

Do Gibbons Live in Dense Forest? A Case Study from Upper Brahmaputra Valley, Assam, India

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Abstract

The present study aimed at predicting the potential habitat of Western Hoolock Gibbon (*Hoolock hoolock*) in the upper Brahmaputra river valley, Assam and to identify the conservation priority areas for systematic conservation of the species taking canopy cover into account. We used the maximum entropy algorithm for the prediction of the potential habitat of Gibbons using its current distribution with 19 environmental parameters as primary predictors. Spatio-temporal analyses of the habitat were carried out using satellite-based remote sensing and GIS techniques for two decades (1998–2018) along with Terra Modis Vegetation Continuous Field product to examine the land use land cover (LULC), habitat fragmentation, Normalized Difference Vegetation Index (NDVI) and tree cover percentage of the study area. To identify the conservation priority area, we applied a cost-effective decision-making analysis using systematic conservation prioritization in R programming. The model predicted an area of 6025.1 km² under high potential habitat, and a major part of it was found to overlap with the dense forest (80.04%) followed by moderately open forest (73.90%) and open forest (65.82%). The LULC change matrix showed deduction of forest areas in the predicted high potential habitat during the study period, while agricultural class showed an increasing trend. The fragmentation analysis indicated that the number of patches and patch density increased from 2008 to 2018 in the 'very dense' and 'dense' canopy regions of the gibbon habitat. Based on the conservation priority analysis, 640 km² area has been proposed to conserve a minimum 10% of the gibbons' habitat. The current analysis revealed that in Upper Brahmaputra Valley most of the areas under dense forest and dense canopy have remained intact over the last two decades, at least within the high potential habitat of gibbons independent of the degree of area change in forest, agriculture and plantation.

Introduction

Primate diversity and abundance in a forest site are affected by the structural variables or quality of the habitat and indirect/direct anthropogenic impacts (Brown et al. 1985, Rylands 1987, Chapman and Peres 2001). Investigation of primate habitat and its insularisation is a major research concern in tropical forest ecosystem (Anderson et al. 2007), as almost 90 % of Primate taxa, in general, are facing highest threat of habitat fragmentation owing to its dependency on tropical forest (Andr n 1994, Marsh 2003). The species-specific habitat requirement of a species is often considered to have correlation with habitat quality and feeding strategy of the concerned species. Therefore, it is important to understand the ecological flexibility or limits of primate communities and species, in order to implement effective management strategies for their future conservation (Harcourt 1998, Lindenmayer 1999, Harcourt 2002). In the Indian context, unfortunately, primates are rarely studied in terms of habitat requirements. Moreover, the major threats to the primates such as habitat loss, habitat fragmentation, and unsustainable economic development are unabated essentially obscuring the conservation processes. Continuous monitoring of habitat and qualitative assessment of species' preferred habitat parameters is an urgent need to improve prioritizing conservation action. In this paper, we present a case report of

Western Hoolock Gibbon (*Hoolock hoolock*) in the Upper Brahmaputra valley with special reference to habitat monitoring.

The species of the genus *Hoolock* are found in different forest types of northeast India (Das et al. 2003, 2009), Bangladesh (Islam and Feeroz 1992, Das et al. 2003), Myanmar (Brockelman et al. 2009), and South China (Fan et al. 2011). Although the habitat characteristics of hoolock gibbons are strongly associated with the abundance of food, it is recognized that they prefer dense canopy forest areas in the tropical forest of northeast India in particular. Due to the high rate of forest fragmentation and habitat degradation in gibbon habitat, the loss of dense canopy is prominent posing a threat to the survival of Western Hoolock Gibbon (*Hoolock hoolock*) present in the south bank of the Brahmaputra River, Assam. Studies on gibbon in India are mainly concentrated on the species' population and behavioural aspects with very little emphasis on the quantification and monitoring of habitat parameters. The frugivory in gibbons are well established (Leighton 1987, Palombit 1992) with known food niche throughout its distribution range. However, minimal efforts have been realized in the associated forest structure evaluation and monitoring. Some research articles and PhD theses are available for gibbon population status and behavioural ecology particularly from northeast India that provide baseline ecological data of the species (e.g., Kakati 1997, Das 2002, Kakati 2004). As a number of primate species coexist in the region (Sharma et al. 2013), it is very important to determine the specific habitat requirement of the species. It is noteworthy that studying sub-populations of gibbons in various pockets of northeast India's forest cannot be conclusive in many ways. Therefore, a landscape level study on habitat with the application of advanced tools and techniques is the need of the hour. Currently, no studies have been reported on gibbon habitat monitoring considering temporal satellite data from the region.

The present study aimed to investigate the site-specific preference of gibbon habitats considering the canopy cover and forest cover by integrating maximum entropy algorithm to predict potential habitat and geospatial tools to incorporate major habitat forms. The study also emphasized to test the hypothesis that hoolock gibbons generally prefer dense forest or closed canopy. This information will provide quantified baseline data for the future conservation of gibbon in the Upper Brahmaputra River stretch in Assam, India. Subsequently, we identified fragmented patches in the gibbon habitat that need to be prioritized for the future conservation of the species. We adopted integer linear programming techniques (prioritizr R package) for the decision-making analysis, considering the canopy tree as a cost for the conservation (Hanson et al. 2018).

Study Area

The study was conducted in the Upper Brahmaputra valley as the hoolock gibbon is distributed on the south bank of the mighty Brahmaputra River. The southern part of the Upper Brahmaputra Valley comprises mainly four districts of Assam viz., Jorhat, Sivsagar, Dibrugarh, and Tinsukia. The study area lies between 94⁰30' E to 96⁰0'E longitudes and 27⁰0'N to 27⁰45'N latitudes covering an area of 9851.20 km² (Fig. 1). Four major protected areas including a National Park fall under this area which signifies the

importance of the landscape in terms of floral and faunal conservation priorities. The vegetation of the study area is identified as wet evergreen forests of the *Dipterocarpus-Mesua* series (Champion and Seth 1968). The climate of the Brahmaputra valley as a whole is similar to the Southeast Asiatic Monsoon climate modified as per local physical conditions (Deka et al. 2013). The valley receives as high as 3900 mm rainfall annually in the extreme northwest and northeast hilly tracts (Nath and Deka 2010). The mean annual temperature ranges from 23⁰ C to 24⁰C.

Methods

The survey was conducted from January, 2017 to December, 2018 for gibbon occurrence and ground verification (ground-truthing). Gibbon locations of both direct sightings and heard calls were collected through handheld GPS. Along with the occurrence locations, the land use pattern was also noted down to prepare LULC supervised classification signature. Occurrence data collected were used in the predictive model thereafter.

Predictive Distribution Model

Maxent software version 3.1.0 (Computer Sciences Department – Princeton University, 2004) was used for predicting the potential distribution area of *H. hoolock*. Nineteen Environmental layers comprising temperature, precipitation, etc. (Supporting information; Appendix S1) and 23 species occurrence data were fed into Maxent, and the final predicted potential distribution area was projected using ArcGIS 10.3. The detailed explanation of ENM methodology using Maxent had been described by Phillips et al. (2006).

The occurrence data of *H. hoolock* was gathered through extensive field surveys conducted along the Upper Brahmaputra valley, Assam, India. A total of 23 independent distribution localities of gibbons were collected from the field, and all localities were used in the final modelling process. Nineteen environmental layers including temperature, precipitation, etc. were downloaded from the WorldClim website (www.worldclim.org) with spatial resolution of 30''(seconds).

The Jackknife validation methodology was performed following the method developed by Pearson et al. (2007), which was shown to be effective for sample sizes of 25 or less. To avoid overfitting of the test data, the regularization multiplier value was set at 0.1 (Phillips et al. 2004). The maximum number of background points were 1000. Linear quadratic and hinge features were used. We selected 80% of the data for training and the rest 20% for testing and 10 percentile threshold rules was employed. A total of 100 runs were set for model building (Flory et al. 2012). AUC (Area Under the receiving operator Curve) was used to test the model's goodness-of-fit. The highest AUC was considered as the best performer. The contributions of the variables were assessed through the Jackknife procedure. The final output was divided into three potential distribution areas that were regrouped with a range of 0–1: Low potential (<0.32); Moderate potential (0.32–0.47); High potential (>0.47).

Preparation of Land Use Land Cover (LULC) Maps and Change Detection Analysis

Data acquisition

Landsat satellite imageries were downloaded from the USGS Earth Explorer viewer (US Geological Survey, <https://earthexplorer.usgs.gov>) to determine the LULC classes and analyse their change over a span of 20 years. The satellite data were of variable dates, selected based on the quality of the data, data availability, and dry season. A total of six Landsat imageries of the same spatial resolution (30 m) were acquired for the years 1998 (Landsat 5), 2008 (Landsat 5) and 2018 (Landsat 8) (Supporting information; Appendix S2). The software packages used in the analyses were ERDAS Imagine 2011, ArcGIS 10.3, and QGIS 3.14.

LULC classification and change detection

A hybrid classification technique was adopted to digitally categorize each Landsat image, since this technique has been shown to perform better in the case of spectral variability of individual land cover features (Mas 1999, Hazarika et al. 2015, Twisa and Buchroithner 2019). Several studies have suggested that hybrid classification produces superior results compared to unsupervised or supervised classification alone (Garcia and Alvarez 1994, Xiao and Weng 2007). The downloaded satellite images were assigned per-pixel signatures and based on the specific DN value of each landscape element, seven different LULC categories were decided viz., agriculture, grassland, forest, plantation, sandbar, settlement, and water (Supporting information; Appendix S3). Vector polygon was drawn around each representative predetermined LULC categories (collected from ground-truthing) to prepare the spectral signatures with minimal confusion points (Gao and Liu 2010). A total of 70 spectral signatures for the respective LULC categories derived from the satellite imagery were recorded using the pixels enclosed by these polygons. These spectral signatures were then used to reclassify the images using a maximum likelihood classification algorithm that classifies the pixels based on the maximum probability of belonging to a particular class (Richards and Jia 2006). Then, the classified images were filtered using a neighbourhood majority function.

The LULC change-transition matrix was computed using the overlay procedure in ArcGIS to quantify the area converted from a particular LULC class to another LULC category during the study period. Later, visual interpretation was used to address the mixed pixels problem (Twisa and Buchroithner 2019).

Accuracy assessment

The non-parametric Kappa test was performed to measure the extent of the classification accuracy to account for diagonal elements and elements in the confusion matrix (Rosenfield and Fitzpatrick-Lins 1986). A confusion matrix was constructed with each row representing LULC classes in the classified

map and each column representing the reference LULC classes. The kappa co-efficient was determined from this matrix for each classified map. Kappa Co-efficient is the degree of agreement or precision between the classified map and the reference data (Rosenfield and Fitzpatrick-Lins 1986, Congalton 1991).

Normalized Difference Vegetation Index (NDVI)

NDVI was calculated using the infrared band (0.77–0.86 mm) and red band (0.62–0.68 mm) of the Landsat image of the year 2018 to compare the forest cover class of the classified image. The NDVI images have been reclassified into three forest cover categories viz., Open Forest, Moderately Open Forest and Dense Forest based on natural breaks given by reclassification tool of ArcMap 10.3.

Percentage Canopy Cover

Terra Modis Vegetation Continuous Field (VCF) product was used to extract the percentage tree cover of the study area. The VCF products is a monthly composite of Terra MODIS 250m and 500m Land Surface Reflectance data, and the product provide a gradation of tree percent cover (percent of a pixel covered by canopy), percent non-tree vegetation (non-tree canopy pixel), and percent non-vegetated (pixel with no vegetation) (<https://lpdaac.usgs.gov>). We constructed a composite image of tree canopy cover (mean aggregated) for the year 2008 and 2018 on the Google Earth Engine platform (GEE). GEE is a platform that allows users to compute its multi-petabyte catalogue of satellite imagery and geospatial dataset with planetary-scale, and export analysis in Geotiff format or tabulated data (Gorelick et al. 2017). We exported the percentage tree cover (250 m spatial resolution) as a TIFF image and reclassified it into three categories following FSI forest cover classification (www.fsi.nic.in) viz., no canopy (0-10%), open canopy (10-40%), dense canopy (40-70%), and Very dense canopy (>70%). We used ArcGIS for the reclassification and extraction of pixel data.

Patch analysis and conservation prioritization

FRAGSTATS v3.3 (McGarigal et al. 2002), a spatial pattern analysis tool has been used to quantify class or patch metrics from the canopy cover raster of 2008 and 2018 cropped for high potential gibbon habitat. The patch or fragments statistics given by FRAGSTATS viz. patch density (PD), mean patch size (MPS), percentage of landscape (PLAND), etc. are very informative indices to compare fragments within the landscape in a quantitative manner.

To minimize the over prediction of Maxent model in terms of conservation planning, prioritizR (Hanson et al. 2020) package in R platform was used to find out the potential feasible areas for conservation action within the high potential zone of the predicted distribution map. A 4 km x 4 km grid map was overlaid on the high potential distribution zone and grids that were in protected areas were excluded using the 'locked

out' function in the conservation problem definition. Also, grids with more than 30% human settlement areas were excluded for feasible conservation planning of gibbon protection in the region. The cost of conservation was assessed based on percentage canopy present in each grid in a scale of 1 to 5 (5=0-20%; 4= 20-40%; 3=40-60%; 2= 60-80%; 1=>80%). The lowest canopy percentage grid was assigned a scale of 5 and the highest was assigned 1. Three different threshold percentages accounting 10%, 15%, and 20% species distribution area were intended to conserve and the problem was defined accordingly. The output maps were then checked for irreplaceability and final maps were prepared.

Results

Predictive Distribution of Western Hoolock Gibbon

The predictive distribution model (Maxent) has shown average model performance with lower AUC value (AUC=0.675) (Fig. 2 [a], [c] & [d]). The presence only model has depicted the highest importance of mean temperature in the coldest quarter of the year (Bio11; 30.7%) out of the all 19 different bioclimatic variables used in the model (Supporting information; Appendix S1).

The output predictive map has shown that the high potential habitat zone comprised the highest area (6025.1 km²) followed by moderate (2003.47 km²) and low potential (1729.19 km²) habitat categories (Fig. 2 [b]).

LULC Change Matrix

Accuracy assessment showed that the kappa values of the LULC classifications were 0.764, 0.693, and 0.757 for 1998, 2008 and 2018 respectively. LULC analyses revealed that agriculture, grassland, and settlement classes covered majority of the study area (9851.2 km²; Table 1; Appendix S4). Plantation and settlement classes showed an increase in area percentage between 1998 and 2018 indicating a significant role of human in land conversion. Urbanization and population expansion are major reasons for the continual surge in settlement areas (102%; Table1). On the contrary, forest areas showed a slight decline (4.5%) during the two decades. Area decrease in forests is expected to be higher, but due to the inclusion of scrublands in the forest class in the current study, the resultant area decline might have shown lower.

Table 1

Area information and change of the LULC classes in the study area (sq. km) during 1988, 2008 and 2018

LULC class	Year			Percentage change (%)		
	1998	2008	2018	1998-2008	2008-2018	1998-2018
Agriculture	2379	2633.9	1885.4	10.7	-28.4	-20.7
Forest	1157.2	1063.9	1105.2	-8.1	3.9	-4.5
Grassland	2667.4	1744.6	1894.3	-34.6	8.6	-29.0
Plantation	934.3	1367.6	1142.5	46.4	-16.5	22.3
Sandbar	1001.5	699.5	675.7	-30.2	-3.4	-32.5
Settlement	1443.5	2019.6	2915.5	39.9	44.4	102.0
Water	268.3	322.1	232.6	20.1	-27.8	-13.3
*Negative (-) sign indicates percentage decrease						

All the classes showed inter-conversion among the classes in both studied periods– 1998-2008 and 2008-2018 (Supporting information; Appendices S5 and S6). The maximum addition of areas from other classes occurred in settlement, agriculture, grassland, and plantation in both periods. Conversion of areas from forest to anthropogenic utilization classes (agriculture, plantation, and settlement) accounted to 300.5 km² and 177.1 km² during 1998-2008 and 2008-2018 respectively (Supporting information; Appendices S5 and S6). On the other hand, forest areas added 261.5 km² and 266.4 km² from other LULC classes in 1998-2008 and 2008-2018 respectively.

The distribution of forest cover among these thresholds was analysed and it was observed that the highest percentage of forest cover was under high potential habitat zone in the year 1998 which gradually decreased in 2008 and 2018 (Fig.3a). Another important land use category i.e. agriculture was highest in 2018 under high potential habitat area (22.71%) of gibbon, that has shown an increasing trend from 1998 onwards (Fig.3b). A similar trend was followed by moderate potential (6.41%, 20.89%, 21.41% for the years 1998, 2008, and 2018 respectively). However, in the low potential habitat, agriculture covered the highest area percentage in the year 2008 (26.58%). The plantation area displayed a minimal decrease in area from 1998 to 2018 in all the three potential thresholds (Fig. 3c).

NDVI and Potential Gibbon Distribution

The final NDVI map of 2018 (Supporting information; Appendix S7) has shown that, the maximum tea plantation area (1148.70 km²) has been included in the total dense forest area (4312.14 km²) that is classified from NDVI. Lesser areas of tea plantation were included in moderate (58.92%) and open forest (60.65%) (Supporting information; Appendix S8).

Overall areas of NDVI classes under various potential habitat areas of gibbon in the study area revealed that the highest percentage area (80.04%) of dense forest was under high potential habitat (Fig.3d). In

moderate potential threshold, 73.90% dense forest was included, and 65.82% dense forest was found in low potential threshold. While comparing NDVI classes omitting the areas of tea plantation in predictive distribution thresholds, it was found that 76.21% dense forest area under high potential threshold (Fig. 3e). In moderate potential threshold, 70.83% dense forest was recorded and 63.69% dense forest was found in low potential threshold. Thus, the dense forest with tea plantation was higher in percentage in high potential habitat zone (Supporting information; Appendix S9).

Tree Canopy Cover Change Matrix

The canopy cover change matrix has shown that 48.8 km² and 2.4 km² area of very dense canopy have been converted to dense canopy and open canopy respectively during 2008-2018 (Supporting information; Appendix S10). At the same time, 205.2 km² of dense canopy converted to open canopy and 368.6 km² of open canopy to no canopy. Chronological conversion from the very dense canopy to dense canopy, dense canopy to open canopy, and open canopy to no canopy is the result of the decrease in tree count and canopy senescence. Conversely, an increase in canopy cover was also observed probably due to canopy growth, which showed area conversion from no canopy to open canopy (724.3 km²), open canopy to dense canopy (828.3 km²), and dense canopy to very dense canopy (199.3 km²).

While comparing tree canopy in the predictive potential habitat of gibbon during the period of 2008-2018, it was found that very dense canopy increased by 141.3 km² in high potential habitat zone whereas, the open canopy decreased by 41.3 km² (Table 2). The highest increase in canopy area was evident in dense canopy in the moderate potential habitat zone (439.3 km²).

Table 2

Canopy cover in different potential habitat in 2008 and 2018 (Area in sq. km)

Canopy Cover	2018			2008			2018-2008		
	HPH	MPH	LPH	HPH	MPH	LPH	HPH	MPH	LPH
NC	52.7	106.9	1113.9	591.8	146.8	890.9	-539.1	-39.9	223.0
OC	4042.6	1509	657.2	4083.9	1504.5	891.9	-41.3	4.5	-234.7
DC	1219.8	267.8	91.5	780.5	234.2	91.5	439.3	33.6	0.0
VDC	694.1	65.6	30.1	552.8	63.2	19.2	141.3	2.4	10.9

Note: No canopy (NC), Open canopy (OC), Dense canopy (DC), Very dense canopy (VDC), High potential habitat (HPH); Moderate potential habitat (MPH) and Low potential Habitat (LPH)

Protected Area Coverage

Overall, the protected area covers 20.82% of the study area (Supporting information; Appendix S11). The protected area covers 17.73% of the total high potential gibbon habitat whereas moderate and low potential habitats of gibbon in the study area include 27.51% and 23.74% of protected forest respectively.

Out of the total, very dense canopy in the study area 95.03% area was within protected range in 2018 whereas the same was 97.19 % for the year 2008. But when compared to the percentage of the total area irrespective of canopy categories only 7.62% very dense canopy was found in 2018 within the protected areas. Likewise, for the year 2008, the percentage of the same was 6.27% (Supporting information; Appendix S12). Furthermore, within the protected range, 75.35 km² has been lost from dense canopy from 2008 to 2018 whereas the very dense canopy increased by 133.17 km² during the same decade. On the contrary, in the non-protected range, a significant increase in dense canopy forest was recorded (548.25 km²) from 2008 to 2018. The very dense canopy was also found to increase in the non-protected range (21.43 km²), but the area addition was comparatively lower than that of the corresponding protected range.

Patch analysis and conservation recommendations

The FRAGSTATS result showed an increase in the number of fragments in both dense and very dense canopy forests from 2008 to 2018 within the high potential gibbon distribution area (Supporting information; Appendix S13). In 2008, the mean patch sizes in dense and very dense canopy areas were found 1.18 km² and 8.02 km² respectively. However, the same was observed to be marginally higher in 2018. The contiguity index of patches of very dense canopy in 2008 was 0.36 and slightly decreased in the year 2018 to 0.34. The mean Euclidian Nearest Neighbour Distance among patches was found highest within very dense canopy (1646.21 m) in the year 2018.

The proposed conservation planning to conserve 10% of the high potential habitat excluding both existing protected areas and high human habitation areas (>30%) showed 40 grids (640 km²) highlighted for conservation planning (Fig. 4 A-F). Similarly, 58 grids (928 km²) and 81 grids (1296 km²) were highlighted to protect 15% to 20% of species' habitat respectively.

Discussion

Gibbon habitat and monitoring is crucial in tropical forests owing to its declining population trend throughout distribution range. The present study revealed the potential impact of forest dynamics in gibbon distribution and survival in the Upper Brahmaputra valley located along the south bank of the Brahmaputra River in Assam. The study area is one of the major habitat zones of western hoolock gibbon in India. Although most of the forested areas of this zone are under legal protection, the heterogeneity of the forest composition and anthropogenic intrusion render the agreement notably. The LULC analyses revealed that Agriculture, Grassland, and Settlement classes covered the majority of the study area. Plantation and Settlement classes showed an increase in area percentage between 1998 and 2018

suggesting a substantial anthropogenic role in land conversion. Urbanization and population expansion are major reasons for the continual surge in settlement areas. On the contrary, forest areas showed a slight decline (4.5%) during the two decades. Area decrease in forests is expected to be higher, but due to the inclusion of scrublands in the forest class in the current study, the resultant area decline might have shown lower. It is also reported that fragmentation is very severe in the lowland rainforest of the Upper Brahmaputra valley and one-third of the forest cover area has been lost in the last century (Sharma et al. 2013). The higher percentage change in forest cover between 1998 and 2008 depicted the ineffective efforts of habitat conservation of the species in the study area. As gibbons are known to prefer dense or pristine forest for living, it is a major concern for conservationist to protect dense forest areas. The shrinkage of forest cover areas in fragments of known gibbon habitats in the study area has also been reported in earlier studies (Kakati 2004, Sharma et al. 2012a, Sharma et al. 2013) due to which the population is eventually exposed to open forest. Therefore, in the present study, the predictive potential habitat of the species is used as a primary tool to compare the habitat of the species on a temporal scale with particular reference to forest covers and canopy covers. Looking at the landscape and other socio-political disturbances in the study area, remote sensing methods used to track biodiversity have also proved to be effective (Turner et al. 2003, Corbane et al. 2015). Nevertheless, ground verification is a necessity for better confidence in the results. The population data on western hoolock gibbon is readily available for the study area as the Upper Brahmaputra valley is considered as the hotspot of gibbon distribution in India (e.g., Kakati 1997, Das 2002, Katakati 2004, Kakati et al. 2009). However, the study area is significantly lacking information on major habitat parameters of the species.

The Maxent model predicted that the area under the high potential habitat zone in the study area is as high as expected. It is noted here that Maxent does not account for the historical distribution of species nor does it recognize physical barriers of the restricted-range species (Peterson et al. 1999, Soberón and Peterson 2005). This may be the explanation for the inclusion of new areas of the species' high potential habitat dependent on bioclimatic suitability. The same argument was also supported by Sarma et al. (2015) in the predictive distribution of eastern hoolock gibbon in Arunachal Pradesh, India. Moreover, extirpation of gibbons and other coexisting primates from several small fragments of the Upper Brahmaputra Valley (Kakati 2004, Sharma et al. 2012a and 2012b, Sharma et al. 2013) demand the study of localized specific habitat needs of the primates in general.

The decreasing trend of forest cover within the high potential habitat of gibbon in the study region over the last two decades and a higher percentage of agriculture in the same habitat zone have shown the importance of agricultural matrix as gibbon habitat. Sarma et al. (2013) also recorded the presence of agricultural land within the potential habitat of the eastern hoolock gibbon in Arunachal Pradesh. Thus, the small fragments of forests surrounded by agriculture and human settlements are significant sites of gibbons in the study area, which contradicts the theory that gibbon's favour contiguous forests as their primary habitat. Nonetheless, the two species of gibbons found in northeast India are reported to occur in forests of variable gradients in terms of quality and structure, and the present study is consistent with several such studies (e.g., Das 2002, Kakati 2004, Kakati et al. 2009, Sharma et al. 2012a, Sharma et al. 2013, Sarma 2015). On the contrary, the present study also confirmed that the highest percentage area of

Dense Forest was found under the high potential habitat zone of gibbons. It is noted here that tea plantation is the key driver that affects the NDVI map of the study area as tea plantations are classified under Dense Forest categories. Since we have omitted the tea plantation areas from Dense Forest zone by testing the output map with ground data, the high potential habitat zone still represents the maximum Dense Forest area even though the tea plantation area is removed.

The canopy cover change in the last decade (2008-2018) in the study area carries a pessimistic outlook due to high change in Very Dense Canopy. Chronological conversion from Very Dense Canopy to Dense Canopy, Dense Canopy to Open Canopy, and Open Canopy to No Canopy might be the result of canopy senescence and decrease in tree count driven by increasing settlements. Conversely, increase in canopy cover was also observed probably due to canopy growth and vegetation succession, which showed area conversion from No Canopy to Open Canopy (724.3 km²), Open Canopy to Dense Canopy (828.3 km²) and Dense Canopy to Very Dense Forest (199.3 km²). While the present study shows minimal conversion of Very Dense Canopy to Open Canopy (2.4 km²), it is of serious concern to the survival of gibbon given the habitat suitability of the study area. Although, area increase in Very Dense Canopy (141.3 km²) within the high potential zone of gibbons over the last decade is encouraging, it is equally important to investigate the precise locations where the canopy has improved. The canopy contiguity is stated to be low in non-protected fragments of the Upper Assam valley (Kakati 2004). Interestingly, more than 80 percent of the high potential habitats of the gibbons are not subjected to legal protection, and there is a hopeful sign of an increasing trend in Dense and Very Dense Canopy in non-protected regions in the study area. However, it was evident from the results that protected areas of the Upper Brahmaputra valley, especially those within the high potential zone of the gibbon habitat, have retained the Very Dense Canopy with minimal change over the last decade to ensure gibbon survival. It may also be argued that gibbons are still more common in dense forests, while there is evidence of gibbons occurring in some rural areas of the Upper Brahmaputra Valley. However, in northeast India, more than 50 percent of gibbon habitat is legally protected (Kumar et al. 2013) while the present study reveals that only 17.73% of the high potential habitat is under legal protection. Out of the 96 RFs in Assam where gibbons are reported to be found (Chetry et al. 2007), the present study area includes as many as 42 RFs. This study therefore strongly supports the implementation of stringent laws on small fragments of rainforests in the Upper Brahmaputra Valley for the potential survival of gibbons, taking into consideration that the species prefers dense forests. It should be mentioned here that gibbons are still present in small isolated fragments of the study area, irrespective of the canopy structure or the condition of the habitat. In view of the narrow geographical range of western hoolock gibbon, the species must survive with a reduced abundance of resources before ecosystem conditions are adequately controlled.

Do gibbons live in dense forest? Our analysis shows that over the last two decades in Upper Brahmaputra Valley, Assam, most of the areas of dense forest, as well as dense canopy, have remained intact, at least within the high potential habitat of gibbons independent of the degree of change in forest, agriculture and plantation covers. The protected area network within the study area is of greater value in ensuring improved protection of the remaining gibbon habitat in the study area. However, the investigation of other

possible causes, such as food availability and food preference, is often a critical concept for recognizing the species' preferred habitat. The decadal changes in forest cover and canopy structure of the study area therefore may be a few of the many drivers that affect habitat preferences of gibbon. On the other hand, knowledge of the population dynamics of the species in the study area can also lead to recognizing the need to study unique viewpoints of the species' ecology as the species is included in the endangered category of the IUCN Red List. Here, in this study, we did not consider the physical conditions of the habitat and the constant land-use pressure posed by the human population on the habitat of the species. Though proposing future conservation areas within the predicted high potential zone of gibbons, we deliberately omitted the current protected areas believing that the species within protected areas are still protected under forest preservation legislation. The human settlement areas have already been filtered to ensure ease of implementing the Conservation Action Plan. However, the cost of the conservation was objectively identified based on the fact that gibbons prefer dense canopy for survival. We also believe that the outcome of this study would be the basis for the comprehensive investigation of factors influencing the responses of gibbons to environmental and climatic changes across their distribution range.

Declarations

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Conflicts of interest –

The authors declare no conflict of interest.

Author contributions –

KS, MKS and PKS are responsible for study design and KS has done data analysis including the statistical analyses and modelling. BS, HB and SSB assisted in performing the geospatial analysis and

writing of the manuscript. BPS and AK worked on the verification of field data as well as contributed in writing the manuscript. Finally, KS, BS and HB prepared the manuscript.

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Figures

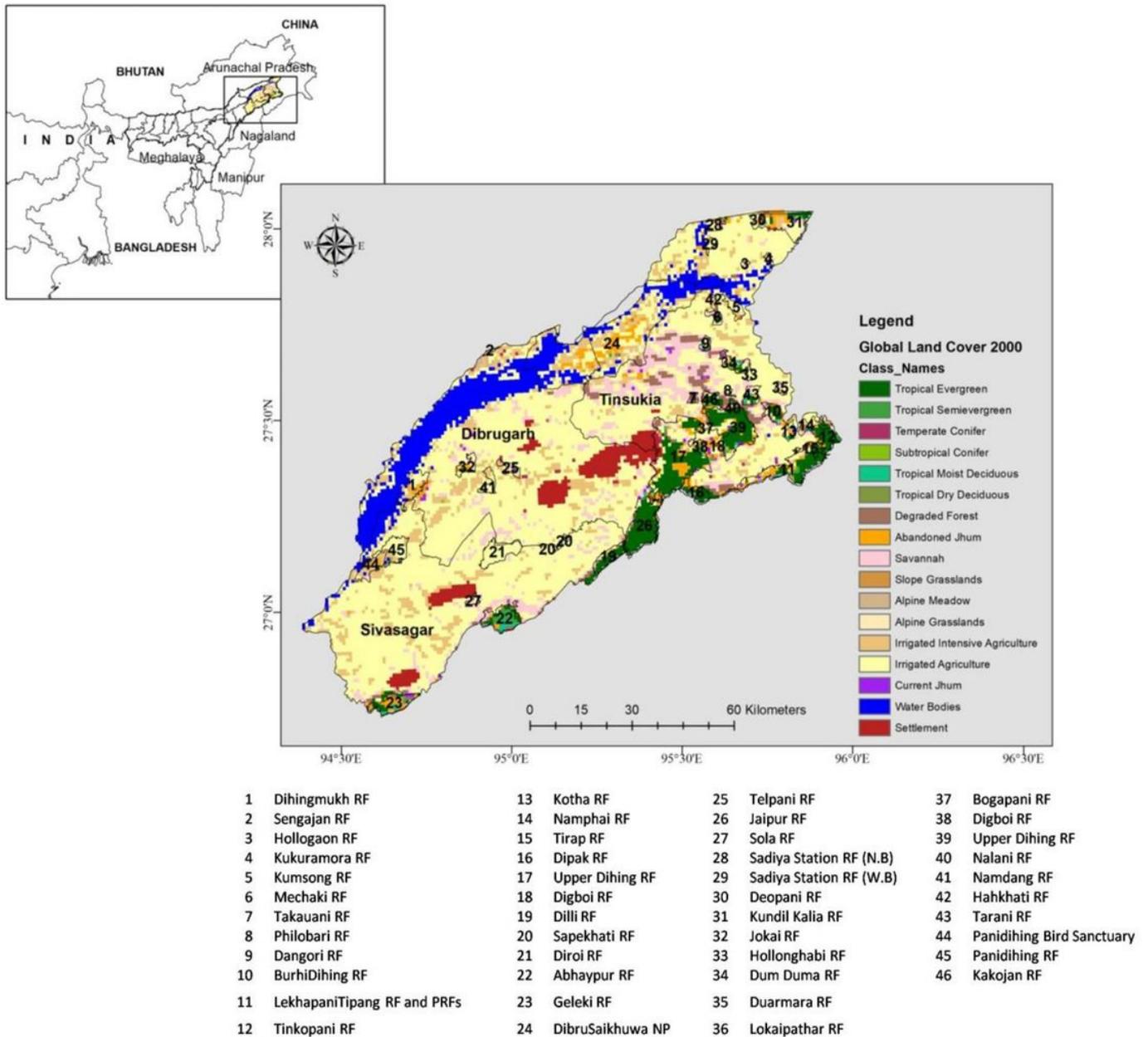


Figure 1

Global Land Cover map (source: <https://forobs.jrc.ec.europa.eu/products/glc2000>) of the study area in the Upper Brahmaputra Valley, Assam, India showing the protected areas (RF: Reserve Forest; PRF: Private Reserve Forest; N.B: North Block; W.B.: West Block; NP: National Park).

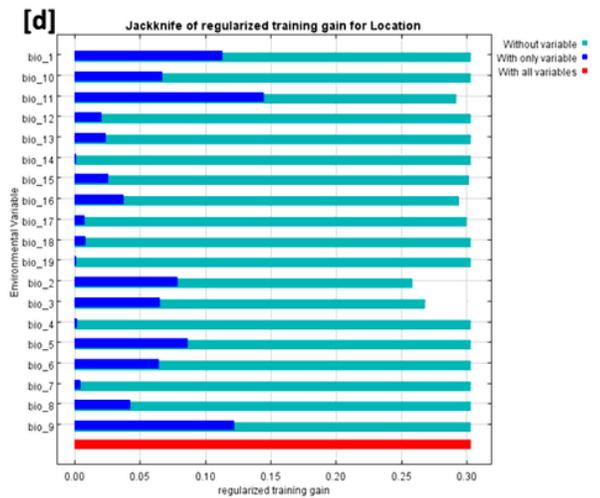
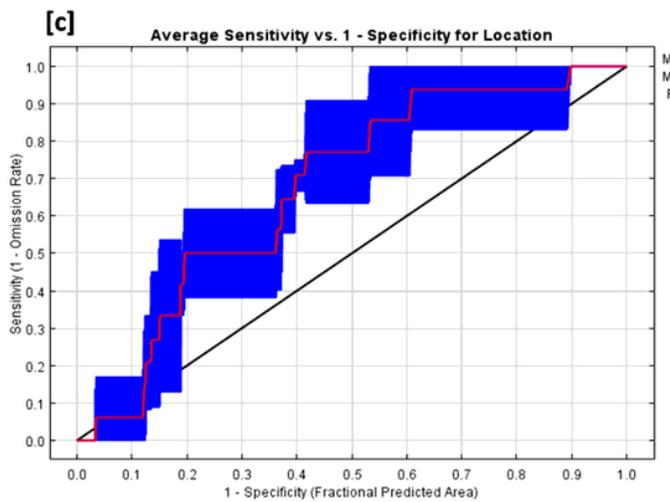
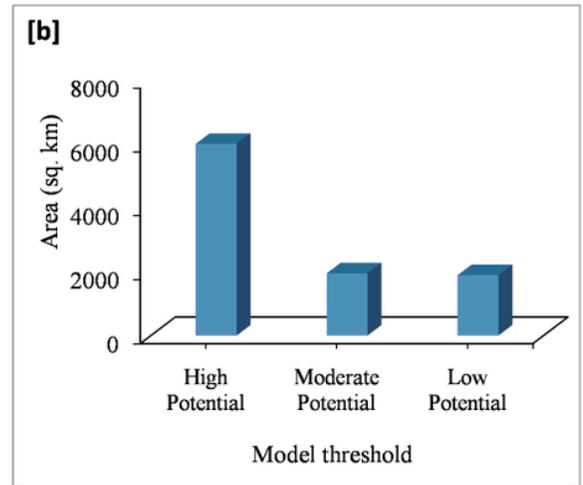
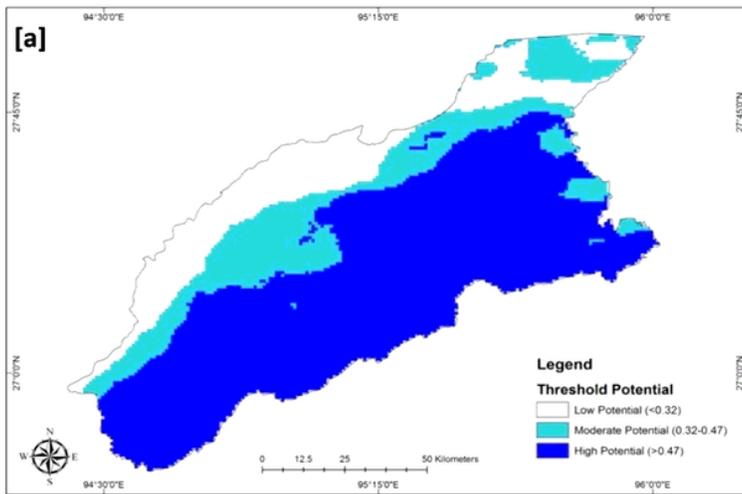


Figure 2

Maxent results [a] predictive distribution map [b] area statistics in different model thresholds [c] ROC curve and [d] Jackknife validation output.

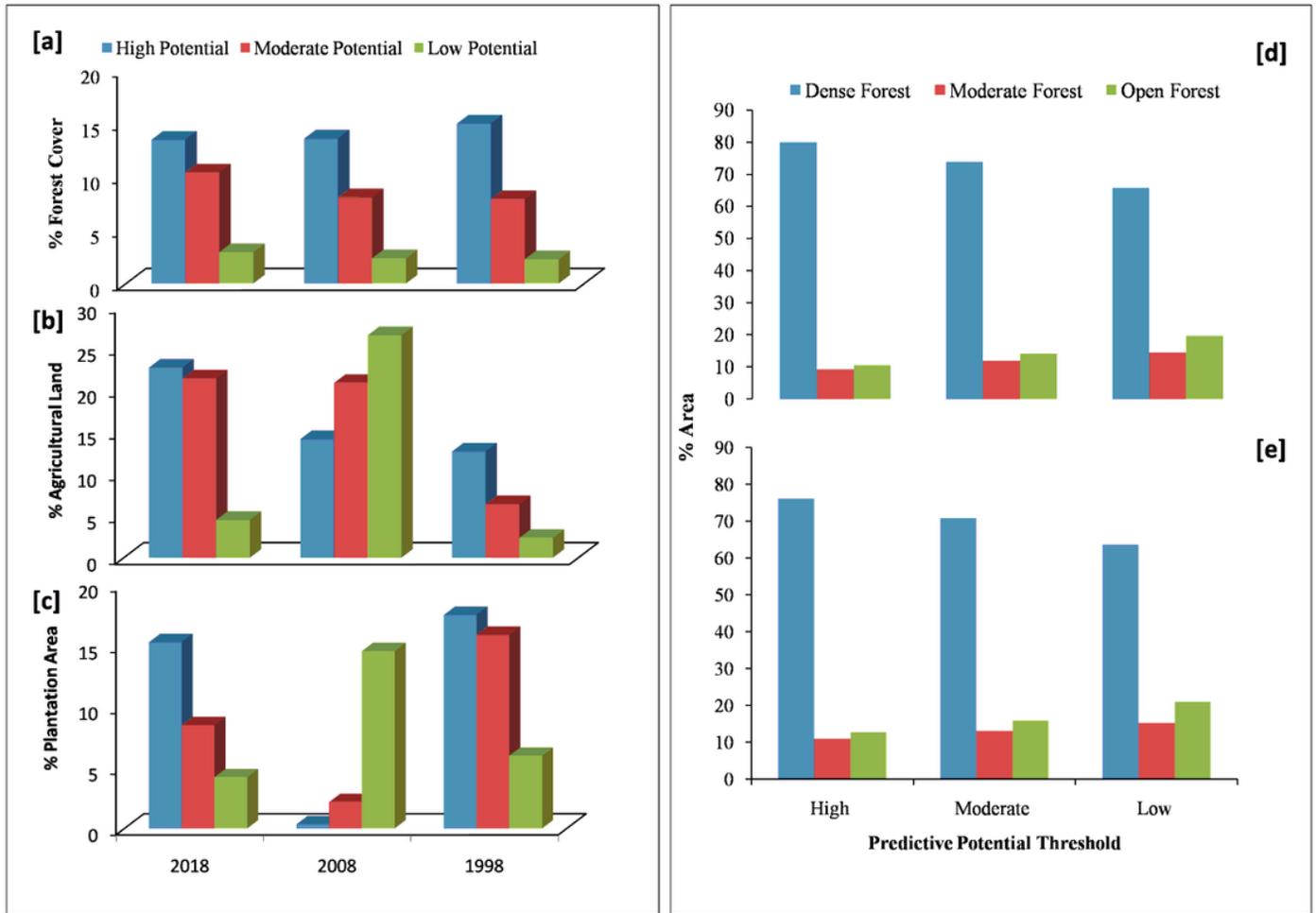


Figure 3

Percentage area of [a] forest [b] agriculture and [c] plantation within different predictive thresholds in the year 2018, 2008, and 1998 and percentage area of dense forest, moderate forest, and open forest derived from NDVI within different predictive thresholds [d] including tea plantation [e] omitting tea plantation

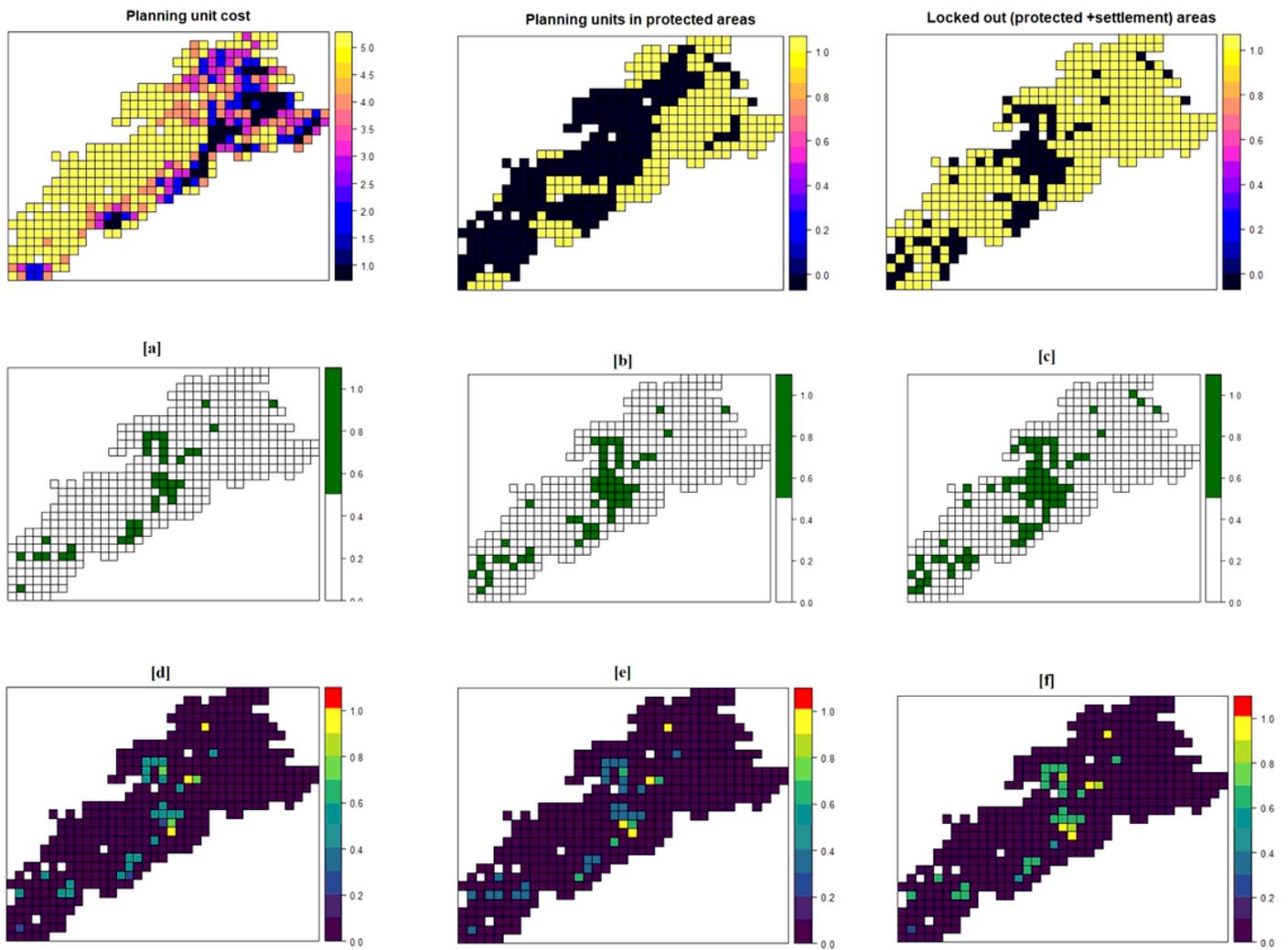


Figure 4

Proposed conservation planning units (4 km x 4 km grids) in the high potential gibbon habitat in Upper Brahmaputra Valley, Assam, India. All protected areas are excluded from the grid map as those are already under prioritized category. Settlement percentage was calculated for each grid cell and the grids having more than 30% settlement land use were excluded from the analysis; [a] to protect 10% of gibbons' habitat; [b] to protect 15% of gibbons' habitat; [c] to protect 20% of gibbons' habitat; [d]; [e] and [f] shows irreplaceability of the proposed units to conserve 10%, 15% and 20% gibbons' habitat respectively (higher the value, more is the irreplaceability; planning replaceable units are shown in purple, blue, green, and yellow colours, and truly irreplaceable planning units are shown in red colour)

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