major dams and reservoirs; extraction of raw materials (cutting, burning, grazing, and re-cutting), and natural degradation (erosion, aggradation, landslides, wildfires, drought, climate change etc.) are the major reasons for depleting forest resources in India (Ramachandran et al., 2018;Davidar et al., 2010; Munsi et al., 2010; ,; Giri et al., 2011; Reddy et al., 2013; Roy et al., 2015; Semwal et al., 2004).

3.4. Impact of cropping factors on ESVs in India

Fig. 5 shows the local estimates of GWR, which demonstrate the total explained variance and predictive power of the explanatory variables (TCA, CP, CY, NIA, and CI) that estimate and predict ESVs. Among the five explanatory variables, the TCA, CP, and NIA are highly associated with ESV compared to CY and CI for 1985, 1995, and 2005 (Fig. 5). In 1985, 1995, the estimated ESV for Gujarat, Rajasthan, Haryana,

[4] http://www.archive.india.gov.in/sectors/water_resources/index.php?id=8.

[5] http://www.archive.india.gov.in/sectors/agriculture/index.php?id=7.

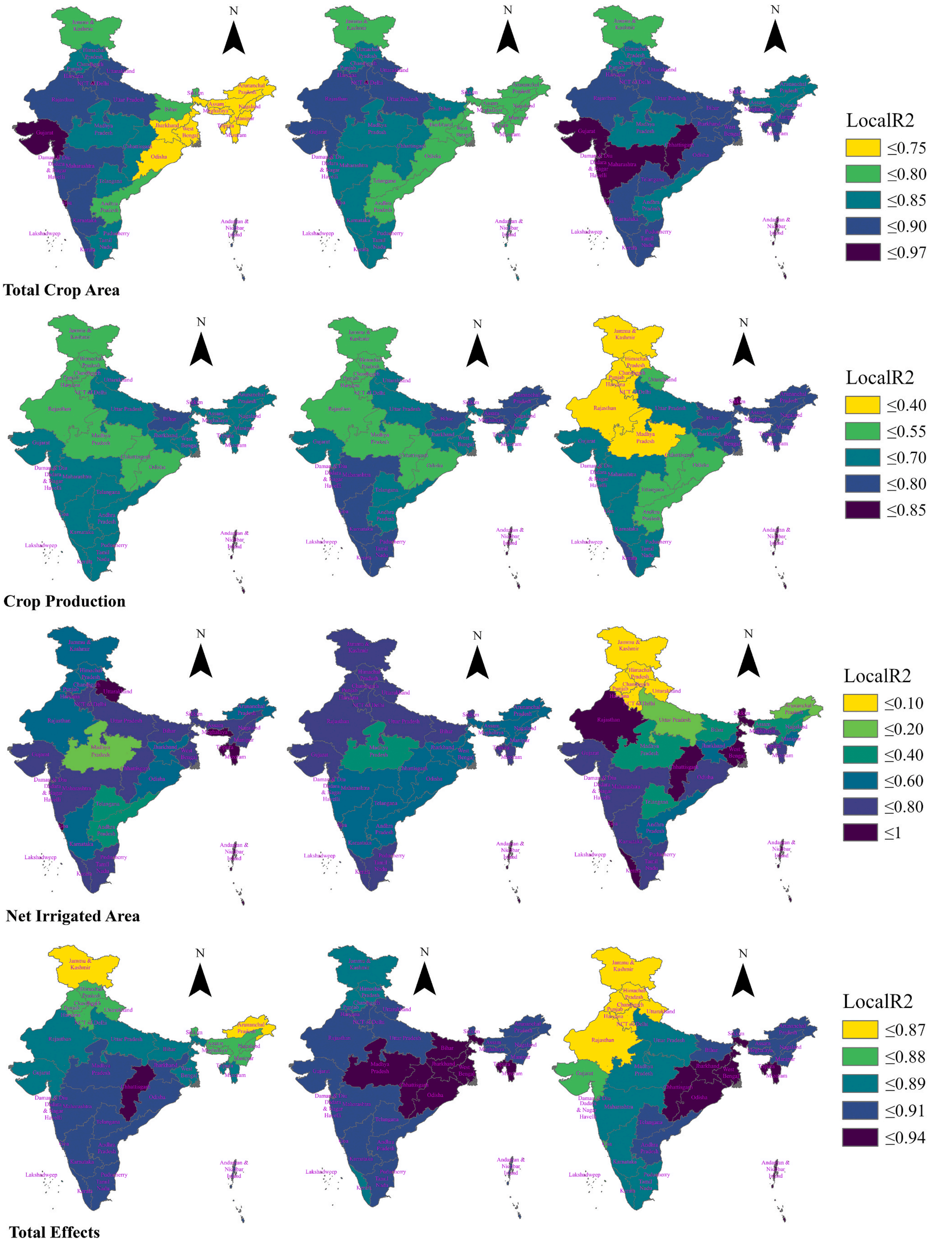

Fig. 5. The local GWR R^2 approximation between the explanatory variables (total crop area, crop production, crop yield, net irrigated area, and cropping intensity) and ESVs.

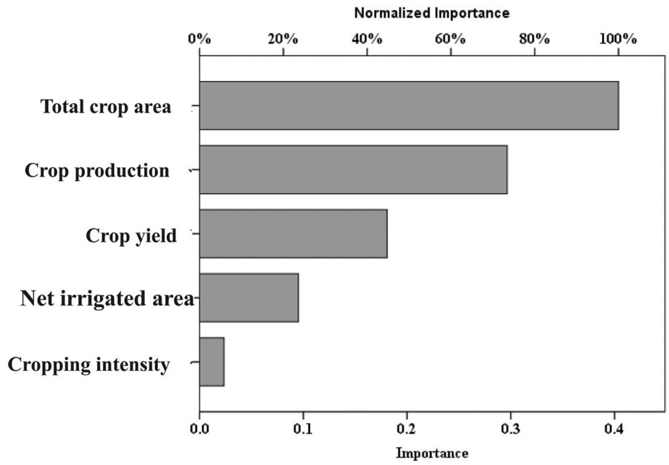

Fig. 6. Normalized importance of the explanatory variables derived from ANN.

Uttarakhand, and Uttar Pradesh were entirely dependent on TCA factors reflected by very high local R^2 approximation. High to moderate local R^2 was observed in Punjab, Himachal Pradesh, Maharashtra, Karnataka, Kerala, Tamilnadu, Chhattisgarh, and Bihar. In 2005, a very high local R^2 was documented for the Central part of the country due to the phenomenal increase in total crop area and resulting ESVs (Fig. 5). Additionally, in 1985 and 1995, this study found that the CI factor does not have a significant impact on ESVs; however, in 2005, the entire Eastern Himalayan states have produced a very low correlation between CI factor and ESV (Fig. 5). In addition, the CP factor has a notable impact on ESVs. The entire Indo-Gangetic Plain regions and the Eastern Himalayan states characterized by high to a very high local R^2 approximation for 1985, 1995, and 2005. Whereas, the Central, Western, and Northern states of India exhibit low to moderate association between CP and ESVs. Additionally, the CY factor shows a negligible to no coefficient of association with ESVs (Fig. 5). Considering the total effects, the Central (Madhya Pradesh, Chhattisgarh), Eastern (West Bengal, Odisha, Tripura, Mizoram, Manipur), and Southern (Andhra Pradesh, Tamil Nadu, Karnataka, Kerala, Telangana) states of India are earmarked by high to very high local R^2 during the research periods. While inspecting the normalized importance and weights of each input derived from the ANN approximation, the TCA factor was found to be the most important to predict ESVs, followed by CP, CY, NIA, and CI, respectively (Fig. 6).

The linear effects of each explanatory factor on different ESs were examined and presented in Fig. 7. For the greenhouse gas regulation service, the highest coefficient of determination value was observed for TCA, followed by CY, NIA, CP, and CI, respectively. The TCA factor has attributed the highest coefficient of determination value for the climate regulation service, followed by CP, CY, NIA, and CI. For water regulation, the coefficient of determination values was ranging from $R^2 = 0.59$ (TCA) to $R^2 = 0.002$ (CI) during the observation period. Concerning the soil formation and retention service, the TCA factor has explained the maximum model variances with high $R^2 = 0.66$ approximation, followed by NIA, CY, CP, and CI. For the waste treatment service, the highest R^2 value was observed for TCA, followed by NIA, CP, CY, and CI. While accounting for the model performances between the biodiversity maintenance service and the explanatory factors, the TCA factor was able to explain the maximum model variances, followed by CY, NIA, CP, and CI. All the explanatory variables performed most accurately with the least unexplained bias and estimates for the food production service. The highest coefficient of determination was estimated for TCA, followed by NIA, CP, CY, and CI, respectively. For the raw material production service and recreation, culture, and aesthetic service, the percentage of model variances ranges from 44% (TCA) to 0.2% (CI) (Fig. 7).

Step-wise multiple linear regression was performed to examine the individual and cumulative effects of the five explanatory variables on ESV (Table 5). A total of 15 pairs of models were constructed to identify the best pair of models for predicting ESVs. Among all models, model 1 explained the maximum model variances (85%) and was found to provide the best prediction of ESVs with the highest $R^2 = 0.85$, followed by model 2 ($R^2 = 0.45$), model 6 ($R^2 = 0.43$), model 13 ($R^2 = 0.43$), model 3 ($R^2 = 0.24$), model 10 ($R^2 = 0.19$), model 11 ($R^2 = 0.14$), model 14 ($R^2 = 0.12$). Among the explanatory factors, TCA (model 1) is exhibiting the most significant influence on ESVs. Model 9 ($P = 0.24$), model 12 ($P = 0.14$), and model 15 ($P = 0.4$) were found statistically insignificant in explaining corresponding model variances. This indicates that the explanatory factors used for the model construction do not have cumulative effects on ESVs, except TCA. Model 10 and model 15 exhibited negative correlations with ESVs (Table 5).

The pairwise correlation matrix performed between the driving factors and ESVs is shown in Fig. 8. All the pairs exhibited statistically significant correlations except the CI factor. The regulating services are highly associated with the other services and produced statistically significant estimates at $p \leq 0.001$. A negative association was observed between CY and the other factors, except CP. It can be seen in Fig. 9 that all the driving factors except CI have produced significant associations with the ESVs. This shows that almost all the explanatory factors that reflect the GR led cropping scenarios in India have strong positive effects on the formation of natural capital and ESs. After evaluating the individual effects of the driving factors on the total ESVs, the TCA factor has produced the highest coefficient of determination (R^2) and least Root Mean Square of Error value, followed by the NIA, CP, and CY (NIA, CP, CY have produced negative associations with ESVs) (Fig. 10). While considering the cumulative effects of all the driving factors (except the CI factor) on multiple ESVs, the highest association was observed between the food production service and the driving factors, followed by waste treatment, soil formation, and retention, water regulation, climate regulation, biodiversity management, greenhouse gas regulation, recreation, and raw material production services (Fig. 11). The strong positive association between the food production and cropping factors indicate that the GR led agrarian expansion had significantly improved the agricultural ESs of the country.

3.5. Limitations and future scope

The present study aims to provide evidence of ESVs change due to agricultural expansion led by the GR in India in a spatially explicit way with satellite data and quantification methods. Although this study has incorporated several valuation approaches and unit values to estimate the per unit ESVs for different key ecosystem services, still it needs to be acknowledged that some limitations exist in the quantification and valuation process as the cause-effect relationship examines in this study requires more socioeconomic data and more rigorous analysis, which is beyond the scope of this study and can be included in the future work. The direct benefit transfer method proposed by Costanza et al. (1997, 2014) was based on the assumption of spatial homogeneity and invariability of unit values specified for an equivalent biome. The direct linkages of existing unit values to corresponding land units without considering the local and regional landscape variability and socio-ecological diversity may produce under- (or over-) estimates. Apart from this, equivalent value coefficients (Xie et al., 2008) were adopted for estimating the cropland equivalent factor, which was mainly calculated for the Chinese landscape. Since a country-level assessment was considered, it was assumed that the equivalent weights for the selected ESs would be spatially invariant. Additionally, not only the cropped area and crop production but several other factors, i.e., the changes of cropping structure, plantation types, landscape composition, and configuration, etc. can also be responsible for the changes in ESVs (Cai et al., 2013; Qiu and Turner, 2015). Liu et al., 2017b revealed that due to the changes in plantation types, an estimated 359.44×10^4 USD cropland ESs has increased, which contributed to 22.97% of the total increase. Our study also indicates that the most

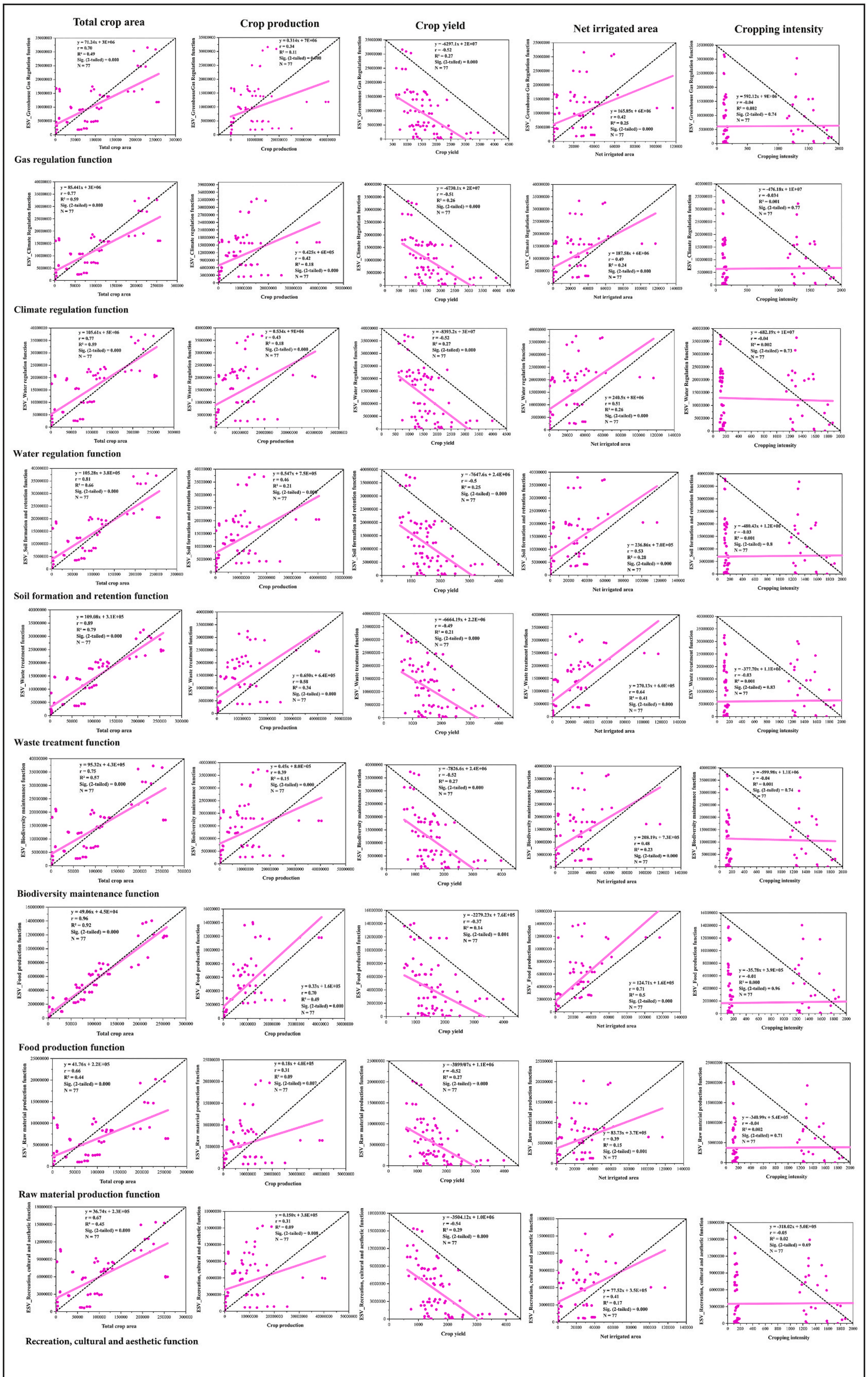

Fig. 7. Simple linear regression model between driving factors and ESs.

Table 5
Stepwise coefficient of determination (R2), Pearson correlation coefficient (r) test between control variables and ESV.

Model	Control variables	r	Sig. (1-tailed)	$_{R}2$	Sig. (1-tailed)	R^2 Change	F	t	Std. Error	Durbin-Watson
1	TCA	**0.92**	0.000	**0.85**	0.000	0	402.45	20.06	19.91	1.58
2	TCA/CP	**0.67**	0.000	**0.45**	0.000	−0.4	57.54	7.59	38.33	1.98
3	TCA/CP/CY	**0.49**	0.000	**0.24**	0.000	−0.21	22.2	4.71	45.08	1.84
4	TCA/CP/CY/NIA	0.36	0.001	0.13	0.002	−0.11	10.5	3.24	48.25	1.76
5	TCA/CP/CY/NIA/CI	0.29	0.007	0.08	0.140	−0.05	6.29	2.51	49.56	1.7
6	CP	**0.65**	0.000	**0.43**	0.000	0	52.06	7.22	39.18	1.85
7	CP/CY	0.32	0.003	0.1	0.007	−0.33	7.75	2.78	49.09	1.75
8	CP/CY/NIA	0.31	0.004	0.097	0.008	−0.003	7.51	2.74	49.17	1.73
9	CP/CY/NIA/CI	0.09	**0.240**	0.01	0.480	−0.087	0.51	0.72	51.55	1.68
10	CY	−0.43	0.000	0.19	0.000	0	16.16	−4.02	46.63	1.62
11	CY/NIA	0.38	0.001	0.14	0.010	−0.05	11.49	3.39	47.95	1.71
12	CY/NIA/CI	0.13	**0.141**	0.02	0.280	−0.12	1.18	1.09	51.3	1.68
13	NIA	**0.66**	0.000	**0.43**	0.000	0	53.1	7.29	39.01	1.59
14	NIA/CI	0.34	0.002	0.12	0.004	−0.31	9.08	3.01	48.68	1.59
15	CI	−0.03	**0.402**	0.001	0.810		0.6	−0.248	51.71	1.67

TCA: Total Crop Area, CP: Crop Production, CY: Crop Yield, NIA: Net Irrigated Area, CI: Crop Intensity.

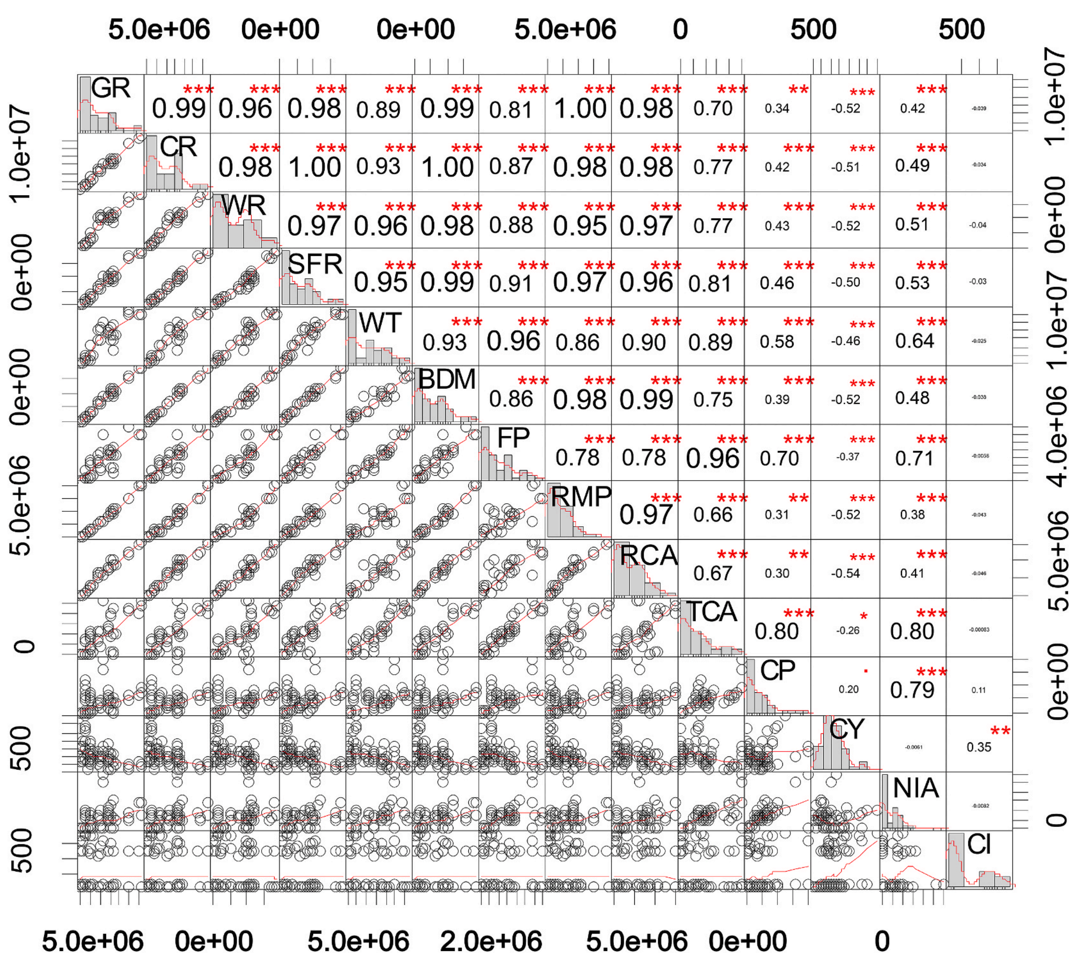

Fig. 8. Correlation matrix between the nine ESs (GR = Greenhouse gas Regulation, CR = Climate Regulation, WR = Water Regulation, SFR = Soil Formation and Retention, WT = Waste Treatment, BDM = Biodiversity Maintenance, FP = Food Production, RMP = Raw Material Production, and RCA = Recreation, Culture, and Aesthetic), and five explanatory factors (TAC = Total Crop Area, CP = Crop Production, CY = Crop Yield, NIA = Net Irrigated Area, and CI = Cropping Intensity).

important feature of a cropland ecosystem is producing multiple key ESs, which creates natural capital. However, this study does not consider the tradeoffs and synergies among the major ESs due to LULC changes. This could help track the overall complementary nature of many interdependent ESs. For instance, the factors (expansion of cropping area, uses of chemical fertilizer, irrigation), which are responsible for the increase of food production service in any given ecosystem, was found to be detrimental for water quality and supply of freshwater services in many cases across the world (Keesstra et al., 2018; Awasthi et al., 2016; Grizzetti et al., 2016; Holt et al., 2016). Finally, the efficacy of emerging approaches, including machine learning-based spatially explicit models, linear and non-linear optimization needs to be assessed under different agro-climatic and geographical conditions, before adopting it as a general solution mechanism for real-world problems. Future research will be directed in this direction to resolve the methodological uncertainties and biases that exist in this valuation study.

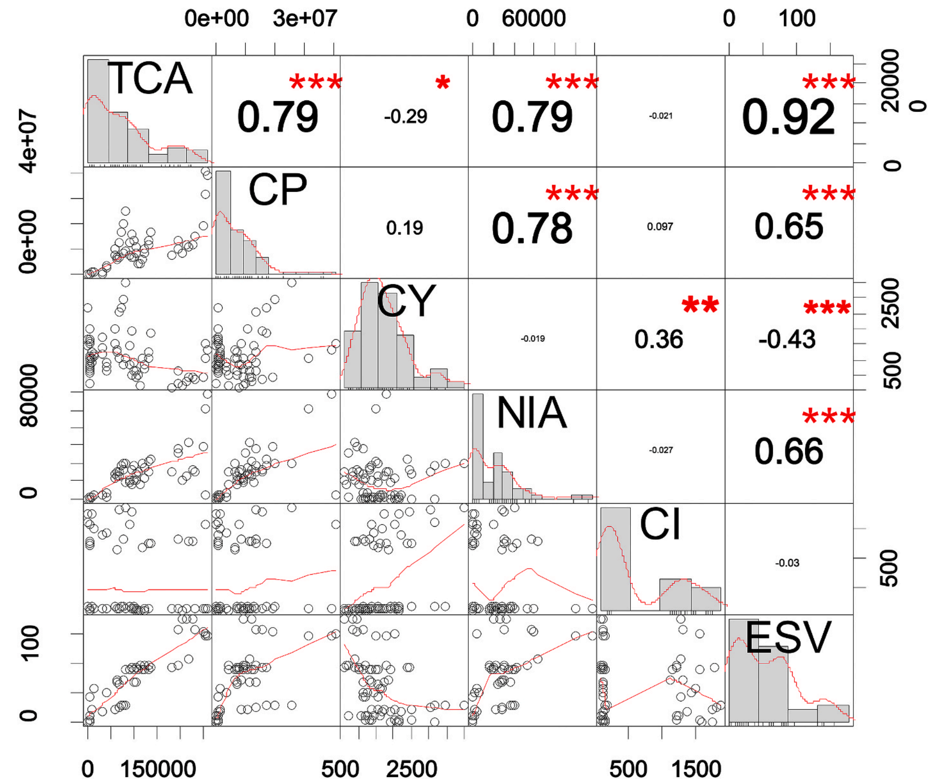

Fig. 9. Correlation matrix between the five explanatory factors (TAC = Total Crop Area, CP = Crop Production, CY = Crop Yield, NIA = Net Irrigated Area, and CI = Cropping Intensity) and ESVs.

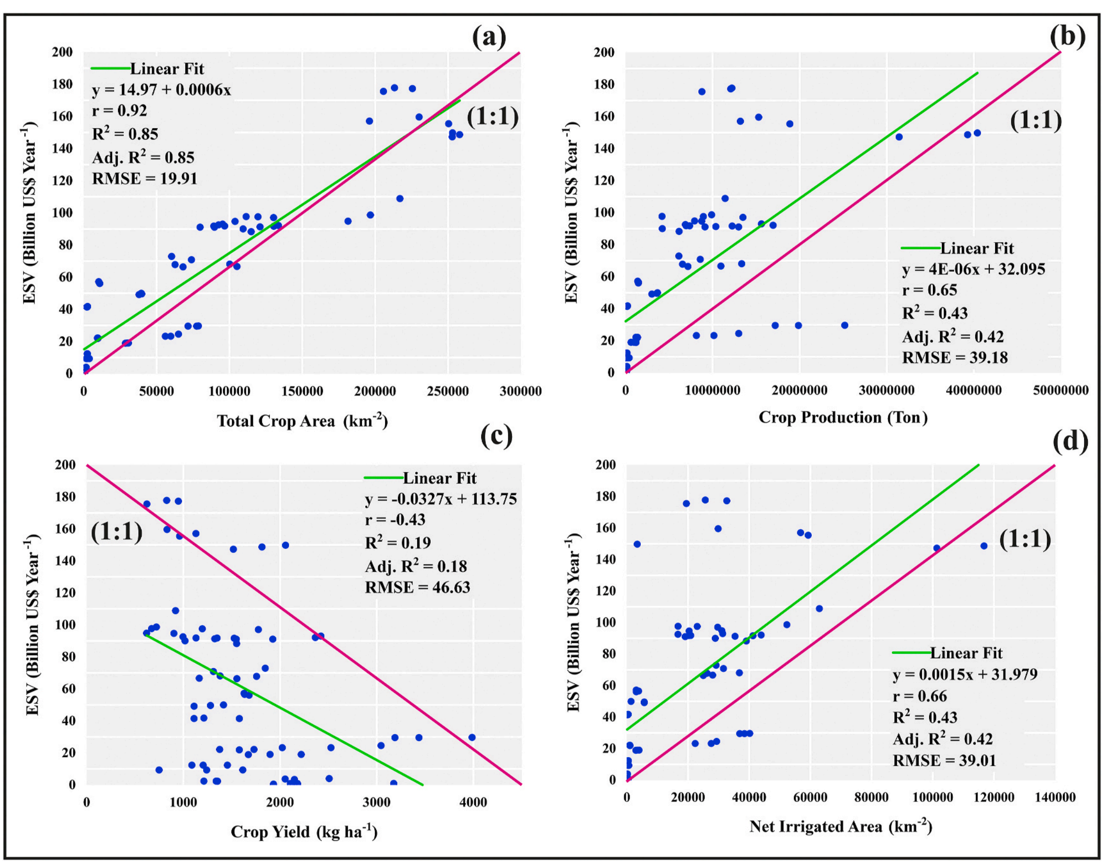

Fig. 10. Coefficient of Determination (R^2) and correlation between the driving factors and ESVs.

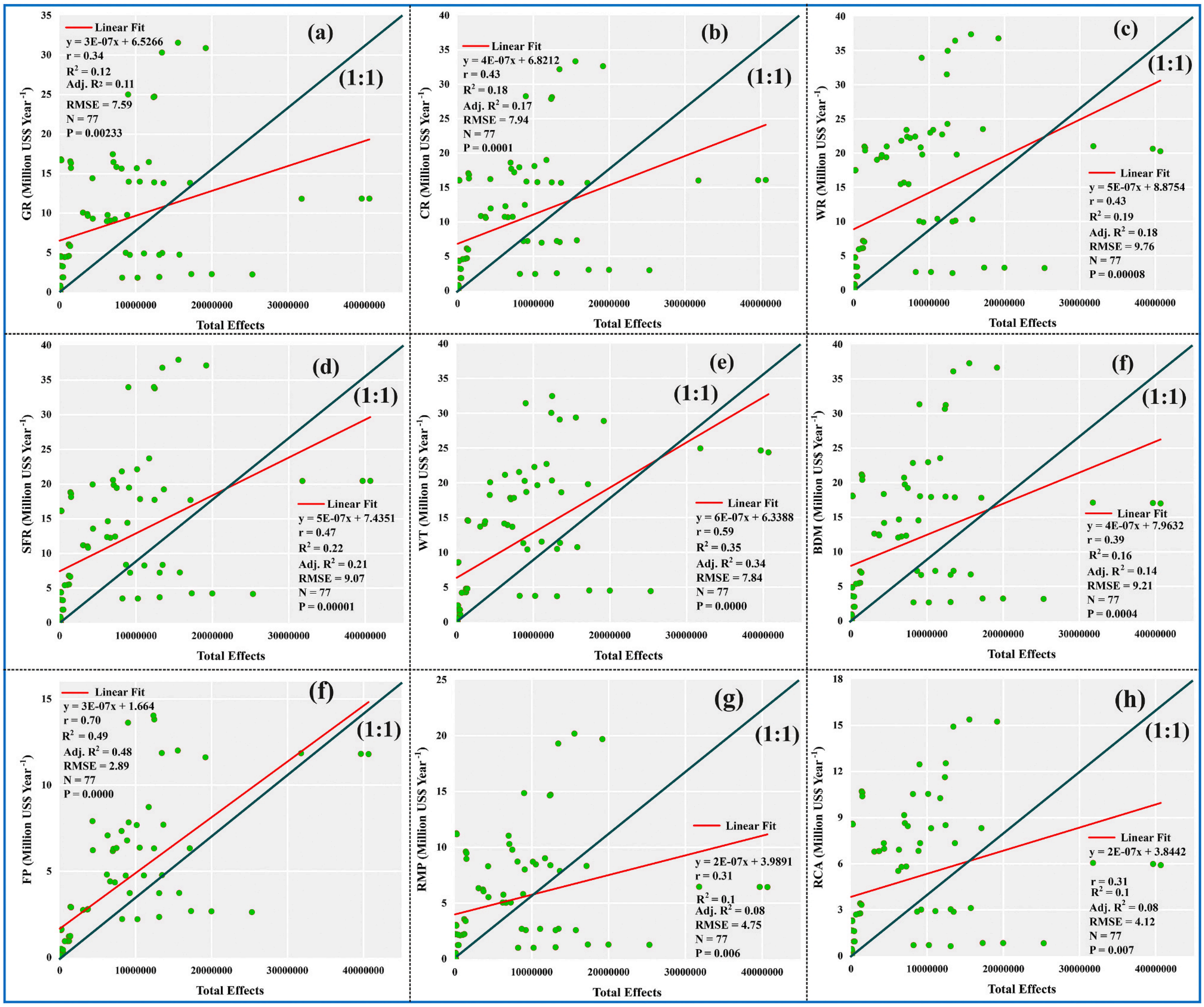

Fig. 11. Coefficient of Determination (R^2) and correlation between the driving factors and 9 ESs.

4. Conclusion

This study examined Indian agrarian ESs at the expense of forests and other natural areas and land reclamation through irrigation programmes. The ESVs of different ecoregions of India were estimated from 1985 to 2005 using remote sensing-based LULC products and crop production statistics. The overall summary and main findings of this study are listed as follows.

1) Using the five unit values, the mean total ESVs (Billion US\$ year^{-1}) of India were estimated 829, 830, and 845 for 1985, 1995, and 2005, respectively.
2) Under GR led agricultural expansion, the average cropland ESVs has increased from 389.32 Billion US\$ year in 1985 to 402.54 Billion US \$ year in 2005 (a net increase of 13.22 Billion US\$ cropland ESVs during 1985–2005). Additionally, cropland has increased substantially during 1995–2005, mainly due to excess monsoon rainfall, and due to the major/minor/small irrigation programs which were launched at different times as the outcome of the GR.
3) Among the five explanatory factors, total crop area has explained the maximum model variance, followed by net irrigated area, crop production, crop yield, and cropping intensity. The crop yield factor was found negatively associated with ESVs, whereas the cropping intensity factor is not significantly correlated with ESVs.
4) A significant forest cover was lost during 1985–2005, mostly due to deforestation, shifting cultivation, timber and fuelwood collection, and wildfires. The alarming rate of forest cover loss, especially in the Eastern and Western Himalayan states of India forms a serious environmental threat for sustainable natural resource management.
5) Among the nine ESs, the strong positive association between the food production service and cropping factors indicates that GR led agrarian expansion has significantly improved the agricultural ESs of the country.
6) While considering the elasticity of ESVs, wetlands, water bodies, and forest land were found to be the most sensitive ecosystems to LULC change.

Therefore, land degradation prevention policies should be implemented for the reclamation of cropland from fallow land and to reduce the over-consumption of agricultural land by intensifying the cropping practices, instead of expanding crop area at the expense of removing forest and natural green cover. The findings of this study also provide beneficial information for farmers, agronomists, environmentalists, planners, land administrators, managers, and decision-makers for sustainable agricultural management as well as natural resources and conservation of the ecosystems of the region.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.111381.

Credit author statement

Srikanta Sannigrahi – Conceptualization; Methodology; Data curation, Writing - original draft, Francesco Pilla - Conceptualization; Supervision; Writing - review & editing. Bidroha Basu – Conceptualization; Writing - review & editing, Arunima Sarkar Basu - Conceptualization; Writing - review & editing. Qi Zhang – Conceptualization; Methodology; Writing - original draft; Writing - review & editing. Suman Chakraborti - Conceptualization; Data curation; Formal analysis; Writing - original draft, P.K. Joshi - Writing - review & editing. Saskia Keesstra - Writing - review & editing. P.S. Roy - Data curation; Writing - review & editing. Paul. C. Sutton - Writing - review & editing. Sandeep Bhatt - Conceptualization; Formal analysis; Shahid Rahmat - Writing - review & editing. Ying Wang - Writing - review & editing. Shouvik Jha - Formal analysis; Visualization, Laishram Kanta Singh - Formal analysis; Writing - review & editing

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