Case Studies in Chemical and Environmental Engineering 7 (2023) 100344

Contents lists available at ScienceDirect

Case Studies in Chemical and Environmental Engineering

journal homepage: www.sciencedirect.com/journal/case-studies-in-chemical-and-environmental-engineering

Case Report

Mapping and assessment of carbon sequestration potential and its drivers in the Eastern Himalayan Region (India)

Manob Das [a,b,*], Ashis Mandal [a], Arijit Das [a], Miguel Inácio [b], Paulo Pereira [b]

[a] Department of Geography, University of Gour Banga, Malda, West Bengal, India
[b] Environmental Management Laboratory, Mykolas Romeris University, Vilnius, Lithuania

ARTICLE INFO

Keywords:
Net primary production
Eastern Himalaya
Carbon sequestration
Climate change
Mountain ecosystems

ABSTRACT

Eastern Himalayan Region (EHR) is a biodiversity hotspot and an ecologically sensitive area. In the last few years, climate change, land use, and land cover (LULC) have substantially affected forest ecosystems and their capacity to store carbon. Therefore, understanding the impacts of these drivers of change on carbon sequestration (CS) is essential. This study aims to assess the spatiotemporal pattern of carbon sequestration in EHR between 2000 and 2020 using net primary production (NPP) as a proxy. NPP was extracted from Moderate Resolution Imaging spectroradiometer (MODIS) data. The impact of natural and human factors on the NPP distribution were also assessed using regression analysis. The results showed that the areas with good NPP (relatively high ecosystem productivity) increased by 12% from 2000 to 2020. Conversely, the areas with poor NPP (relatively low ecosystem productivity) decreased from 39.92% (2000) to 34.42% (2020). The normalized difference vegetation index (NDVI) increased in the last 20 years (15% from 2000 to 2020). Land surface temperature (LST) increased pre-monsoon and decreased post-monsoon (winter). The correlation analysis showed that urban population growth ($r = -0.464$) and LST ($r = -0.393$) negatively impacted NPP. On the other hand, NDVI ($r = 0.857$), vegetation cover (VC) ($r = 0.679$), and human development index (HDI) ($r = 0.741$) had a positive correlation with NPP. Multiple linear regression (MLR) models showed that human (urbanisation and total population growth) and natural (such as VC) factors significantly impacted NPP. The total population growth had a weak positive relationship with NPP ($r = 0.143$). NPP increase can be attributed to effective management strategies (e.g., restoration).

1. Introduction

The mountain regions represent unique areas for detecting climate change and its impact on the ecosystems [1,2]. They are also more sensitive to climate fluctuations than lowlands [3]. Previous works highlighted that climate change impacts would be greater in high-altitude [4]. It has become one of the biggest environmental threats to mountain forest ecosystems [5,6]. These negative impacts will negatively affect mountain ecosystem services (ES), such as flood and erosion regulation, carbon sequestration, food production, water supply and recreation [7,8]. Some works showed that climate change, particularly the temperature increase, has a crucial impact on ecosystems [9,10]. Also, changes in climatic parameters such as precipitation and temperature or evapotranspiration affect the atmosphere's carbon dioxide and its interaction with the ecosystems [11,12]. The alteration of evapotranspiration and photosynthesis affects the ecosystem's productivity [13,14]. The Intergovernmental Panel on Climate Change (IPCC) [15] stated that mountainous areas are highly sensitive concerning climate change and alter carbon sequestration dynamics. Carbon sequestration is affected by several factors, such as climate, land use/-land cover (LULC) pattern, vegetation cover, and local conditions, such as topography or soil properties [16,17]. Anthropogenic activities such as agriculture intensification, urbanisation and population density also impact carbon sequestration significantly [8,18]. For instance, they are responsible for carbon dioxide emissions [19]. Therefore, it is key to understand the natural and anthropogenic factors that influence the spatiotemporal distribution of carbon [12,20–23].

Several methods have been employed to estimate carbon sequestration using NPP (such as Carbon Exchange between Vegetation, Soil and Atmosphere (CEVSA) and Boreal Ecosystem Productivity Simulator (BEPS) [16]. Observational and remote sensing methods have been used

* Corresponding author. Department of Geography, University of Gour Banga, Malda, West Bengal, India.
E-mail addresses: dasmanon631@gmail.com (M. Das), ashism811@gmail.com (A. Mandal), arijit3333@gmail.com (A. Das), rinacio.miguel@gmail.com (M. Inácio), pereiraub@gmail.com (P. Pereira).

https://doi.org/10.1016/j.cscee.2023.100344
Received 21 February 2023; Received in revised form 15 March 2023; Accepted 25 March 2023
Available online 31 March 2023
2666-0164/© 2023 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

Abbreviations:

EHR	Eastern Himalayan Region
LULC	Land Use and Land Cover
NPP	Net Primary Production
MODIS	Moderate Resolution Imaging spectroradiometer
NDVI	Normalized Difference Vegetation Index
LST	Land Surface Temperature
VC	Vegetation Cover
HDI	Human Development Index
MLR	Multiple Linear Regression
ES	Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change (IPCC)
CEVSA	Carbon Exchange between Vegetation, Soil and Atmosphere
BEPS	Boreal Ecosystem Productivity Simulator
NASA	National Aeronautics and Space Administration
GPP	Gross Primary Production
APAR	Absorbed Photosynthesis Active Radiation
LUE	Light Use Efficiency
VPD	Vapour Pressure Deficit
VIF	Variance Expansion Factor
SDGs	Sustainable Development Goals
NAPCC	National Action Plan on Climate Change
NMSHE	National Mission for Sustaining the Himalayan Ecosystems

to monitor vegetation health dynamics at regional and global scales [24,25]. Moderate Resolution Imaging Spectroradiometer (MODIS) and the National Aeronautics and Space Administration (NASA) provide remote sensing data to assess vegetation dynamics and surface temperature, such as land surface temperature (LST). Gross primary production (GPP) and NPP derived from MODIS have been used to monitor vegetation health and productivity [26,27]. NPP is one of the most important components of the carbon cycle and can represent their capacity to store carbon [28,28,29]. NPP measures the total amount of organic materials per unit area [30,31]. It is computed as the difference between the amount of carbon absorbed through photosynthesis and the release of carbon through respiration [32,33]. NPP plays also can serve as a proxy to estimate the capacity of an ecosystem to supply food, wood and fibres [34,35] and fix carbon [36,37]. Anthropogenic activities transform the landscape, altering carbon storage and fluxes [38]. Therefore, acquiring knowledge about the impact of human activity on the carbon budget is essential to mitigate climate change [39–41].

Mountainous environments are sensible to LULC and climate change. These areas supply several ES [42–44]. They are critical in developing countries [45]. Eastern Himalayan Region (EHR) population is highly dependent on the ES supplied by mountains. Recent studies showed that mountainous ecosystems had been exposed to several threats, such as urbanisation, agriculture intensification and tourism [46,47]. Here, the ES supply depends on ecosystem conditions [48,49], especially forests. These areas have been subjected to intense LULC, affecting their capacity to store carbon [50]. Therefore, understanding NPP spatiotemporal dynamics is key to ensuring EHR's continuous ES flow. EHR is considered a biodiversity hotspot in India and an ecologically sensitive area. EHR has recently experienced environmental challenges due to climate change and urbanisation, triggering dangerous natural hazards, such as landslides [51,52]. This work aims to map and assess the NPP spatiotemporal pattern to estimate carbon sequestration in EHR from 2000 to 2020.

2. Materials and methods

2.1. Study area

The EHR extends over eight states in Eastern India (Fig. 1): Sikkim, the Hilly region of West Bengal, Assam, Tripura, Arunachal Pradesh,

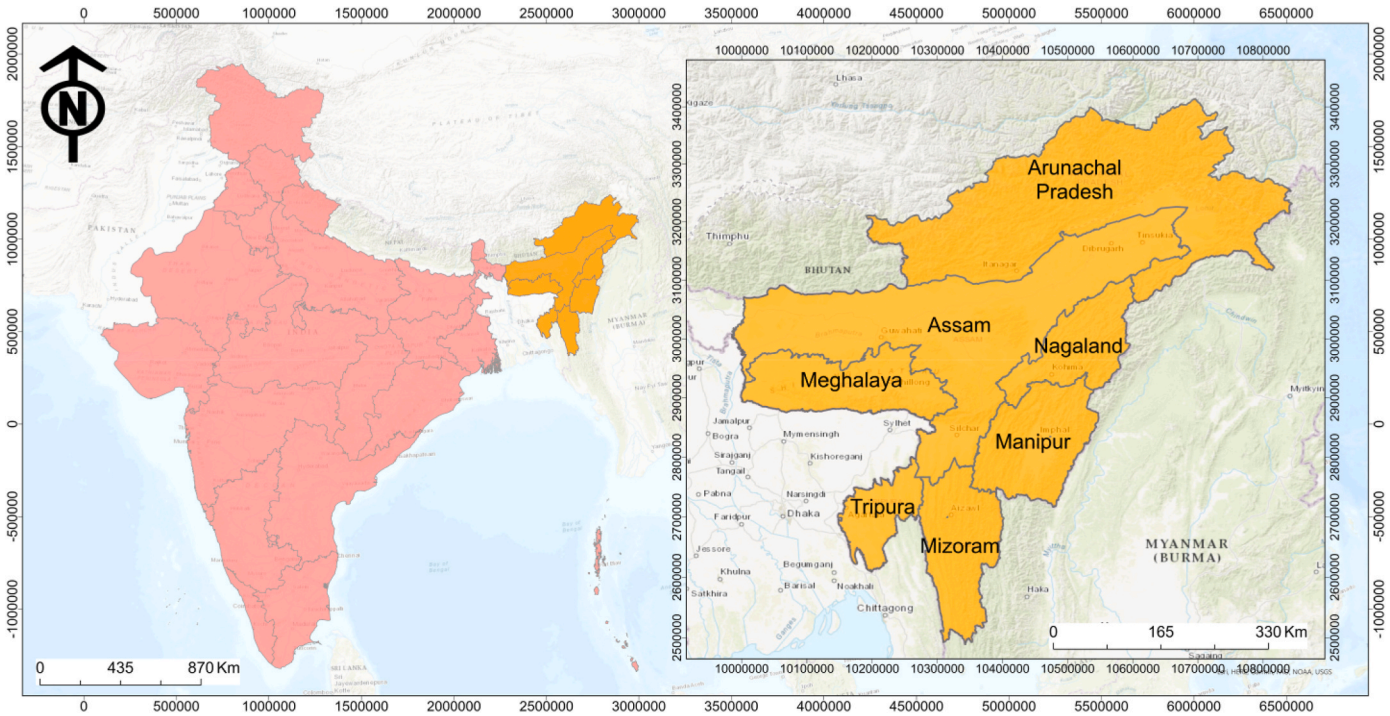


Fig. 1. Study area.

Manipur, Meghalaya, and Nagaland and occupies an area of 273326 km^2. This study considers seven states in Eastern India (except Sikkim and the hilly region of West Bengal) [53,54]. This region's population is about 456 million. The climate is subtropical, with mild winter [55]. 65% of EHR vegetation and forest cover are located in this region [56]. The hilly topography makes this area highly vulnerable to natural hazards [57]. The LULC changed recently due to urban expansion, Jhum cultivation and deforestation [58]. These recent changesdisrupted the region's ecological balance, affecting the population's wellbeing [59, 60].

2.2. Data sources and processing

The framework used in this article is presented in Fig. 2. In this study, MODIS data has been used to map and assess NPP in EHR. MODIS sensors provide GPP for 8 days, monthly and annually from 2000 at 1000 m resolution [45]. The annual NPP is the summation of the daily GPP minus the growth and maintenance of respiration [45]. The daily GPP is the function of the absorbed photosynthesis active radiation (APAR) and light use efficiency (LUE) of the vegetation (maximum). Later on, this value is revised by daytime vapour pressure deficit (VPD) to measure plants' water stress [61] and minimum temperature (daily) to measure temperature limitations for plants [45]. Thus, APAR can be expressed in terms of the function of the photosynthetically active radiation or PAR and the refraction of PAR (absorbed by the fPAR).

NPP maps have been normalized yearly (2000, 2010 and 2020) for better comparison (Supplementary data- M1). They were classified into five classes ranging into very low (<0.20), low (0.20–0.40), moderate (0.40–0.60), high (0.60–0.80) and very high (>0.80). All the analyses were developed using ArcGIS [62,63]. Vegetation cover and temperature significantly impact the spatial distribution of the NPP [57]. Thus, in this study, normalized difference vegetation index (NDVI) and land surface temperature (LST) maps derived from MODIS were also assessed. The land surface temperature (LST) has been developed for three seasons, namely-monsoon (June to September), pre-monsoon (December to February) and post-monsoon (June to May), to show the variation of land surface temperature (LST) over the areas for the years 2001, 2010, and 2020. 2001 has been used for land surface temperature (LST) as the images were not available for 2000.

2.3. Explanatory variables

NPP is affected by various natural (e.g., topography and climate) and anthropogenic (e.g., LULC) factors [64–67]. Therefore, it is crucial to understand the drivers that can change NPP [65], especially in fragile environments such asEHR. Based on the previous research [64,65], this study explores the relationship between NPP and humans (urbanisation rate, urban population growth, total population growth of the state, human development index) and natural factors (vegetation cover, NDVI, annual precipitation, slope, altitude). In total, 10 driving factors have been considered. Table 1 shows the datasets used in this study, and Table 2 shows these variables' descriptive statistics.

Variance expansion factor (VIF) analysis was conducted to identify the collinearity among the selected variables. The variables with a VIF value lower than 7.5 were considered for the analysis (Table 2) [21]. VIF values ranged from 2.47 to 14.11, and the Tolerance value ranged from 0.071 to 0.351. The highest VIF was observed in NDVI (14.11) and the lowest in total population growth (2.47). Five factors (urban population growth, human development index, NDVI, LST and vegetation cover) have been selected for the regression analysis. The description of the variable at the state level has been shown in the Supplementary section (Table S1).

2.4. Statistical analysis

A Spearman correlation was applied to assess the relationship between NPP and the independent variables, and the significant

Table 1
Explanatory variables used in this study.

Variable	Description	Source
Human Development Index (HDI)	A composite index combining knowledge, health and standard of living	https://globaldatalab.org/
Urban population growth (%)	Growth of urban population in the state in the last 10 years	https://censusindia.gov.in/
Total population growth (%)	Growth of the total population of the state in the last 10 years	https://censusindia.gov.in/
Vegetation cover (%)	Percentage of forest cover area in the state	Forests Reports (2021) https://fsi.nic.in/forest-report-2021-details
Land surface temperature (°C)	Mean land surface temperature across the state in EHR (2020)	USGS (https://earthexplorer.usgs.gov/) (1000mm)
The normalized difference vegetation index	Vegetation health status of the state in EHR (2020)	USGS (https://earthexplorer.usgs.gov/) (1000 m)
Annual precipitation (mm)	Average precipitation across the state in EHR	IMD (https://mausam.imd.gov.in/)
Slope (°)	The average slope of the state in EHR extracted from DEM	USGS (https://earthexplorer.usgs.gov/) (30 m)
Altitude (meters)	The average elevation of the state in EHR extracted from DEM	USGS (https://earthexplorer.usgs.gov/) (30 m)

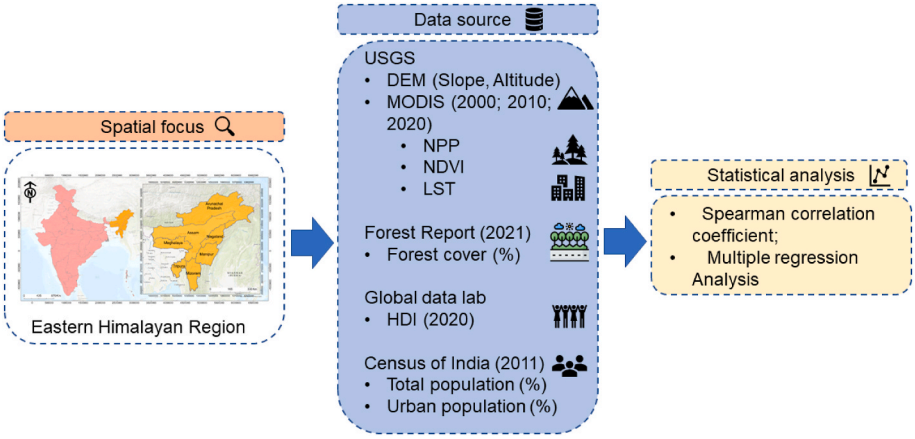


Fig. 2. Methodological framework of the study.

Table 2
Descriptive statistics of the explanatory variables used in this study. VIF (Variance expansion factor).

Variable	Mean	Maximum	Minimum	Standard deviation	Kurtosis	Tolerance	VIF
Human Development Index (HDI)	0.66	0.70	0.61	0.03	0.17	0.209	4.77
Urban population growth (%)	3.60	5.94	0.04	2.08	−0.11	0.337	2.97
Total population growth (%)	19.33	29.95	−0.58	10.19	2.09	0.351	2.47
Vegetation cover (%)	71.12	84.53	36.09	15.93	5.78	0.00	–
Land surface temperature (°C)	27.73	31.28	20.17	3.79	2.54	0.00	–
The normalized difference vegetation index	0.66	0.73	0.56	0.05	0.91	0.071	14.11
Annual precipitation (mm)	2277.43	2818.00	1881.00	494.58	−2.79	0.098	10.18
Slope (°)	9.32	15.79	2.53	5.23	−1.84	0.00	–
Altitude (meters)	782.85	1678.19	93.30	558.12	−0.47	0.138	7.24

correlation was considered at a $p < 0.05$. A multi-linear regression (MLR) analysis was carried out to understand the impact of human (urban population growth, human development index) and natural factors (NDVI, LST and vegetation cover) on NPP. All the statistical analysis was carried out in SPSS (version 22).

3. Results

Fig. 3 shows the spatiotemporal pattern of NPP in EHR in 2000, 2010 and 2020. In the EHR, northern, eastern and southeastern parts, there is high NPP. In 2000, the average NPP was 9710 kg C/m^2, 9698 kg C/m^2 in 2010 and 10089 kg C/m^2 in 2020. Between 2000 and 2020, the areas with good NPP slightly increased, and those with poor NPP declined. The areas with poor NPP decreased from 39.92% (2000) to 39.72% (2010) and 37.72% (2020). On the other hand, the areas with moderate NPP increased from 18.23% (2000) to 18.62% in 2010 and 22.62% in 2020. Overall, a slight increase in NPP was observed in the EHR from 2000 to 2020.

NDVI spatiotemporal analysis results are shown in Fig. 4. High NDVI values were observed in EHR's northern, eastern and southeastern parts, and low NDVI values were located along the Brahmaputra River (flowing from northeast to southwest). The mean NDVI was 0.5483 in 2000, 0.5487 in 2010, and 0.6321 in 2020 (increased by about 15.33% from 2000 to 2020). The areas with very high NDVI increased from 39.69 km^2 (2000) to 93.20 km^2 (2020), and the areas with high NDVI decreased from 133.20 km^2 (2000) to 121.53 km^2 (2020). The areas with very low and low NDVI decreased from 8.20 km^2 (2000) to 6.86 km^2 (2020) and 13.43 km^2 (2000) to 9 km^2 (2020).

Fig. 5 shows the LST spatiotemporal pattern during pre-monsoon, post-monsoon and winter in 2001, 2010 to 2020 in EHR. The results showed that LST increased during pre-monsoon and post-monsoon and decreased in the winter season. There were also spatial variations of LST in EHR. For example, EHR's central, southern and eastern parts were high. The lowest LST was observed in the northern parts of EHR. For example, in pre-monsoon and post-monsoon, LST increased by about 1.39% and 3.36% from 2001 to 2020. In winter, LST decreased by about 5.17% from 2001 to 2020. In 2000, the mean LST in pre-monsoon and post-monsoon was 25.9 °C and 24.11 °C, increasing to 26.26 °C and 24.92 °C in 2020. The mean LST in 2010 slightly decreased (24.25 °C) compared to the previous year (2001) during the pre-monsoon season. In winter, the mean LST was 17.2 °C in 2001 and 18.34 °C in 2010, which decreased to 16.31 °C in 2020. The maximum LST in winter decreased by 9.02% from 2001 to 2020. The results showed that in post-monsoon, there was an increase of LST in EHR (LST increased by about 35.33%). The view of the landscapes from Darjeeling and Kurseong are shown in Fig. 6.

The correlation results showed that NPP had a significant positive correlation with NDVI ($r = 0.857$) and NPP had a significant negative correlation with slope ($r = 0.-821$) and altitude ($r = -0.964$) (Table 3). The MLR model R^2 value was 0.882. The best NPP predictors were urban population growth (%), vegetation cover (%), LST and total population growth (%). The adjusted R^2 value was 0.686, showing that the predictor variables significantly influenced the dependent variable (Supplementary data Table S2).

4. Discussion

The study found that the areas with good NPP improved in the last 20 years. NPP in EHR has improved mainly due to increased vegetation cover in the region. In the previous works, it was well-recognized that vegetation cover significantly impacted the NPP and its spatial distribution [68,69]. Kumar et al. [55] conducted a study in the EHR and

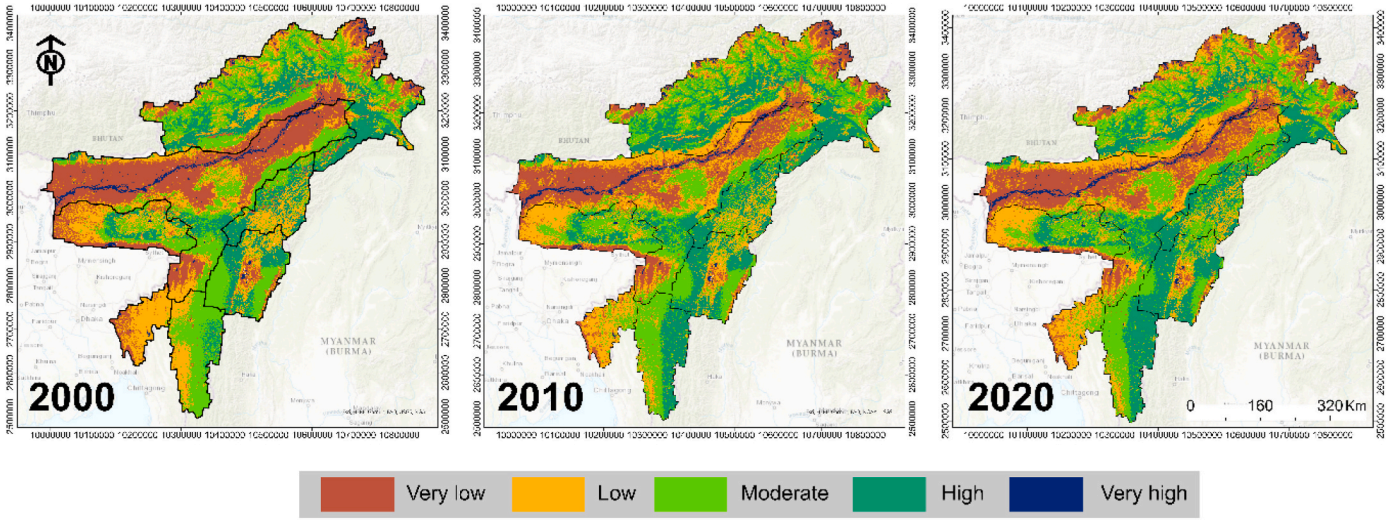


Fig. 3. NPP pattern in EHR in 2000, 2010and 2020.

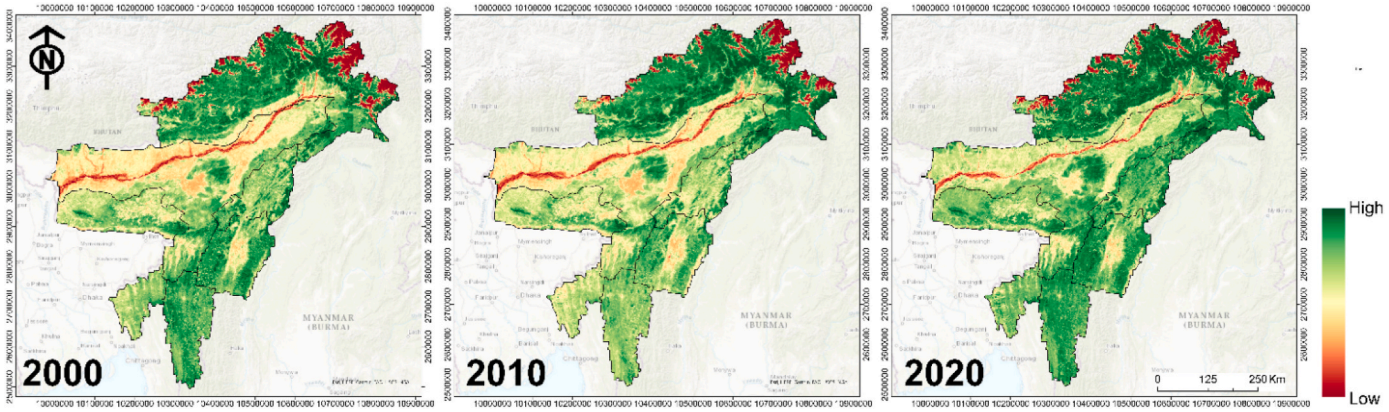


Fig. 4. NDVI pattern in EHR in 2000, 2010 and 2020.

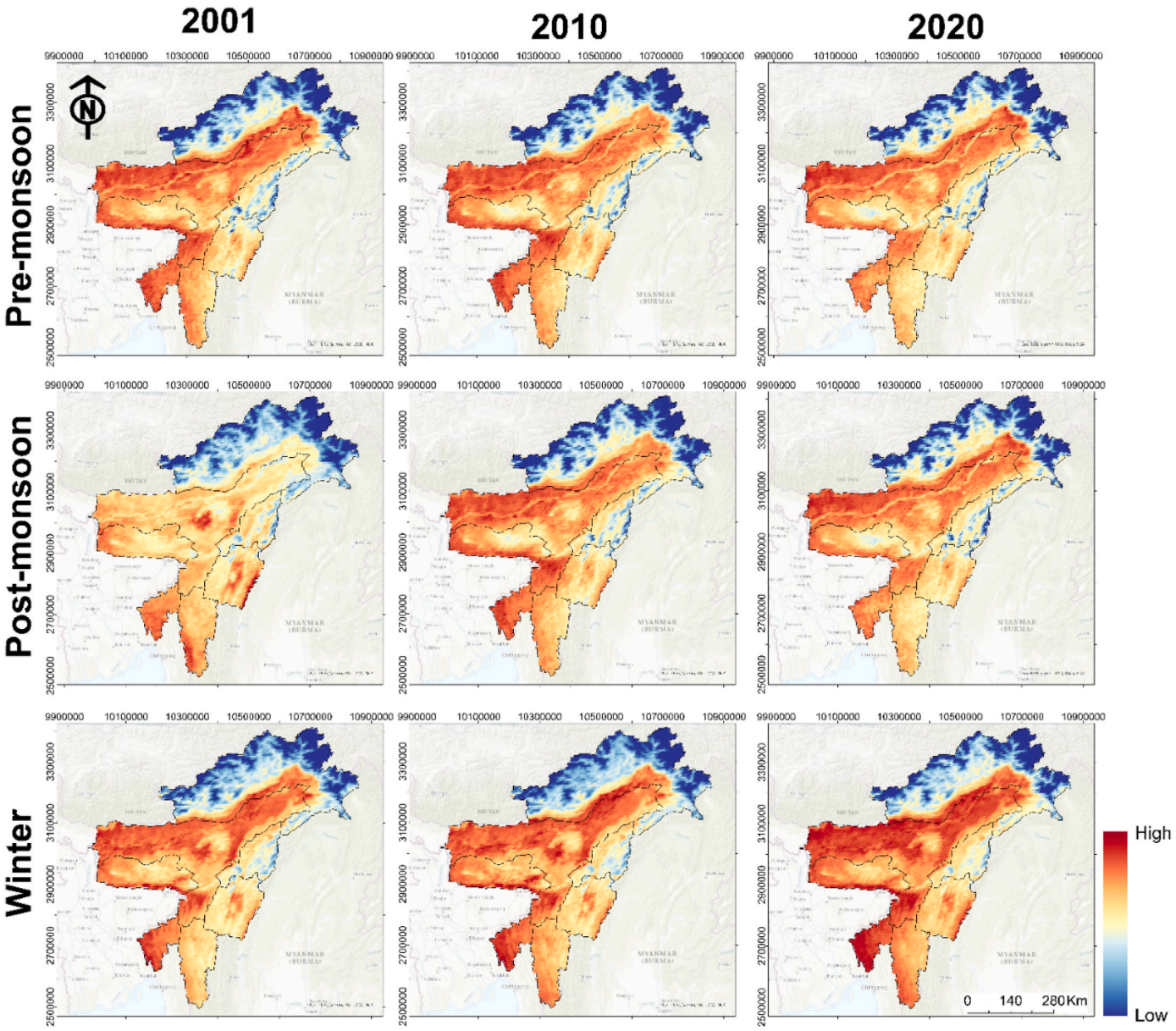


Fig. 5. LST pattern in EHR from 2000 to 2020.

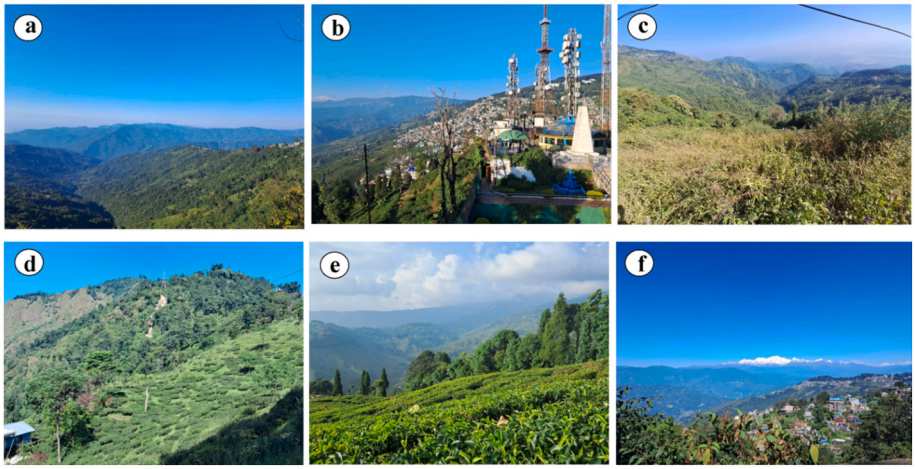


Fig. 6. View of the landscape in the EHR (Darjeeling and Kurseong region of EHR) (a) dense vegetation cover (b) urbanisation in the mountainous area (c) grass and bush lands (d) tea plantation (e) tea garden in EHR (f) view of the settlement expansion.

reported that forest cover areas in the EHR increased from 1990 to 2019. The mean NDVI value in the EHR has increased in the last 20 years. For example, in 2019, the mean NDVI value was 0.002, reaching 0.007 in 2019 (increased by more than 200%). This study also found that the NDVI value increased from 0.548 (2000) to 0.632 (2020). According to a study carried out by Kumar et al. [55] and Punitha et al. [70] and they found that NDVI value in the EHR has significantly increased in the last few decades mainly due to the forest (conservation and restoration efforts and agriculture intensification (Jhum cultivation).

The results also showed that there were also spatial variations of the NPP across the states in the EHR. For example, the highest NPP was found in Manipur, and the lowest NPP value was found in Tripura. Different socio-economic and demographic settings characterize the states. The northern and southeastern parts of the EHR were characterized by relatively high NPP compared to other regions. Thus, it indicates that the spatial distribution of NPP is affected by several factors. In the previous studies, it was well documented that the spatial distribution of NPP is largely affected by various natural and anthropogenic factors [57]. Previous works found that precipitation was the main NPP driver [71]. Also, the anthropogenic factors (LULC) affect NPP importantly [72]. Li et al. [73] found that urbanization harmed NPP in mainland China. Similar results were identified elsewhere [74,75]. Also, the carbon cycle is dramatically affected [76,77]. Overgrazing is another driver that reduces importantly NPP, mainly in developing countries [78,79]. The results also showed that there were temporal variations of NPP in EHR. For example, the areas with good NPP increased in 2000 compared to 2020 in EHR. The temporal variations of NPP are affected mainly by the temporal variation of the eco-environmental conditions, such as changes in the vegetation cover, precipitation, LST and LULC types [80,81]. This study also found that the mean NDVI value was 0.548, which increased to 0.632 in 2020, and LST in the winter decreased by about 5.17% in the last 20 years. Climate change (such as the changes in LST) significantly impacts the spatial distribution of the NPP [80]. According to Liu et al. [82], the temperature was one of the important components of increasing the local ecosystem productivity in temperature-restricted areas. The temperature increase may impact the NPP negatively and positively [82]. The NPP is affected mainly by vegetation productivity (such as NDVI) [80,83]. The study also found that good NPP characterized the areas with good vegetation productivity (NDVI) in EHR. Particularly, the northern and southeastern parts of the EHR were characterized by relatively good vegetation productivity and NPP. Thus, the changes in these bio-physical components significantly affected the spatial distribution of the NPP in the EHR.

In India, few studies were carried out in different parts of the Himalayan regions [84–87] to understand the factors affecting vegetation productivity (NDVI) in the EHR. For example, Munsi et al. [88] conducted a study in the Shiwalik range of the Himalayas. Their results showed that human disturbances played a significant role in controlling vegetation productivity and forest cover. Sharma et al. [89] also carried out a study in the North-Western Himalayan region and showed that fragmentation of forest landscape was one of the severe threats in the Himalayan region. In this study, also, from the correlation results, it was found that NDVI had a significant positive correlation ($p < 0.05$) with NDVI ($r = 0.857$) and urban population growth had a negative correlation with urban population growth ($r = -0.469^{ns}$).

The results showed a positive correlation between vegetation cover and NPP ($r = 0.542$) and urban population negatively correlated with NPP ($r = -0.41$). Thus, natural and human factors significantly influence the NPP in any region [57]. The regression results found that urban population growth, VC, LST, total population growth, and altitude significantly impacted the NPP ($r^2 = 0.882$). Therefore, as observed in previous works, anthropogenic factors play an essential role in NPP [90].

4.1. Limitations and future research directions

This study contributes importantly to understanding the NPP and carbon sequestration in EHR. However, it has several limitations. Firstly, in this analysis, we have used datasets with different resolutions. For example, the land surface temperature data has been used with a spatial resolution of 1000 m, and DEM has been used with a 30 m. Therefore, the datasets with similar spatial resolution could be better. Secondly, only a few datasets, such as (urban population growth and vegetation cover) have been used at the administrative level (state level). Using the data at the district or block levels could be better for better future analysis. The availability of datasets with a better temporal resolution would be helpful to conduct a better analysis. Thirdly, the variables affecting NPP have been assessed using few natural factors (land surface temperature, NDVI) and anthropogenic (urban population growth, total population growth) factors. Other factors also affect NPP, such as vegetation types, soil types, and solar radiation [85]. These factors can enhance the better results. Therefore, in the future, these factors must be considered to understand better the factors affecting NPP.

4.2. Policy implications

The Himalayas have experienced many changes due to climate change, natural hazards and urbanisation [91–93]. It is expected that they will increase in the future [94]. A healthy environment is essential to maintain the flow of the ES, such as regulating ES (carbon

Table 3
Correlation between variables. Significant correlations at $p < 0.05$* and $p < 0.01$**.

Parameters	Average (normalized) Net primary production (NPP)	Human development index (HDI)	Urban population growth (%)	Total population growth (%)	Average vegetation cover or VC (%)	Average land surface temperature or LST (°C)	Average normalized difference vegetation Index (NDVI)	Average annual precipitation (mm)	Average slope (degree)	Average altitude (meters)
Average (normalized) Net primary production (NPP)	–									
Human development index (HDI)	0.741	–								
Urban population growth (%)	−0.464	−0.408	–							
Total population growth (%)	0.143	−0.259	0.036	–						
Average vegetation cover or VC (%)	0.679	0.222	0.036	0.607	–					
Average land surface temperature or LST (°C)	−0.393	0.222	−0.143	−0.393	−0.500	–				
Average normalized difference vegetation Index (NDVI)	0.857*	0.704	−0.214	−0.214	0.571	−0.286	–			
Average annual precipitation (mm)	−0.478	−0.641	0.159	0.518	−0.120	−0.139	−0.797*	–		
Average slope (°C)	0.643	0.074	0.000	0.143	0.679	−0.821*	0.714	−0.339	–	
Average altitude (meters)	0.500	−0.111	−0.071	0.321	0.464	−0.964**	0.393	−0.020	0.857*	–

sequestration, climate regulation, flood regulation, erosion regulationand purification); provisioning ES (food, fodder, medical plants, timber) and cultural ES (landscape aesthetics, and recreation) [95,96]. Achieving the United Nations Sustainable Development Goals (SDGs) is essential. For example, forest cover loss will affect NPP and increase poverty (Goal 1: No Poverty) and food security (Goal 2: No Hunger). The Himalayan region provides opportunities for health and a good environment [97,98] (Goal 3: Good Health and Wellbeing). The EHR urban expansion in the EHR (particularly in Darjeeling, Kalimpong) may lead to challenges related to clean water and sanitation (Goal 6: Clean Water and Sanitation), urban areas livability (Goal 11: Sustainable Cities and Communities), urban heat island, greenhouse gases emission (Goal 13: Climate Action) and land degradation (Goal 14: Life on land). Several measures have been taken to address the threats experienced by EHR, such as National Action Plan on Climate Change (NAPCC) and National Mission for Sustaining the Himalayan Ecosystems (NMSHE). These strategies aim to comprehend sustainable development in the Himalayan region. The main concern in the Himalayan region is the uncontrolled degradation of natural resources due to human activities. The estimation of NPP to detect carbon sequestration potential is one of the significant indicators for ecosystem health and sustainable development. Estimating carbon sequestration from NPP helps understand the ecosystem's response to climate change. It can also provide significant aspects of effective management of ecosystems, natural resources, and estimation of plant yields. Thus, EHR is one of the fragile and sensitive ecosystems, and carbon sequestration estimation is crucial for maintaining ecosystem flow and livelihood sustainability.

5. Conclusions

The results showed that NDVI in the last 20 years increased. NDVI value from 2000 to 2020 increased from 0.5483 to 0.6321 (increased by about 15.33%). The NPP results showed that the areas with good NPP increased while those with poor NPP decreased. The areas with good NPP were mainly concentrated in the northern, eastern and southeastern parts of the eastern Himalayas. Relatively poor NPP characterized the areas located along the Brahmaputra River. The mean NDVI value from 2000 to 2020 improved in the last 20 years. The areas with high NDVI values are concentrated in the northern, western and southern parts of EHR, and the areas with lower NDVI values were located along the river (Brahmaputra River). The mean LST increased in pre-monsoon and post-monsoon seasons. Contrary, LST decreased in winter. The correlation results showed that natural factors such as NDVI had a significant positive correlation with NPP. The regression results showed that NDVI, vegetation cover, urban population growth, and the land surface temperature had significantly affected NPP in the EHR. Thus, this study suggests effective restoration and management of the vegetation cover to improve ecosystem health and support the livelihood of the mountainous communities. The outcomes of this work can be critical to EHR sustainable management since it is an important biodiversity hotspot.

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.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cscee.2023.100344.

References

[1] M. Rogora, L. Frate, M.L. Carranza, M. Freppaz, A. Stanisci, I. Bertani, G. Matteucci, Assessment of climate change effects on mountain ecosystems through a cross-site analysis in the Alps and Apennines, Sci. Total Environ. 624 (2018) 1429–1442.

[2] R.M. Ramachandran, P.S. Roy, Vegetation response to climate change in Himalayan hill ranges: a remote sensing perspective, Plant Diversity in the Himalaya Hotspot Region 1 (2018) 369–392.

[3] H. Pauli, S.R. Halloy, High mountain ecosystems under climate change, in: Oxford Research Encyclopedia of Climate Science, 2019.

[4] A. Gobiet, S. Kotlarski, M. Beniston, G. Heinrich, J. Rajczak, M. Stoffel, 21st century climate change in the European Alps—a review, Sci. Total Environ. 493 (2014) 1138–1151.

[5] K. Tse-ring, E. Sharma, N. Chettri, A.B. Shrestha, Climate Change Vulnerability of Mountain Ecosystems in the Eastern Himalayas, International centre for integrated mountain development (ICIMOD), 2010.

[6] B. Dhakal, R.R. Kattel, Effects of global changes on ecosystems services of multiple natural resources in mountain agricultural landscapes, Sci. Total Environ. 676 (2019) 665–682.

[7] R.K. Chaturvedi, R. Gopalakrishnan, M. Jayaraman, G. Bala, N.V. Joshi, R. Sukumar, N.H. Ravindranath, Impact of climate change on Indian forests: a dynamic vegetation modeling approach, Mitig. Adapt. Strategies Glob. Change 16 (2) (2011) 119–142.

[8] N.H. Ravindranath, N.V. Joshi, R. Sukumar, A. Saxena, Impact of climate change on forests in India, Curr. Sci. (2006) 354–361.

[9] G.T. Pecl, M.B. Araújo, J.D. Bell, J. Blanchard, T.C. Bonebrake, I.C. Chen, S. E. Williams, Biodiversity redistribution under climate change: impacts on ecosystems and human wellbeing, Science 355 (6332) (2017) eaai9214.

[10] R.D. Ward, D.A. Friess, R.H. Day, R.A. Mackenzie, Impacts of climate change on mangrove ecosystems: a region by region overview, Ecosys. Health Sustain. 2 (4) (2016), e01211.

[11] S. Seneviratne, N. Nicholls, D. Easterling, C. Goodess, S. Kanae, J. Kossin, F. W. Zwiers, Changes in Climate Extremes and Their Impacts on the Natural Physical Environment, 2012.

[12] C.C. Ummenhofer, G.A. Meehl, Extreme weather and climate events with ecological relevance: a review, Phil. Trans. Biol. Sci. 372 (1723) (2017), 20160135.

[13] Q. Gao, Y. Guo, H. Xu, H. Ganjurjav, Y. Li, Y. Wan, S. Liu, Climate change and its impacts on vegetation distribution and net primary productivity of the alpine ecosystem in the Qinghai-Tibetan Plateau, Sci. Total Environ. 554 (2016) 34–41.

[14] M. Lindner, M. Maroschek, S. Netherer, A. Kremer, A. Barbati, J. Garcia-Gonzalo, M. Marchetti, Climate change impacts, adaptive capacity, and vulnerability of European forest ecosystems, For. Ecol. Manag. 259 (4) (2010) 698–709.

[15] I.P.C.C. Spm-Ipcc-Wgii, Summary for Policymakers. *Climate Change*, 2014.

[16] Z. Qiu, Z. Feng, Y. Song, M. Li, P. Zhang, Carbon sequestration potential of forest vegetation in China from 2003 to 2050: predicting forest vegetation growth based on climate and the environment, J. Clean. Prod. 252 (2020), 119715.

[17] J. Campo, A. Merino, Variations in soil carbon sequestration and their determinants along a precipitation gradient in seasonally dry tropical forest ecosystems, Global Change Biol. 22 (5) (2016) 1942–1956.

[18] J. Li, Z.X. Zhou, Natural and human impacts on ecosystem services in Guanzhong-Tianshui economic region of China, Environ. Sci. Pollut. Control Ser. 23 (7) (2016) 6803–6815.

[19] P. Ciais, C. Sabine, G. Bala, L. Bopp, V. Brovkin, J. Canadell, P. Thornton, Carbon and other biogeochemical cycles, in: Climate Change 2013: the Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, 2014, pp. 465–570.

[20] Z.A. Rahaman, A.A. Kafy, A.A. Faisal, A. Al Rakib, D.M. Jahir, M. Fattah, M. T. Rahman, Predicting microscale land use/land cover changes using cellular automata algorithm on the northwest coast of peninsular Malaysia, Earth Systems and Environment 6 (4) (2022) 817–835.

[21] A. Guo, J. Yang, X. Xiao, J. Xia, C. Jin, X. Li, Influences of urban spatial form on urban heat island effects at the community level in China, Sustain. Cities Soc. 53 (2020), 101972, https://doi.org/10.1016/j.scs.2019.101972.

[22] F. Pei, X. Li, X. Liu, S. Wang, Z. He, Assessing the differences in net primary productivity between pre-and post-urban land development in China, Agric. For. Meteorol. 171 (2013) 174–186.

[23] T. Paz-Kagan, M. Shachak, E. Zaady, A. Karnieli, Evaluation of ecosystem responses to land-use change using soil quality and primary productivity in a semi-arid area, Israel, Agric. Ecosyst. Environ. 193 (2014) 9–24.

[24] N.C. Brouwers, R. Van Dongen, G. Matusick, N.C. Coops, G. Strelein, G. Hardy, Inferring drought and heat sensitivity across a Mediterranean forest region in southwest Western Australia: a comparison of approaches, Forestry: Int. J. Financ. Res. 88 (4) (2015) 454–464.

[25] M.C. Reeves, L.S. Baggett, A remote sensing protocol for identifying rangelands with degraded productive capacity, Ecol. Indicat. 43 (2014) 172–182.

[26] M. Zhao, S.W. Running, Drought-induced reduction in global terrestrial net primary production from 2000 through 2009, Science 329 (5994) (2010) 940–943.

[27] N.C. Brouwers, N.C. Coops, Decreasing Net Primary Production in forest and shrub vegetation across southwest Australia, Ecol. Indicat. 66 (2016) 10–19.

[28] W. Liang, Y. Yang, D. Fan, H. Guan, T. Zhang, D. Long, D. Bai, Analysis of spatial and temporal patterns of net primary production and their climate controls in China from 1982 to 2010, Agric. For. Meteorol. 204 (2015) 22–36.

[29] A.C. Morel, M. AduSasu, S. Adu-Bredu, M. Quaye, C. Moore, R. Ashley Asare, Y. Malhi, Carbon dynamics, net primary productivity and human-appropriated net primary productivity across a forest–cocoa farm landscape in West Africa, Global Change Biol. 25 (8) (2019) 2661–2677.

[30] J. Li, Z.X. Zhou, Natural and human impacts on ecosystem services in Guanzhong-Tianshui economic region of China, Environ. Sci. Pollut. Control Ser. 23 (7) (2016) 6803–6815.

[31] D. Geng, L. Liang, J. Wang, T. Huang, L. Xiang, W. Shuguo, Estimation of NPP in Xuzhou based on improved CASA model and remote sensing data, in: 2019 8th International Conference *on Agro-Geoinformatics (Agro-Geoinformatics)*, IEEE, 2019, July, pp. 1–6.

[32] B. Zhou, Z. Liao, S. Chen, H. Jia, J. Zhu, X. Fei, Net primary productivity of forest ecosystems in the Southwest Karst region from the perspective of carbon neutralisation, Forests 13 (9) (2022) 1367.

[33] J.H. Park, J. Gan, C. Park, Discrepancies between global forest net primary productivity estimates derived from MODIS and forest inventory data and underlying factors, Rem. Sens. 13 (8) (2021) 1441.

[34] A. Mayer, L. Kaufmann, G. Kalt, S. Matej, M.C. Theurl, T.G. Morais, K.H. Erb, Applying the Human Appropriation of Net Primary Production framework to map provisioning ecosystem services and their relation to ecosystem functioning across the European Union, Ecosyst. Serv. 51 (2021), 101344.

[35] C. Zhou, A. Elshkaki, T.E. Graedel, Global human appropriation of net primary production and associated resource decoupling: 2010–2050, Environ. Sci. Technol. 52 (3) (2018) 1208–1215.

[36] X. Liu, F. Pei, Y. Wen, X. Li, S. Wang, C. Wu, Z. Liu, Global urban expansion offsets climate-driven increases in terrestrial net primary productivity, Nat. Commun. 10 (1) (2019) 1–8.

[37] A. Anav, P. Friedlingstein, C. Beer, P. Ciais, A. Harper, C. Jones, M. Zhao, Spatiotemporal patterns of terrestrial gross primary production: a review, Rev. Geophys. 53 (3) (2015) 785–818.

[38] N. Clerici, M.L. Paracchini, J. Maes, Land-cover change dynamics and insights into ecosystem services in European stream riparian zones, Ecohydrol. Hydrobiol. 14 (2) (2014) 107–120.

[39] N.J. Van den Berg, H.L. van Soest, A.F. Hof, M.G. den Elzen, D.P. van Vuuren, W. Chen, K. Blok, Implications of various effort-sharing approaches for national carbon budgets and emission pathways, Climatic Change 162 (4) (2020) 1805–1822.

[40] D. Hemming, R. Betts, M. Collins, Sensitivity and uncertainty of modelled terrestrial net primary productivity to doubled CO2 and associated climate change for a relatively large perturbed physics ensemble, Agric. For. Meteorol. 170 (2013) 79–88.

[41] M. Zhao, S.W. Running, Drought-induced reduction in global terrestrial net primary production from 2000 through 2009, Science 329 (5994) (2010) 940–943.

[42] L.D. Bhatta, B.E.H. van Oort, N.E. Stork, H. Baral, Ecosystem services and livelihoods in a changing climate: understanding local adaptations in the Upper Koshi, Nepal, International Journal of Biodiversity Science, Ecosystem Services & Management 11 (2) (2015) 145–155.

[43] P. Kandel, D. Tshering, K. Uddin, T. Lhamtshok, K. Aryal, S. Karki, N. Chettri, Understanding social–ecological interdependence using ecosystem services perspective in Bhutan, Eastern Himalayas, Ecosphere 9 (2) (2018), e02121.

[44] P. Pereira, M. Inacio, I. Bogunovic, M. Francos, D. Barcelo, W. Zhao, Ecosystem services in mountain environments: benefits and threats, Pirineus 177 e068 (2022).

[45] S. Chaudhary, A. McGregor, D. Houston, N. Chettri, Spiritual enrichment or ecological protection?: a multi-scale analysis of cultural ecosystem services at the Mai Pokhari, a Ramsar site of Nepal, Ecosyst. Serv. 39 (2019), 100972.

[46] J. Gao, X. Tang, S. Lin, H. Bian, The influence of land use change on key ecosystem services and their relationships in a mountain region from past to future (1995–2050), Forests 12 (5) (2021) 616.

[47] V. Balthazar, V. Vanacker, A. Molina, E.F. Lambin, Impacts of forest cover change on ecosystem services in high Andean mountains, Ecol. Indicat. 48 (2015) 63–75.

[48] C. Luederitz, E. Brink, F. Gralla, V. Hermelingmeier, M. Meyer, L. Niven, H. von Wehrden, A review of urban ecosystem services: six key challenges for future research, Ecosyst. Serv. 14 (2015) 98–112.

[49] M.R. Felipe-Lucia, B. Martín-López, S. Lavorel, L. Berraquero-Díaz, J. Escalera-Reyes, F.A. Comín, Ecosystem services flows: why stakeholders' power relationships matter, PLoS One 10 (7) (2015), e0132232.

[50] H.W. Hintz, Grassland dynamics: long-term ecological research in tallgrass prairie, J. Environ. Qual. 28 (5) (1999) 1685.

[51] N. Chettri, K. Aryal, S. Thapa, K. Uddin, P. Kandel, S. Karki, Contribution of ecosystem services to rural livelihoods in a changing landscape: a case study from the Eastern Himalaya, Land Use Pol. 109 (2021), 105643.

[52] T. Dorji, J.D. Brookes, J.M. Facelli, R.R. Sears, T. Norbu, K. Dorji, H. Baral, Socio-cultural values of ecosystem services from Oak forests in the eastern Himalaya, Sustainability 11 (8) (2019) 2250.

[53] K. Giri, The first report of indigenous free-living Diazotroph Kosakoniasacchari isolated from Himalayan alder-based shifting cultivation system in Nagaland, India, J. Soil Sci. Plant Nutr. 19 (3) (2019) 574–579.

[54] P. Chakraborty, S. Ghosal, Status of mountain-tourism and research in the Indian Himalayan Region: a systematic review, Asia-Pacific Journal of Regional Science (2022) 1–35.

[55] R. Kumar, A.J. Nath, A. Nath, N. Sahu, R. Pandey, Landsat-based multi-decadal spatio-temporal assessment of the vegetation greening and browning trend in the Eastern Indian Himalayan Region, Remote Sens. Appl.: Society and Environment 25 (2022), 100695, https://doi.org/10.1016/j.rsase.2022.100695.

[56] S.K. Jain, V. Kumar, M. Saharia, Analysis of rainfall and temperature trends in northeast India, Int. J. Climatol. 33 (4) (2013) 968–978.

[57] S. Paul, T.K. Das, R. Pharung, S. Ray, N. Mridha, N. Kalita, A.K. Singh, Development of an indicator based composite measure to assess livelihood

sustainability of shifting cultivation dependent ethnic minorities in the disadvantageous Northeastern region of India, Ecol. Indicat. 110 (2020), 105934.
[58] A.R. Devi, T. Shimrah, Assessment of land use and land cover and forest fragmentation in traditional landscape in Manipur, Northeast India, Int. J. Environ. Sci. Technol. 19 (10) (2022) 10291–10306.
[59] M.C. Wambulwa, R. Milne, Z.Y. Wu, R.A. Spicer, J. Provan, Y.H. Luo, J. Liu, Spatiotemporal maintenance of flora in the Himalaya biodiversity hotspot: current knowledge and future perspectives, Ecol. Evol. 11 (16) (2021) 10794–10812.
[60] J. Rajeev, S. Hukum, Carbon sequestration potential of disturbed and non-disturbed forest ecosystem: a tool for mitigating climate change, Afr. J. Environ. Sci. Technol. 14 (11) (2020) 385–393.
[61] Q. Mu, M. Zhao, F.A. Heinsch, M. Liu, H. Tian, S.W. Running, Evaluating water stress controls on primary production in biogeochemical and remote sensing based models, J. Geophys. Res.: Biogeosciences 112 (G1) (2007).
[62] R. Jafari, L. Bakhshandehmehr, Quantitative mapping and assessment of environmentally sensitive areas to desertification in central Iran, Land Degrad. Dev. 27 (2) (2016) 108–119.
[63] Y. Zheng, C. Ren, Y. Xu, R. Wang, J. Ho, K. Lau, E. Ng, GIS-based mapping of Local Climate Zone in the high-density city of Hong Kong, Urban Clim. 24 (2018) 419–448.
[64] Y. Ji, G. Zhou, T. Luo, Y. Dan, L. Zhou, X. Lv, Variation of net primary productivity and its drivers in China's forests during 2000–2018, Forest Ecosystems 7 (1) (2020) 1–11.
[65] Y. Zhou, D. Yue, J. Guo, G. Chen, D. Wang, Spatial correlations between landscape patterns and net primary productivity: a case study of the Shule River Basin, China, Ecol. Indicat. 130 (2021), 108067.
[66] H. Zhu, A. Lin, L. Wang, Y. Xia, L. Zou, Evaluation of MODIS gross primary production across multiple biomes in China using eddy covariance flux data, Rem. Sens. 8 (5) (2016) 395.
[67] Q. Wang, J. Zeng, S. Leng, B. Fan, J. Tang, C. Jiang, W. Shui, The effects of air temperature and precipitation on the net primary productivity in China during the early 21st century, Front. Earth Sci. 12 (4) (2018) 818–833.
[68] N.B. Mishra, K.P. Mainali, Greening and browning of the Himalaya: Spatial patterns and the role of climatic change and human drivers, Sci. Total Environ. 587 (2017) 326–339.
[69] B.R. Parida, A.C. Pandey, N.R. Patel, Greening and browning trends of vegetation in India and their responses to climatic and non-climatic drivers, Climate 8 (8) (2020) 92.
[70] P. Punitha, M.A. Ansari, D.K. Pandey, R. Daya, D. Shiv, P.K. Sharma, N. Prakash, Shifting cultivation in North East India: social dimension, cross cultural reflection and strategies for improvement, Indian J. Agric. Sci. 88 (6) (2018) 811–819.
[71] T. Koellner, L. De Baan, T. Beck, M. Brandão, B. Civit, M. Margni, R. Müller-Wenk, UNEP-SETAC guideline on global land use impact assessment on biodiversity and ecosystem services in LCA, Int. J. Life Cycle Assess. 18 (2013) 1188–1202.
[72] W. Jiao, Y. Chen, W. Li, C. Zhu, Z. Li, Estimation of net primary productivity and its driving factors in the Ili River Valley, China, Journal of Arid Land 10 (5) (2018) 781–793.
[73] Y. Jiang, R. Wang, Q. Peng, X. Wu, H. Ning, C. Li, The relationship between drought activity and vegetation cover in Northwest China from 1982 to 2013, Nat. Hazards 92 (2018) 145–163.
[74] J. Li, Z. Wang, C. Lai, X. Wu, Z. Zeng, X. Chen, Y. Lian, Response of net primary production to land use and land cover change in mainland China since the late 1980s, Sci. Total Environ. 639 (2018) 237–247.
[75] G. Tian, Z. Qiao, Assessing the impact of the urbanisation process on net primary productivity in China in 1989–2000, Environ. Pollut. 184 (2014) 320–326.
[76] C. Jiang, Z.F. Wu, J. Cheng, Q. Yu, X.Q. Rao, Impacts of urbanisation on net primary productivity in the Pearl River Delta, China, Int. J. Plant Prod. 9 (4) (2015) 581–598.
[77] P. Dlamini, P. Chivenge, V. Chaplot, Overgrazing decreases soil organic carbon stocks the most under dry climates and low soil pH: a meta-analysis shows, Agric. Ecosyst. Environ. 221 (2016) 258–269.
[78] J. Liu, J. Diamond, China's environment in a globalising world, Nature 435 (2005) 1179.
[79] A. Buyantuyev, J. Wu, Urbanisation alters spatiotemporal patterns of ecosystem primary production: a case study of the Phoenix metropolitan region, USA, J. Arid Environ. 73 (2009) 512–552.
[80] Z. Wang, J. Zhong, H. Lan, Z. Wang, Z. Sha, Association analysis between spatiotemporal variation of net primary productivity and its driving factors in inner Mongolia, China during 1994–2013, Ecol. Indicat. 105 (2019) 355–364.
[81] Q. Gao, Y. Guo, H. Xu, H. Ganjurjav, Y. Li, Y. Wan, S. Liu, Climate change and its impacts on vegetation distribution and net primary productivity of the alpine ecosystem in the Qinghai-Tibetan Plateau, Sci. Total Environ. 554 (2016) 34–41.
[82] Y. Liu, W. Jia, M. Huang, Y. Li, Z. Wu, Y. Zhang, Y. Li, Response of vegetation net primary productivity to climate change in the Qilian Mountains since recent 51 years, Acta Bot. Boreali Occident. Sin. 35 (3) (2015) 601–607.
[83] W. Zhou, C. Gang, F. Zhou, J. Li, X. Dong, C. Zhao, Quantitative assessment of the individual contribution of climate and human factors to desertification in northwest China using net primary productivity as an indicator, Ecol. Indicat. 48 (2015) 560–569.
[84] C. Milesi, C.D. Elvidge, R.R. Nemani, S.W. Running, Assessing the impact of urban land development on net primary productivity in the southeastern United States, Remote Sens. Environ. 86 (2003) 401–410.
[85] W. Liang, Y. Yang, D. Fan, H. Guan, T. Zhang, D. Long, D. Bai, Analysis of spatial and temporal patterns of net primary production and their climate controls in China from 1982 to 2010, Agric. For. Meteorol. 204 (2015) 22–36.
[86] B. Tao, K. Li, X.M. Shao, M.K. Cao, The temporal and spatial patterns of terrestrial net primary productivity in China, J. Geogr. Sci. 13 (2) (2003) 163–171.
[87] M. Munsi, G. Areendran, P.K. Joshi, Modeling spatio-temporal change patterns of forest cover: a case study from the Himalayan foothills (India), Reg. Environ. Change 12 (2012) 619–632.
[88] M. Munsi, S. Malaviya, G. Oinam, P.K. Joshi, A landscape approach for quantifying land-use and land-cover change (1976–2006) in middle Himalaya, Reg. Environ. Change 10 (2010) 145–155.
[89] M. Sharma, A. Chakraborty, J.K. Garg, P.K. Joshi, Assessing forest fragmentation in north-western Himalaya: a case study from Ranikhet forest range, Uttarakhand, India, J. For. Res. 28 (2017) 319–327.
[90] Q. Gao, Y. Guo, H. Xu, H. Ganjurjav, Y. Li, Y. Wan, S. Liu, Climate change and its impacts on vegetation distribution and net primary productivity of the alpine ecosystem in the Qinghai-Tibetan Plateau, Sci. Total Environ. 554 (2016) 34–41.
[91] Y. Ji, G. Zhou, T. Luo, Y. Dan, L. Zhou, X. Lv, Variation of net primary productivity and its drivers in China's forests during 2000–2018, Forest Ecosystems 7 (2020) 1–11.
[92] A. Saha, S.C. Pal, M. Santosh, S. Janizadeh, I. Chowdhuri, A. Norouzi, R. Chakrabortty, Modelling multi-hazard threats to cultural heritage sites and environmental sustainability: the present and future scenarios, J. Clean. Prod. 320 (2021), 128713.
[93] S. Sekhri, P. Kumar, C. Fürst, R. Pandey, Mountain specific multi-hazard risk management framework (MSMRMF): assessment and mitigation of multi-hazard and climate change risk in the Indian Himalayan Region, Ecol. Indicat. 118 (2020), 106700.
[94] J. Rusk, A. Maharjan, P. Tiwari, T.H.K. Chen, S. Shneiderman, M. Turin, K.C. Seto, Multi-hazard susceptibility and exposure assessment of the Hindu Kush Himalaya, Sci. Total Environ. 804 (2022), 150039, https://doi.org/10.1016/j.scitotenv.2021.150039.
[95] A. Bera, B.P. Mukhopadhyay, D. Das, Landslide hazard zonation mapping using multi-criteria analysis with the help of GIS techniques: a case study from Eastern Himalayas, Namchi, South Sikkim, Nat. Hazards 96 (2) (2019) 935–959.
[96] S. Bera, B. Guru, T. Oommen, Indicator-based approach for assigning physical vulnerability of the houses to landslide hazard in the Himalayan region of India, Int. J. Disaster Risk Reduc. 50 (2020), 101891.
[97] P. Lamsal, L. Kumar, K. Atreya, K.P. Pant, Forest ecosystem services in Nepal: a retrospective synthesis, research gaps and implications in the context of climate change, Int. For. Rev. 20 (4) (2018) 506–537.
[98] M.V. Balzan, J. Caruana, A. Zammit, Assessing the capacity and flow of ecosystem services in multifunctional landscapes: evidence of a rural-urban gradient in a Mediterranean small island state, Land Use Pol. 75 (2018) 711–725.