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Forest Cover Change and Its Impact on Ecosystem Service Value of the Chure and Terai Region of Nepal †

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Abstract: Appropriate information on forest cover and spatio-temporal forest phenomena is essential for natural resource management and sustainable development. It is one of the main factors affecting the ecosystem and the corresponding service value it brings to humans. In recent times, forest cover in developing countries including Nepal has been declining which significantly impacted forest ecosystem services. Therefore, this study aims to assess the impact of forest cover changes on ecosystem service value of Chure and Terai region of Nepal. In this study, we used remote sensing techniques and geographic information systems to extract forest cover types based on object-based image analysis (OBIA) techniques from the Landsat TM/ ETM/OLI in Chure and Terai region since 1994 -2018. Furthermore, the ecosystem service value (ESV) coefficient per unit area provided by forest cover is taken from previous studies and adjusted to take into account annual inflation or purchasing power to enable appropriate ESV estimates of impacting forest covering area. In 1994, 40.02% of forest covered the highest area and found decreased quite faster till 2004 (28.87%), and afterwards a gradual decrease till 2018 arriving to 26.52%. As a consequences, monetary value of ecosystem services decreased significantly from 78.7 billion in 1994 to 43.2 billion in 2018. The findings of this study could open the door better forest conservation policy formulation and development management intervention.

Keywords: ecosystem service value; forest cover change; OBIA

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1. Introduction

Forest cover changes are the functional component of the ecosystem and are a clear indicator of global ecological shifts. Changes in biodiversity have an impact on Ecosystem services (the benefit of nature to human in terms of economy). The extent to which individuals and their residences are susceptible, to fluctuations, in the weather, economy or political landscape is also influenced by these shifts. However, despite the existence of ecosystem services (ES), there is a gap in planning and policy for preserving and managing our resources. This gap often results in losses and compromises, in the provision of ecosystem services [1].

Forests provide a multitude of ecosystem services that greatly contribute to the well-being of humans. But, in countries, like Nepal, the importance and value of these services offered by trees are not fully appreciated[2]. Nepal has been experiencing transformations, in its forest coverage in the Terai and Chure regions. This area is ecologically diverse, directly influences the quality of the environment, and offers a number of ecosystem services to areas downstream [3]. When examining the period between 1990 and 2005 it is estimated that 7.9% of Nepal's forest and woodland habitats have been lost due to habitat change[4]. The eastern chure region of Nepal has 73.0% (1,384,445 ha) of its total area covered by forests, according to the results of the most recent forest resource assessment (2010–2014) [5]. The majority of the forest area (76%) is located outside of protected areas, and the annual rate of change in forest cover between 2001 and 2010 was 0.21%[6]. Forest ecosystems become less resilient as a result of plant-biodiversity degradation, and it becomes harder for them to adapt to shifting environmental conditions. Ecosystem services have been declining in recent decades as a result of an enormous and mostly irreversible loss of the natural and biological diversity, which brought ever-increasing demand for these services. The many societal benefits that ecosystems and their ecological functions provide can be expressed through the economic valuation of biodiversity ecosystem services [4]. Chure is a hilly region that stretches the whole length of southern Nepal, from east to west. To increase awareness and communicate the significance of ecosystem services, the assessment and valuation of ecosystem services based on LULC can be a useful tool in this part of country.

In this study, the information extracted from satellite imageries using Remote Sensing was used in detection of extent and rate of forest cover change over time. Freely available Landsat data of every five years interval was taken from United States Geological Survey and used to process and classify the data using Object-Oriented Image Analysis (OBIA) technique to derive the Forest Cover change Information. The forest cover change information was used to estimate and analyze the corresponding ESV values contributed particularly by forest since it has greater impact than other LULC type.

2. Materials and Methods

2.1. Study Area

The study area covers approximately 849 km in length and 24 to 72 km in width, covering the Chure and Terai belt of Nepal. It spans an area of 39, 236 sq. km between latitudes 26.36° and 29.17° North and longitudes 80.05° and 88.20° East. It runs east to west in 33 administrative districts of Nepal. India borders it on the east, west, and south internationally. The Middle Mountain Region shares the study area's northern boundary.

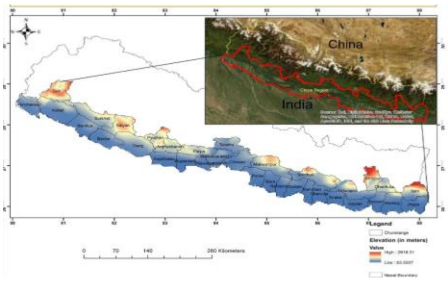


Figure 1. Study Area Map.

2.2. Image Classification Method

The goal of object-based classification is to identify an object with a defined meaning area based on the general shape, texture of a pixel in the image and spatial connectivity. Through the utilization of a segmentation technique that relies on predetermined parameters we were able to achieve the desired generalization. We assessed the attributes of each segment by considering spatial, spectral and temporal scales, in our object-based image classification approach[7]. Object-oriented analysis provides benefits such as meaningful statistics, the use of semantic concepts in information extraction, topological features (neighbour, super-object, etc.), shape features (area, length/width, etc.), and the contiguous relationship between real-world objects and image objects. There is more potential for object-based analysis, which could lead to greater accuracy[8]. Object-based classification has the capability to be significantly more accurate than pixel-based classification because it eliminates the chance of misclassifying individual pixels[9].

2.3. Image Mosaicking

The technique known as "image mosaicking" creates a smooth, merged image by combining two or more images that significantly overlap[10]. Since edges define boundaries, they are a fundamentally important problem in image processing. Strong intensity contrasts, or a change in intensity from one pixel to the next, are what define edges in images. While maintaining the key structural elements of an image, edge detection dramatically lowers the amount of data and filters out irrelevant information. An image's 2-D spatial gradient is measured by the Sobel operator. It is typically applied to an input grayscale image in order to determine the approximate absolute gradient magnitude at each point. The two 3x3 convolution masks used by the Sobel edge detector estimate the gradient in the x-direction (columns) and the gradient in the y-direction (rows)[11].

2.4. Segmentation

Segmentation is based on four mathematical principles: a union set of regions makes up the image, regions are not allowed to overlap, and neighboring region homogeneity criteria differ[12]. The primary function of the segmentation algorithm is to combine (image) elements according to the homogeneity parameter or, alternatively, to differentiate them from neighboring regions[13]. The segmentation process in a region-based algorithm begins with seed points. After that, similarity criteria are calculated for every area that is spatially adjacent. Based on a statistical hypothesis test that examines the average across regions, the similarity criteria are determined. If the cost is less than the similarity value, the regions are combined into larger objects. Adopted are the following criteria for the union of two neighbouring regions, A and B:

- Based on the average test, A and B are similar.
- The resemblance approaches the specified limit.
- A and B are spatially close (B is the closest neighbour among A neighbours, and A is the closest neighbour among B neighbours).

2.5. Indices

In order to identify and detect non-vegetation indices, remote sensing indices have been used extensively. Indices enable the acquisition of ecological information from satellite imagery through the analysis of multi- or hyperspectral bands.[14]

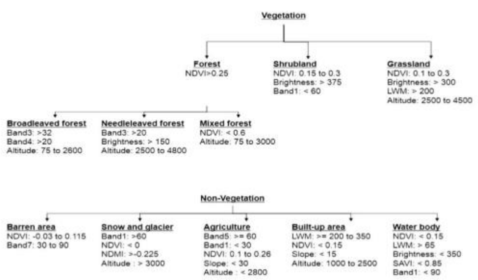


Figure 2. Indices.

By measuring the difference between near-infrared light, which vegetation strongly reflects, and red light, which vegetation absorbs, the Normalized Difference Vegetation Index (NDVI) quantifies vegetation. The NDVI is always between -1 and +1.

$$NDVI= (NIR-R) / (NIR+R) \tag{1}$$

Certain wavelengths in the spectrum are absorbed and others are reflected when sunlight strikes an object. For the purpose of photosynthesis, the pigment chlorophyll in leaves strongly absorbs visible light (between 0.4 and 0.7 μm). Conversely, the near-infrared light (0.7–1.1 μm) is strongly reflected by the leaf's cell structure. These light wavelengths affect plants more when they have more leaves, in that order. NDVI is widely acknowledged as a good indicator of terrestrial vegetation productivity due to its many benefits, including its simplicity of algorithm, ability to distinguish vegetated areas from other surface areas, and greater sensitivity to detect green vegetation than using a single band[15]. Furthermore, ratios do not account for the spectral dependencies of canopy-background interactions, additive atmospheric (path radiance) effects, and canopy reflectance, particularly those related to canopy shadowing[16].

2.6. Classification and Accuracy Assessment

The segmented layers are further used to classify the image objects. Nearest Neighbor, which is a sample-based classification algorithm combines predefined feature sets based on user-defined samples, to assign objects to classes. Assessing accuracy serves as a means of locating potential error sources as well as a comparator[17]. Comparing field data or training data at multiple locations within the image is a useful method of assessing relative accuracy; this is similar to how digital orthophotos and terrain models are assessed for spatial accuracy using ground checkpoints[18]. A confusion matrix compares the relationship between known reference data and the results of the classification based on the classes. To control only those cases that might have been mistakenly classified by chance, the Kappa statistic is employed[19].Both the random accuracy and the observed (total) accuracy can be used to calculate this. Stratified random sampling was the method we employed. It is possible to create stratified random points that are proportionate to the distribution of the image's classes.

$$\text{Kappa} = (\text{total accuracy} - \text{random accuracy}) / (1 - \text{random accuracy}) \quad (2)$$

2.7. Landsat Image

Governments, corporations, industries, civilian organizations, and educational institutions have all used LANDSAT data globally. Among the many uses for which the data are employed is global change. The two main sensors on the LANDSAT 8 satellite are the Thermal Infrared Sensor (TIRS) and the Operational Land Imager (OLI). National Aeronautics and Space Administration (NASA) and the U.S. government continued the Landsat Program as an extension. S. Together, the USGS and Landsat managed the area.

2.8. Online Inflation Calculator

The Consumer Price Index (CPI) can be used to calculate the inflation rate using a fairly straightforward formula. The Bureau of Labor Statistics (BLS) compiles the Consumer Price Index (CPI) each month by surveying thousands of prices across the nation. Unlike the majority of online calculators, months and years and provides both the inflation-adjusted price and the total cumulative inflation. The ESV coefficients for the TP were also updated and modified by Xie et al. using Costanza's global database [20].

Table 1. ESV Coefficient.

Equivalent Biome	**ESV coefficient**[20]	**ESV coefficient**[21]
Swamp	14785	8939.26
Woodland	969	2168.84
Shrubland	-	1089.19
Grassland	232	565.88
Cropland	92	699.37

Barren land	-	59.83

3. Results and Discussions

For mapping and change detection of forest cover, Landsat images with a spatial resolution of 30 m, orthorectified, maximum cloud free, enhanced thematic mapper (TM), enhanced thematic mapper plus (EMT+), an operational land imager, and thermal infrared sensor (OLI/TIRS) image are utilized. The Landsat images of 1994 to 2018 each with 5 years interval were downloaded from the USGS. Table 2 shows Images acquired, acquisition date along with their particular spectral information.

Table 2. Landsat Images used.

Year	Acquisition Date	Bands
1994	30/12/1993-1/1/1995	R, G, B, NIR, SWIR, SWIR-2, Thermal IR
1999	30/12/1998-1/1/2001	R, G, B, NIR, SWIR, SWIR-2, Thermal IR
2004	30/12/2003-1/1/2005	R, G, B, NIR, SWIR, SWIR-2, Thermal IR
2009	30/12/2008-1/1/2010	R,G,B, NIR,SWIR,SWIR-2, Thermal IR
2014	30/12/2013-1/1/2015	R, G, B, NIR, SWIR, SWIR-2, Thermal IR, EMT+
2018	30/12/2017-1/1/2019	R, G, B, NIR, SWIR, SWIR-2, Thermal IR, OLI, TIRS

The satellite image was segmented using a multi-resolution algorithm that locally minimized the average heterogeneity of image objects for a given resolution. a multiresolution segmentation technique that combines spectral and spatial properties to identify each individual object in the image. Scale, shape, and compactness were among the parameters that were combined to perform a segmentation. The segmentation of the Landsat images using scale 32, shape 0.1, and compactness 0.5 allowed for the distinct identification of two adjacent features.

Remote sensing indices and basic spectrum data from satellite imagery were computed on previously segmented image objects. In our study, to differentiate between areas with and without forest cover, we used the Normalized Difference Vegetation Index (NDVI) [14]. The threshold that used for calculating NDVI value as: Forest cover (NDVI>0.25) and Non-Forest Cover (NDVI<=0.25) [14].

Assign class algorithm was used for image classification. By calculating NDVI, two classes were assigned to the pixels of NDVI calculated images to distinguish Forest and non- forest based on threshold value that is NDVI value of forest and non-forest. In order to facilitate the identification of forest cover features and enhance the visual interpretation of satellite images, false colour composites were employed. About 120 sample points were collected from Google Earth pro by following Stratified Random Sampling technique for the purpose of Accuracy Assessment. Finally, In order to assess the accuracy of Land Use Land Cover Classification, the Kappa coefficient and Overall accuracy were computed.

The classified raster image from 1994 BS-2018 BS within the five years' was converted to vector format, where each class represents a distinct polygon. Finally, the area of polygon containing pixel of forest was calculated by using ArcGIS 10.4 software. A forest cover change map was created using Arc Map by determining the changes in forest cover, specifically from forest to non-forest, forest to forest, non-forest to forest, and non-forest to non-forest, between the two consecutive series of years (1994-1999, 1999-2004, 2004-2009, 2009,2014, 2014-2018).

The inflation of the coefficient was calculated at different time periods from 1994 to 2018ADThe Consumer Price Index (CPI) was used to adjust the ESV coefficients for the years 1994, 1999, 2004, 2009, 2014, and 2018 using the Inflation Calculator on the US Department of Labor's Bureau of Labor Statistics website. Finally, the Spatial distribution of ESV of 1994, 1999, 2004, 2009, 2014 and 2018 were depicted in subsequent maps. The kappa coefficient for classification of images of years 1994AD, 1999AD, 2004AD, 2009AD, 2014AD and 2018AD were found to be 80.00%, 81.67%, 75.00%, 70.00%, 78.33% and 73.33% respectively. Similarly, the overall accuracy was found to be 90%, 90.83%, 87.50%, 85%, 89.17% and 86.67% respectively This indicates that the classification achieves a reasonable level of precision when contrasted with Google Earth, which has better spatial resolution compared to Landsat 4-5 (TM), Landsat-7 (ETM+), and Landsat-8 (OLI and TIRS). Table 3 shows results of the accuracy assessment based on images of the specified year. Table 4 represents details of area obtained from classified images of each year. Table 5 shows percentage change data of forest cover in comparison with succeeding years. Table 6 represents ecosystem service value used, table 7 represents computed ESV values of the image and table 8 represents ESV change compared with succeeding years.

Table 3. Image Classification Accuracy Assessment.

Images year (AD)	1994	1999	2004	2009	2014	2018
Overall Accuracy	90%	90.83%	87.5%	85%	89.17%	86.67%
Kappa Coefficient	80%	81.67%	75%	70%	78.33%	73.33%

Table 4. Forest Cover Statistics of Chure and Terai.

Year (AD)	Forest Cover (Ha)	Landcover (Ha)	Percent Forest Cover
1994	2683357.92	5829970.10	40.02
1999	1904320.50		32.66
2004	1683498.52		28.87
2009	1651903.38		28.33
2014	1569459.96		26.92
2018	1545579.19		26.52

Table 5. Forest Cover Change Statistics of Chure and Terai.

Year (AD)	Forest Cover (Ha)	Change(AD)	Change in Forest Cover	Percent change in forest
1994	2683357.92	1994-1999	-779037.42	-13.36
1999	1904320.50	1999-2004	-220821.98	-3.78
2004	1683498.52	2004-2009	-31595.13	-0.54
2009	1651903.38	2009-2014	-82443.43	-1.41
2014	1569459.96	2014-2018	-23880.77	-0.40
2018	1545579.19			

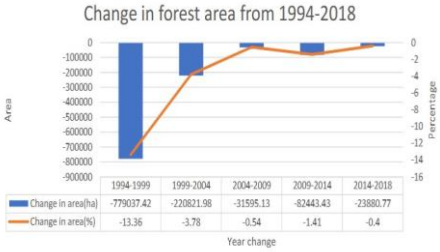


Figure 3. Change in Forest Area from 1994 to 2018.

Table 6. ESV Statistics of Chure and Terai.

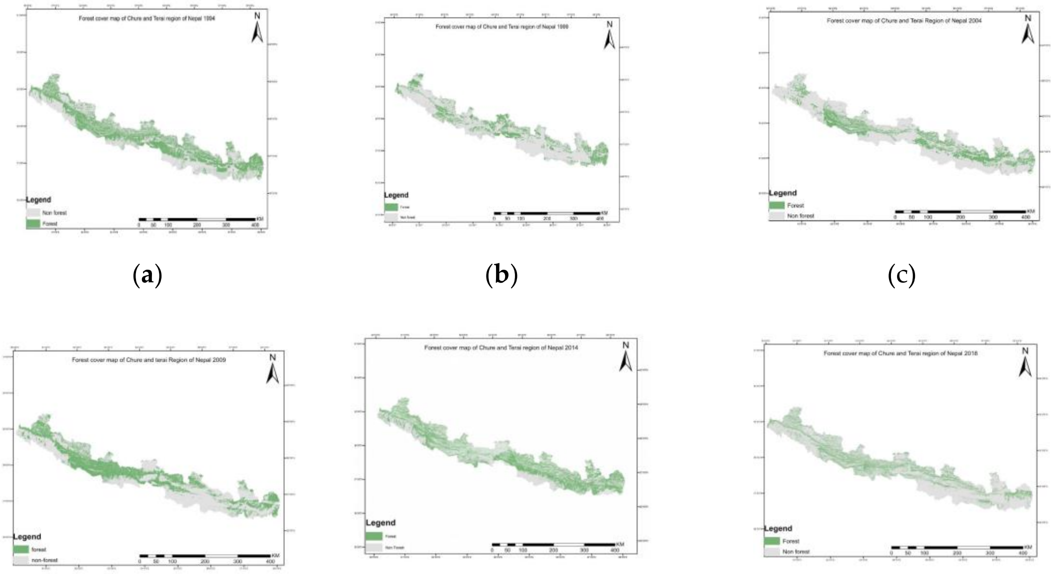
Year (AD)	Xie et al.(2003)	1994	1999	2004	2009	2014
ESV coefficient ($ha^1)	2168.84	1745.1	1961.15	2210.62	2520.28	2792.11

Table 7. Total Ecosystem Service Value.

Year (AD)	Forest Cover (Ha)	ESV coefficient (USD per ha)	Total ESV (10^8USD)
1994	2683357.92	1745.10	46.8
1999	1904320.50	1961.15	37.3
2004	1683498.52	2210.62	37.2
2009	1651903.38	2520.28	41.6
2014	1569459.96	2792.11	43.82
2018	1545579.19	2958.63	45.7

Table 8. Ecosystem Service Value change.

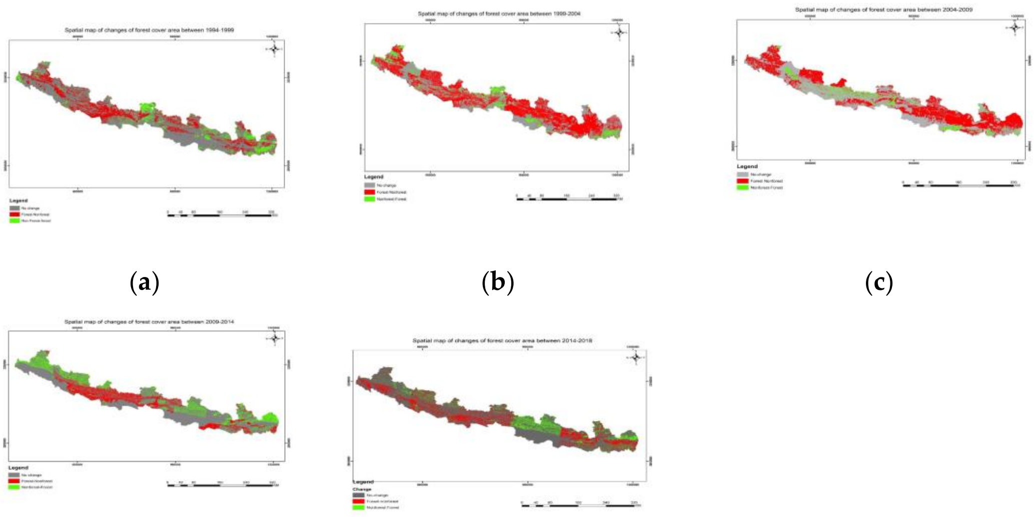
Year (AD)	ESV Value (10^8) in 2019	Year from-to (AD)	ESV Change(10^8USD)
1994	78.7	1994-1999	22.8
1999	55.8	1999-2004	6.6
2004	49.2	2004-2009	0.7
2009	48.5	2009-2014	1.5
2014	46.9	2014-2018	3.7
2018	43.2		



(**a**) (**b**) (c)

(**d**) (**e**) (**f**)

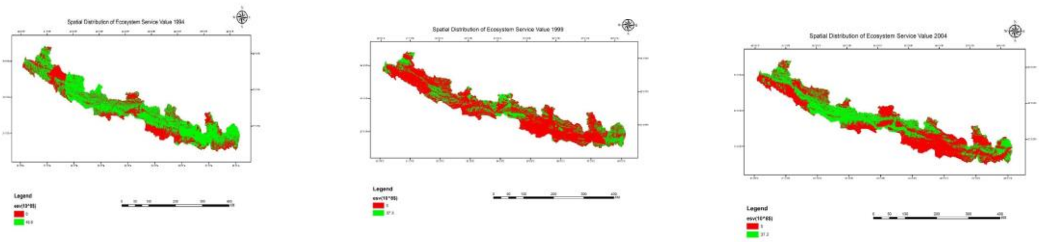
Figure 4. Forest CoverArea Maps of the Chure and Terai region of Nepal for (**a**) 1994; (**b**) 1999; (**c**) 2004; (**d**) 2009; (**e**) 2014; (**f**) 2018.



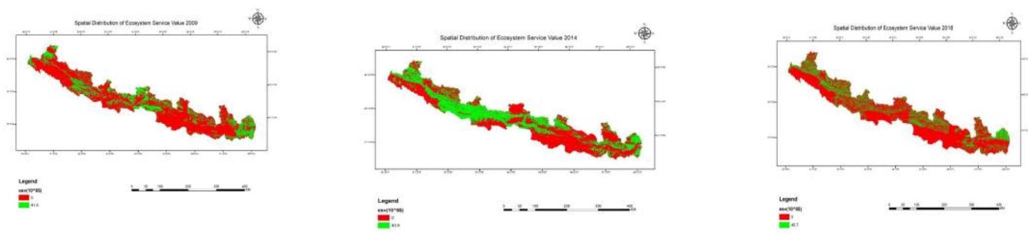
(**a**) (**b**) (**c**)

(**d**) (**e**)

Figure 5. Forest Cover change map from (**a**) 1994 to 1999; (**b**) 1999 to 2004; (**c**) 2004 to 2009; (**d**) 2009 to 2014; (**e**) 2014 to 2018.



(**a**) (**b**) (**c**)



(d) **(e)** **(f)**

Figure 6. Maps of Ecosystem Service Value for (**a**) 1994; (**b**) 1999; (**c**) 2004; (**d**) 2009; (**e**) 2014; (**f**) 2018.

4. Conclusion

The ESV in Chure and Terai has increased by 3.58*10^8USD from 1994 to 2018. The gain of ESV in Chure and Terai is due to rising change of bare land to forest, transformation of abandoned agricultural areas to forest etc. The increase in ESV implies better ecosystem activities and thus its services. Forests are vital habitats of the animal while shrubs serve as pasture for livestock and geodesic animals. From 1999 to 2009 there is an increase in ESV (25.64*10^8USD) which is proportional to the forest cover increase which indicates ecosystem activities rises with increase in dense forest. This also indicates forest act as home of plant and animal biodiversity along. With increase in forest, our study shows, and the increase of ecological activities thus the ecosystem service value. Similarly, from 1994 to 1999 there is decrease in ESV (9.48*10^8), which is less in comparison to increase, mainly due to anthropogenic activities, natural calamities etc. Which brought slight decrease in ESV value. In the same way, from 2014 to 2018 there is decrease in ESV (28.69*10^8), which indicates the fall of ecosystem activities in the recent past years, but there is an increase in ESV at overall from 1994 to 2018AD, which indicates the positivity in ecosystem service in Chure and Terai from the past two decades. Ultimately, mapping Chure and Terai's ecosystem services value (ESV) can help manage ecosystem services by highlighting the spatial location that requires immediate attention.

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