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ORIGINAL PAPER

Biomass Carbon and Tree Cover Dynamics Assessment (2000–2010) on Agriculture Landscape in India: Geospatial Interpretation

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Abstract

This paper assesses the remote sensing datasets of biomass carbon on the agricultural landscape and their decadal change dynamics due to variation in tree cover dominance using geospatial technology in India. Remote sensing data showed that in the year 2000, 16.9% of all agricultural land (28.02 million hectares) in India had agroforestry land (at least 10% tree cover) which was further increased to 22.5% (37.30 million hectares) over 10 years (up to the year 2010). The total biomass carbon estimate in the year 2000 was found 1868.75 million tons of carbon (≈1.87 Pg C) over the Indian agriculture landscape (≈166 million hectares). Out of which approximately 1039 million tons (≈1.04 Pg C) of biomass carbon come from trees (with 55.7% contribution). Total biomass carbon loss between the periods of 2000 and 2010 was observed 31.19 million tons, whereas gain was 170.02 million tons. The decadal biomass carbon net gain was 138.83 million tons due to an increase in agroforestry land by 5.6% (9.27 million hectares). The mean biomass carbon in India increased from 11.29 to 12.13 t C ha^{-1} in 10 years, whereas the global mean increment is 20.4 to 21.4 t C ha^{-1} during the same base periods (Zomer et al in Sci Rep 6:29987, https://doi.org/10.1038/srep29987, 2016). Our analysis critically addressed one of the past research gaps of the biomass carbon-related findings in the agriculture landscape due to tree cover variation. Such understanding will assist significantly agroforestry decision-makers of India in enhancing future harmonized blueprint for agroforestry.

Keywords Biomass carbon · Tree cover · Agroforestry · GIS · India

Introduction

India is the seventh largest country in the world by area and is home to a 1.3 billion human population. The country is characterized by the immense diversity of soil, topography, climate, flora, fauna, and ecosystems (FAO 2017). The country has experienced land-use transformation over the century in agriculture, industry, and urbanization by deforestation (Tian et al. 2014; Roy et al. 2015). A total of 60.5% of land areas (1.79 M km^2) are under agricultural land comprising arable land (53.2%), under permanent crops (3.8%), and pastures (3.5%) (World Bank 2010). It is one of the largest agriculture-producing countries and contributes 23% of the total economy and involves 59% of the country's labor force (FAO 2017). The country has witnessed increased agricultural productivity over the last few decades (Chand and Parappurathu 2012; Pingali 2012). It has the potential to increase production as large areas of croplands are used for subsistence agriculture despite the lack of chemical inputs and modern technology (George 2014; ICAR 2015). The

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population of the country is predicted to reach over 1.6 billion in 2050 and the country needs more production to meet the demands of the population (UN-Pop 2017).

The impact of agriculture intensification on the environment cannot be neglected (Rockstrom et al. 2017; Tilman et al. 2017; Ramankutty et al. 2018; Springmann et al. 2018). A large amount of carbon biomass is produced from the agriculture sector of the country, mainly from agriculture residues and during the time of processing (ElMekawy et al. 2013, 2014). The loss of carbon from the agricultural land has a major impact on climate change (Gibbs et al. 2007; Canadell and Raupach 2008; van der Werf et al. 2009; West et al. 2010; Burney et al. 2010; Tilman et al. 2011; Johnson et al. 2014; Smith et al. 2014; Wollenberg et al. 2016). It is still uncertain whether such loss of carbon stock can be minimized by increasing farm yield and reducing the land-use and cover transformation (Williams et al. 2018). Therefore, sustainable production is important to mitigate climate change. Agroforestry has the potential to sequester carbon and also benefit the environment and socioeconomic (IPCC 2000). The role of agroforestry in soil fertility has already been established in terms of higher nitrogen, phosphorus, potash, and organic matter (Rizvi et al. 2011; Ahmad et al. 2021). Trees in agroforestry increased microbial activities and reduced soil erosion.

GIS, modeling, and algorithms have been used in various disciplines of sciences for solving many problems (Shaikh et al. 2021a, 2021b, 2021c; Ansari et al. 2020; Hassan et al. 2020; Ahmad and Goparaju 2016; Qayum et al. 2020; Farooq et al. 2018). Many studies were conducted on carbon stock in agriculture in different regions of the world and India as well (Rizvi et al. 2011; Lamb et al. 2016; Williams et al. 2018). Williams et al. 2018 studied the carbon stock biomass in the agricultural landscape and natural systems of Africa, Europe, and South America. Rizvi et al. 2011 reported the carbon stock in poplar agroforestry systems in northwestern India. The study highlights the carbon storage of 27–32 t ha^{-1} in boundary, whereas it was 66–83 t ha^{-1} in the agri-silviculture domain in the 7th year. Sahoo et al. 2019 quantified the active and passive carbon pools from total soil organic carbon in different land-use systems in northeast India. Remote Sensing plays a great role in measuring biomass because it is fast, accurate, and cost-effective, and widely used by global researchers for biomass assessment (Zheng et al. 2004; Baccini et al. 2004; Kumar and Mutanga 2017). Thenkabail et al. (2004) used multi-date IKONOS images data and regression models to evaluate wet and dry biomass in oil palm plantations in West Africa. Foody et al. (2003) used Landsat TM data to estimate the tropical forest biomass based on vegetation indices, multiple regression equation, and neural networks in Brazil, Malaysia, and Thailand. Muukkonen and Heiskanen (2005) used ASTER satellite data combined with forest inventory data for measuring forest biomass. They used stand-wise ASTER reflectance, non-linear regression, and neural networks for predicting biomass. Solberg et al. (2010) used interferometric X-band SAR for forest biomass estimates by generating each SRTM pixel from a field inventory in combination with airborne laser scanning (ALS) and concluded Interferometric X-band SAR is found good for forest biomass monitoring and mapping. Goparaju et al. (2021) used Landsat series (1989, 2000, 2010, and 2018) data for modeling temporal dynamics of above-ground biomass using different vegetation indices based on ground sampling in the northern dry tropical forest of India.

The aims of the present study are as follows: (1) To estimate biomass carbon and tree cover dominance of agriculture landscape for the years 2000 and 2010 at the country level of India. (2) To understand the spatial distribution pattern and temporal gain/loss of biomass carbon in India as a whole and within various agro-ecological regions. The implication of this study critically addressed one of the past research gaps of the biomass carbon-related findings in the agriculture landscape of India due to tree cover variation. Such understanding will assist significantly agroforestry decision-makers of India in enhancing future harmonized blueprint for agroforestry ventures.

Materials and Methods

The global tree covers and biomass carbon in agriculture land geo-tiff datasets (a continuous image) for the years 2000 and 2010 were downloaded from the website (http://apps.worldagroforestry.org/global-tree-cover/index.html) (Zomer et al. 2016) to estimate the biomass carbon over India and their temporal trend and the relationship with trees cover percent. The MOD44B MODIS VCF Coll. 3—Tree Cover (Hansen et al. 2003) data were used for mapping tree cover, whereas MOD44B MODIS VCF—Collection 5 data were used as an improvement (DiMiceli et al. 2011; Zomer et al. 2016).

The method for biomass carbon estimate was derived by combining remote sensing-based analysis of tree cover on agricultural land by modeling (IPCC Tier 1 default evaluation) the above- and below-ground carbon stocks (Zomer et al. 2016). The initial databases used for biomass carbon were percent tree cover (MODIS Vegetation Collection 5:2000–2010) (DiMiceli et al. 2011), Global Land Cover 2000 (GLC 2000) for agriculture mask (Zomer et al. 2014), and Global Biomass Carbon Map for the year 2000 and Aridity-Wetness Index (Zomer et al. 2016). The quality of datasets on agricultural land and forest clearings by partial validation showed an improvement (Zomer et al. 2016).

IPCC Tier 1 default evaluation was used for biomass carbon that is 5 tC ha^{-1} for the agriculture lands which have no tree cover (0% tree cover) and increases linearly from 0 to 100 percent tree cover over the map "Global Biomass Carbon Map for the Year 2000" (Ruesch and Gibbs 2008). The IPCC GPG Tier 1 method for evaluation of vegetation carbon stocks estimates the use of both above-ground biomass and below-ground biomass which varies significantly for each GLC_2000 land-use class.

We have used the vector datasets of agro-ecological regions (Ahmad et al. 2019) of India and its evaluation is highly suitable in identifying the potential agroforestry harmonized design (Gajbhiye and Mandal 2000; Ahmad et al. 2021). Here, agroforestry landscape is defined as those agricultural lands that have at least 10% tree cover (Zomer et al. 2016; Ahmad et al. 2021). Tree cover percent data for the years 2000 and 2010 were used to identify the agroforestry landscape.

All the above datasets were estimated in the GIS domain for meaningful interpretation as per our objectives of study which will address in future agroforestry development strategies/planning as one of the potential research gaps in India. The methodology adopted for this study is given in the flow diagram (Fig. 1).

Results and Discussion

Remote sensing data showed that in the year 2000, 16.9% of all agricultural land (28.02 million hectares) in India had agroforestry land (at least 10% tree cover) which was further increased to 22.5% (37.30 million hectares) over 10 years (up to the year 2010). A similar finding has been observed by Ahmad et al. 2021 while evaluating the agroforestry environment in India.

The total biomass carbon estimate in the year 2000 was found to be 1868.75 million tons of carbon (≈1.87 Pg C) over the Indian agriculture landscape (≈166 million hectares) out of which approximately 1039 million tons (≈1.04 Pg C) of biomass carbon come from trees (with 55.6% contribution).

Similarly, the total biomass carbon estimate in the year 2010 was found 2007.58 million tons of carbon (≈2.01 Pg C) over the same agricultural landscape base (≈166 million hectares) out of which approximately 1177.58 million tons (≈1.18 Pg C) of biomass carbon come from trees (with 58.7% contribution). Grigorov and Assenov (2020)

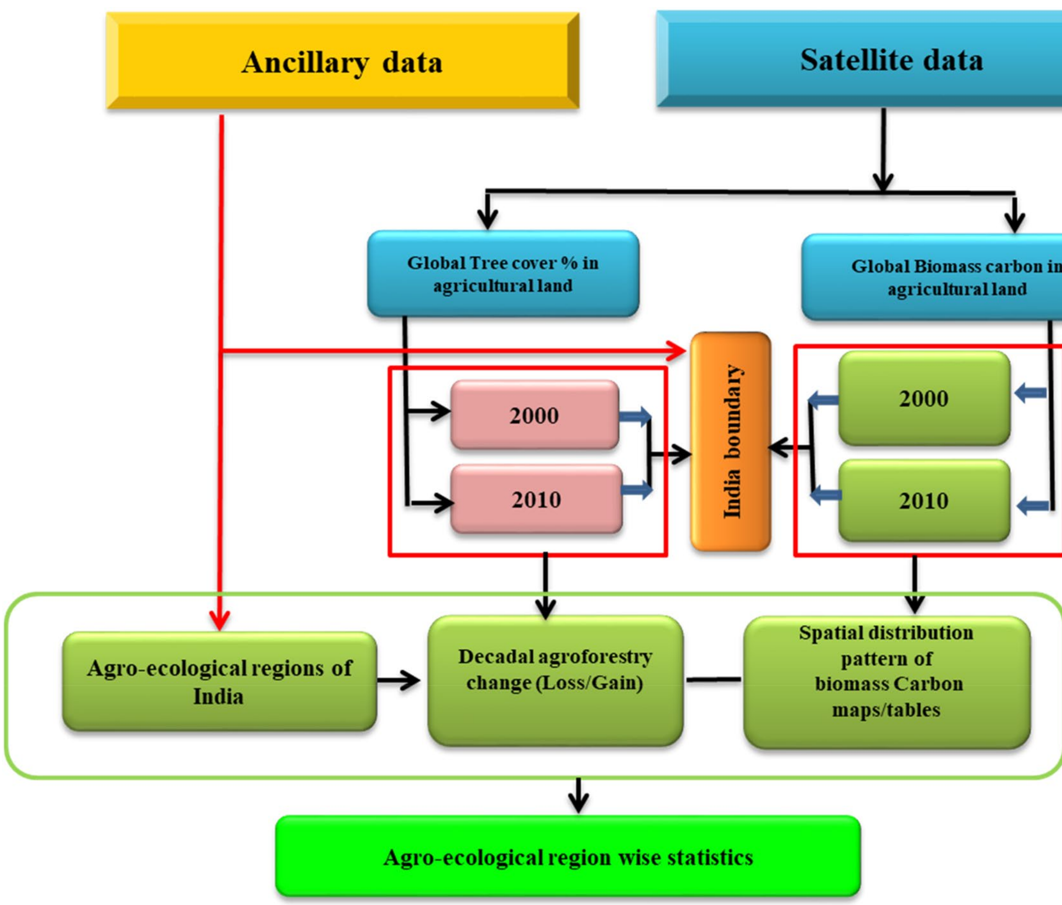

Fig. 1 Flow diagram showing the methodology

study investigated similar findings while evaluating tree cover in the agricultural landscape in Mala Planina. The Forest Survey of India (FSI) evaluated the forest tree carbon stock of India which is approximately 6.5 times higher than the agricultural tree carbon stock (our finding) and shows an increasing trend between the period (1994 and 2004) (https://fsi.nic.in/carbon-reports).

Let us consider there is no tree (0% tree cover) in the agricultural landscape (166 million hectares which are constant in both the year) then the total baseline default value of biomass carbon will be 830 million tons (@5tC/ha: Zomer et al. 2016). The 1039 million ton (≈1.04 Pg C) and 1178 million ton (≈1.18 Pg C) biomass carbon in the year 2000 and 2010, respectively, purely comes from trees. The decadal (2000–2010) biomass carbon net gain was found to be 138.83 million tons which is due to an increase in tree cover (at least 10%) by 5.6% (due to a decadal increase in agroforestry land by 9.27 million hectares). The mean biomass carbon in India increased from 11.29 to 12.13 t C ha^{-1} in 10 years, whereas the global mean increment is 20.4 to 21.4 t C ha^{-1} during the same base periods (Zomer et al. 2016).

The biomass carbon category-wise spatial distribution pattern (Fig. 2) and area-wise for the year 2000 are given in Table 1.

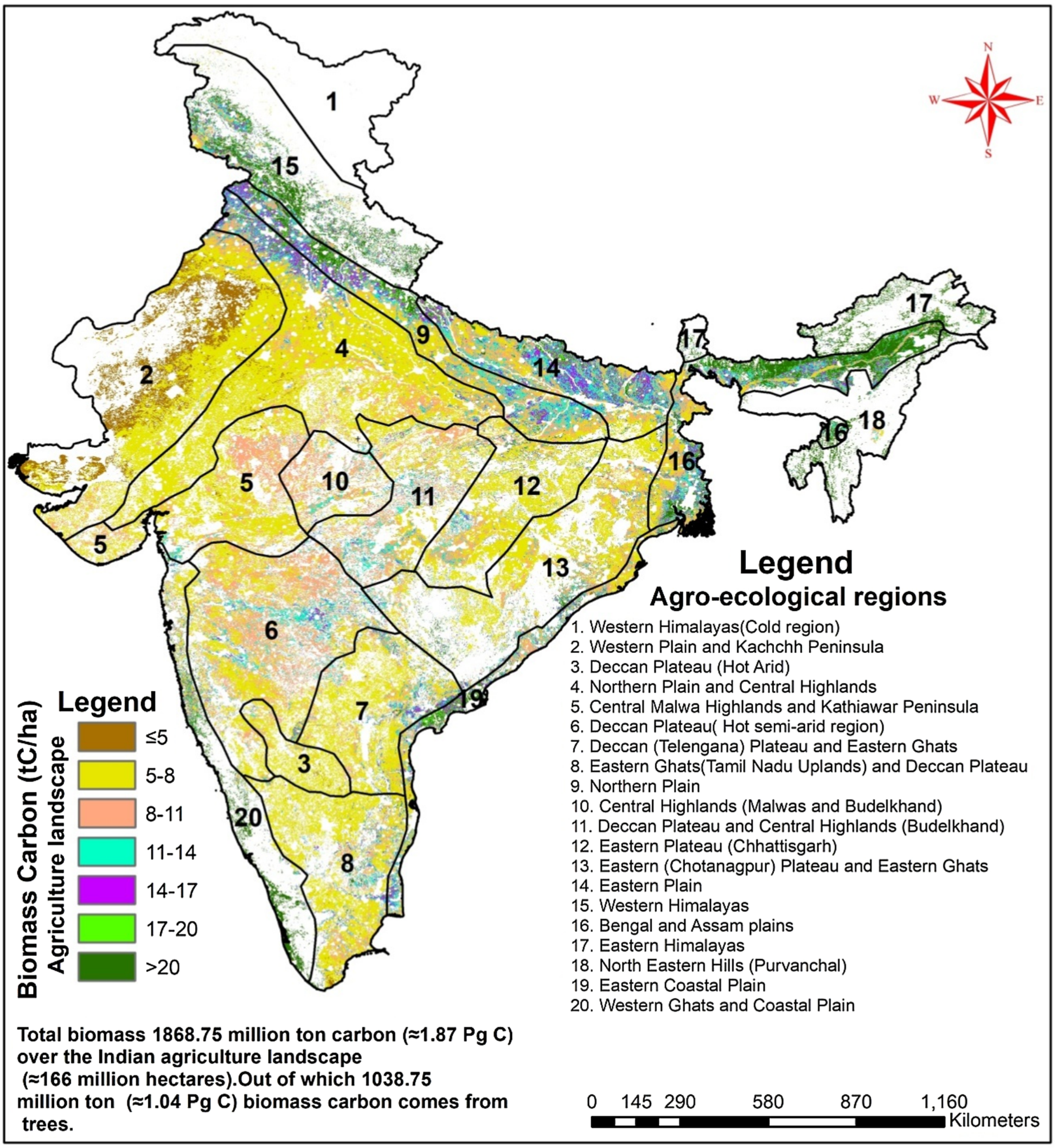

Fig. 2 Spatial distribution pattern of biomass Carbon (the year 2000) on agriculture landscape overlaid over agro-ecological regions of India

Table 1 Biomass carbon for the year 2000 in India

Biomass carbon (t C ha^{-1})	Area(million hectares)
≤5	7
5–8	74
8–11	42
11–14	17
14–17	9
17–20	5
>20	12
Total	166

Approximately 70% and 26% of agricultural land in India showed medium (5–11: tC ha^{-1}) and high (> 11: tC ha^{-1}) biomass carbon sources, respectively. Eight agro-ecoregions of India showed biomass carbon greater than 100 million tons (Table 2) and the highest (272 million tons) was found in "Bengal and Assam plains." The agricultural land in "Bengal and Assam plains" has significantly high agroforestry extent because of biophysical suitability where trees mix remarkably due to socio-economic connection in the form of taungya and home gardens (Kumar 1999; Bhatt and Bujarbaruah 2006; Ahmad et al. 2021).

The Ecosystem-wise decadal biomass carbon temporal dynamics (Fig. 3) in India revealed the gain of biomass was maximum in "Semi-Arid Ecosystem" (by 12.7%) followed by "Humid-Perhumid Ecosystem" (by 11.7%), "Coastal Ecosystem" (by 8.5%), and "Arid Ecosystem" (by 8.4%). The loss was observed only in the "Sub-Humid Ecosystem" by 0.5%.

The biomass carbon decadal change showed a loss in 24.9% of agricultural land (41.3 million hectares), whereas a gain in 56.3% of agricultural land (93.4 million hectares). The 18.8% of total agricultural land (approximately 31.2 million hectares) has shown no change in biomass carbon. The majority of decadal biomass carbon loss was observed in four agro-ecoregions of India and the maximum was in the "Northern plain." Five agro-ecoregions of India showed adequate gain (greater than 10 million tons) of carbon, the highest gain (28.72 million tons) was in the "Deccan Plateau (Hot semi-arid region)." Such results demand adequate synergic strategies to enhance agroforestry extent in various agro-ecoregions of India in the new potential zone as per land suitability(Ahmad et al. 2021).

Table 2 Agro-ecological regions wise statistics (2000–2010) of biomass carbon (million tons) and area (million hectares) of India

Agro-ecological region of India	TAGF-2000	TAGF-2010	TGA	TAA	Biomass carbon on agriculture land		Decadal change	
					TB-2000	TB-2010	GAIN	LOSS
Deccan Plateau (Hot semi-arid region)	1.1	3.49	29.33	16.71	154.79	183.51	28.72	
North Eastern Hills (Purvanchal)	0.935	1.00	11.46	1.07	75.58	70.99		4.59
Bengal and Assam plains	3.958	6.97	13.43	10.42	226.41	272.12	45.72	
Eastern Himalayas	1.473	1.51	8.83	1.59	73.45	76.43	2.98	
Eastern Coastal Plain	1.502	2.39	6.60	4.44	54.01	61.71	7.70	
Eastern (Chota nagpur) Plateau and Eastern Ghats	1.173	1.69	27.43	10.84	102.17	112.98	10.81	
Eastern Plateau (Chhattisgarh)	0.648	0.35	14.63	7.92	69.05	67.07		1.99
Deccan Plateau and Central Highlands (Bundelkhand)	0.766	1.22	15.47	7.30	70.58	72.05	1.48	
Eastern Plain	3.027	1.46	12.02	9.89	123.02	111.28		11.74
Western Plain and Kachchh Peninsula	0.066	0.17	34.49	17.83	107.17	115.44	8.27	
Northern Plain and Central Highlands	1.935	2.03	32.98	24.13	197.21	198.18	0.97	
Western Himalayas (Cold region)	0.02	0.11	14.42	0.21	2.04	2.84	0.80	
Northern Plain	3.587	2.38	12.25	10.21	128.26	115.38		12.88
Western Himalayas	4.003	4.34	19.65	5.61	109.83	114.95	5.12	
Central Malwa Highlands and Kathiawar Peninsula	0.057	2.09	17.42	9.43	74.41	98.14	23.73	
Western Ghats and Coastal Plain	1.687	2.06	12.16	3.37	91.97	96.70	4.74	
Eastern Ghats (Tamil Nadu Uplands) and Deccan Plateau	0.94	1.60	18.74	10.32	87.03	100.75	13.72	
Deccan Plateau (Hot Arid)	0.027	0.06	4.54	2.48	17.02	18.49	1.48	
Deccan (Telangana) Plateau and Eastern Ghats	0.99	1.48	15.93	8.79	77.18	84.85	7.67	
Central Highlands (Malwas and Bundelkhand)	0.126	0.90	7.06	2.92	27.58	33.72	6.14	
Grand total	28.02	37.30	328.82	165.46	1868.75	2007.58	170.02	31.19

TAGF total agroforestry area, *TGA* total geographical area, *TAA* total agriculture area, *TB* total biomass, *GAIN* increase in biomass, *LOSS* decrease in biomass

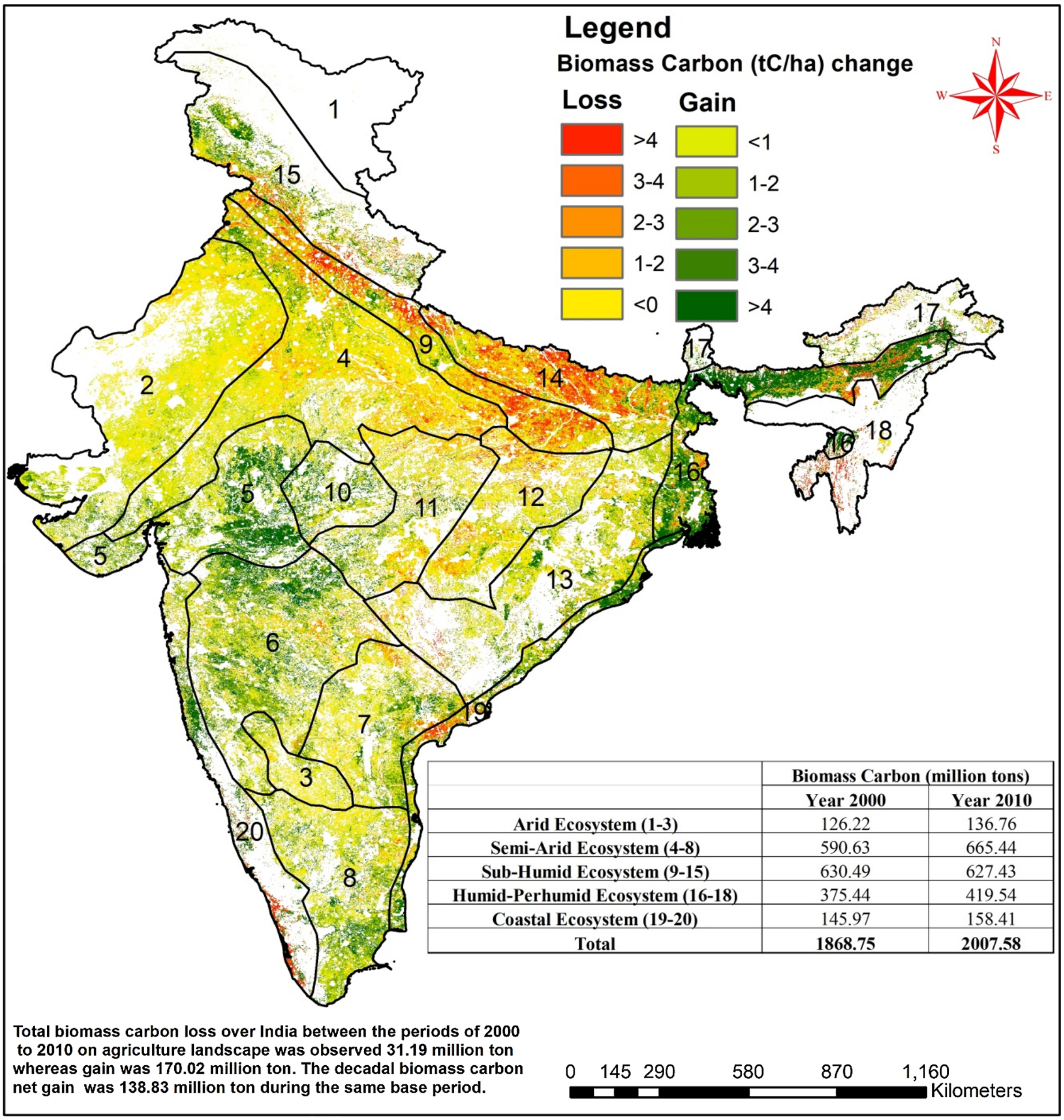

Fig. 3 Biomass carbon change dynamics (year: 2000–2010) on the agriculture landscape of India

Conclusion

This study addressed one of the past research gaps of biomass carbon and tree cover dynamics in the Agricultural Landscape (Agroforestry contribution) in India. Furthermore, it also evaluated decadal change dynamics due to variation in tree cover dominance.

The decadal (2000–2010) biomass carbon net gain was found to be 138.83 million tons (or an increase of 7.4%) which is due to an increase of 5.6% in agroforestry land (tree cover at least 10%). The mean biomass carbon in India in the year 2010 was found 12.13 t C ha^{-1}, which is significantly low (approximately 57% of the global average). There is a need to increase the tree cover percent in the agricultural landscape to increase the biomass carbon in the agroforestry domain.

The agro-ecoregions such as “Northern plain” and “Eastern Plain” had shown a significant decadal loss of carbon which needs to be prioritized in the future. The maps and tables generated here will significantly assist the decision-makers of India in enhancing future agroforestry prospects.

NASA’s Global Ecosystem Dynamics Investigation mission uses high-resolution lidar instrument and advanced statistical models to reach a major milestone with the release of its newest datasets of above-ground forest biomass and the carbon product with higher precision than in the past providing a foundation for future missions till January 2023 (Evan 2022). Such a high-resolution product will remove estimates' uncertainty and will provide better results and serve significantly in the future.

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