

# IMPACT OF COAL MINING, THERMAL PLANTS, ANTHROPOGENIC ACTIVITIES ON WILDLIFE CORRIDORS FOR NATIONAL PARKS AND WILDLIFE SANCTUARIES IN THE STATE OF MADHYA PRADESH, INDIA

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**KEY WORDS:** Human-Wildlife conflict; Landuse Land Cover analysis; Sustainable Development Goals (SDG); Bandipur, Pench-Satpuda corridor

### ABSTRACT:

To the rampant rise in urban settlements and human population, the national parks, wildlife sanctuaries, and national tiger reserves of middle and southern India have been intruded upon by human settlements regularly. These are adjoined by paths called as 'wildlife corridors' especially the tiger and elephant corridors which are used as a means for migration. Bandipur and Pench-Satpuda national parks have one such essential pocket of wildlife corridors the Bandipur corridor interconnects the population of 8000 plus elephants between Mysuru and Wayanad in southern India whereas the Pench-Satpuda corridor sustains 120 plus tigers between Pench-Satpuda Tiger Reserve in middle India. To assess this it's imperative to assess the pattern of wildlife movements, changes in the animal habitats in terms of habitat cluster zones, land-use changes, the onset of human settlements and anthropogenic activities are to be monitored. For this, land use land cover (LULC) changes for these corridors were analyzed across two decades using geospatial and remote sensing technique. The study finds a organized deprivation of dense forests and open forests respectively, thus indicating large-scale destruction. The study also found the net area changes of dense forests and open forests which were diverted for agriculture activities indicating extensive encroachment of forest land for human settlement. The classification was monitored for water bodies that have reduced, indicating shrinkage during the duration under research. The existence of substantial coal deposits in the wildlife corridor and operational coal mining in the proximity of the wildlife corridor is a matter of grave concern which has been highlighted in the research. We examine to identify long-term sustenance and protection of such corridors for preserving the natural habitat. Thus, with such suitability in wildlife monitoring, we can mark an increasing need for adaptable, tenable, and secure wildlife management as illustrated under the Sustainable Development Goals (SDG 15 mentioned under United Nations).

## 1. INTRODUCTION

The ever-lasting effects of rising global temperatures due to anthropogenic emissions, the migration from rural to urban sectors, and an overall increase in total population with the gradient rise in anthropological changes are a few out of extrapolated reasons for the bludgeoning problems that challenge and grip the world. To balance the livelihood, earth's life and support system, preserve the biodiversity and genetic resource pool, watershed preservation, protection and recharge, carbon storage and sequestration for all such limited purposes forest ecosystems and vegetation services play strong dynamics which help to maintain checks and balances [Adamack and Gruber, 2014]. Several studies have shown that there has been an annual forest cover loss with global ramifications where the annual forest cover clearances occurred due to expansion of agricultural land, over-harvesting of firewood, and overgrazing by animals. [Bay et al., 2014, Caragiulo et al., 2015].

Globally, forests and vegetation cover serve as the second-biggest reserves of carbon stocks and carbon sequestration, the first being the presence of ice-caps and glaciers. At a regional level,

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biodiversity-rich areas impress the conservation of forests and the wildlife sustained with them. While on the one end, wildlife habitats serve as a repository of the gene carriers and biodiversity on one hand, and additionally, there is intense pressure on these resources for anthropogenic activities such as agriculture-commercial plantations, mining, urbanization, industrialization, and so on [Galodha and Gupta, 2021]. These challenges perse lead to habitat losses, ecological fragmentation, discontinuity and the introduction of new forms of land use. To preserve and maintain the habitat blocks which include "Wildlife Corridors" for these multiple blocks of habitat that are involved and concerned. These wildlife corridors act as "sinks" and the wildlife migration populations acts as "source" where the populations are migrating and surviving. Substantive habitat areas and patches play a key role in preserving and protecting migratory species. With the presence of limited resources, there is a fight for space and energy, and the diffusion-scattering of populations with distant habitats enhances the chances of survival of species. Human-wildlife conflict enhances in locations leading to the loss of wildlife corridors [Galodha and Gupta, 2021]. Some corridors are crucial and require more protection than the others due to their Project Tiger and National Park status. These are the ones that preserve "critically endangered" species of Indian tigers (*Panthera tigris*). The loss of wildlife corridors can lead to mass extinction and escalate the human-wildlife conflict. Some wildlife corridors are

invariably important for the long-term survival of wildlife these corridors are "Critical Wildlife corridors" [Miller et al., 2016].

India is one of the hot spots in the category of biologically diverse countries and with just 2.4% of the total land area of the world; the known biological diversity of this country contributes 8% to the known global biological diversity. The forest cover of India is estimated at 708,273 km<sup>2</sup>, which is 21.54% of the geographical area of the country. While India is endowed with rich natural resources, at the present time it is hosting the 2nd largest human population in the world, a majority of which is largely dependent on the natural resources for livelihood, survival and sustenance [Banerjee et al., 2020] [Jhala et al., 2015].

The central part of India comprises the leeward side of western ghats and is surrounded by the flood plains of Narmada and Tapi river has a rich forest cover and the state of Madhya Pradesh has the largest forest cover in the country. There are several National Parks (an area set aside under the provisions of the Wildlife (Protection) Act, 1972, for the conservation of wildlife and its habitat), Tiger Reserves (areas with a high population of tigers declared for the conservation of tigers and its habitat and usually includes areas of a National Park), and Wildlife Sanctuaries in this state, the prominent ones being the Kanha Tiger Reserve, Pench Tiger Reserve, Satpuda Tiger Reserve, and Panna Tiger Reserve. These three Tiger Reserves, along with the Melghat Tiger Reserve in the neighboring state of Maharashtra form a large "Complex of protected zones" (see Figure 1) [Banerjee et al., 2020] [Jhala et al., 2015].

[?, ?, ?]. In this paper we have worked on to identifying the

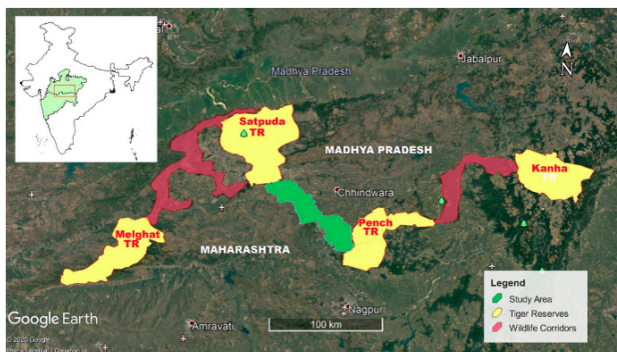


Figure 1: Google Earth image showing the important tiger reserves of central India and with their corresponding linkages, the green and the red portions that link the national park's are the study area for our research. Source: [Banerjee et al., 2020]

wildlife tiger migration and connectivity zones for the "Critically protected complex" in the state of Madhya Pradesh. Furthermore, this research paper deals with multiple objectives enumerated as below:

1. Landscape-level analysis that includes the changes in Land Use and Land Cover (LULC) of the wildlife corridor connecting four important Tiger Reserves in Central India, the Pench Tiger Reserve, Kanha Tiger Reserve, Melghat Tiger Reserve, and Satpuda Tiger Reserve, covering a substantial time-period between 2000 up until 2021. This wildlife corridor is one of the most important tiger corridors of Central India, Tiger Protected Area Complex as it is located right in

the middle of this protected zone and the disruption of this corridor will lead to the disruption and isolation of genetic resources within the Tiger Reserves located north, south, west, and east of this reserve. (Figure 1) [Banerjee et al., 2020] [Leal et al., 2016].

2. The change in the area was also monitored and studied as part of the research work from the year 2000 to 2021 for different categories ie. Water, Dense forest, Moderate forest, and Bare soil.
3. CO<sub>2</sub> emissions as part of carbon stocks were monitored and determined to measure the changes in the CO<sub>2</sub> stock. These changes were seen through the period 2000-to 2021 focused on January.
4. The circuitscape model and parameters were used to monitor and check the connectivity of tiger migration across the wildlife corridors between the protected complex across the 4 tiger reserves.

Thus, this study is one of its kind to analyze the wildlife tiger connectivity hot-spots, LULC changes, carbon stock changes, and the land use planning for this critical wildlife corridor, connecting two important tiger reserves and the implications it holds for the long-term conservation of wildlife in the landscape and also taking into the account of potential challenges to the long-term sustenance of this corridor such as coal mining, deforestation, the encroachment of forest land for agriculture, and other anthropogenic activities [Banerjee et al., 2020] [Mondol et al., 2009].

## 2. STUDY AREA AND DATA

The rich forests of Central India are home to a wide variety of flora and fauna. These large tracts of forests occur in large isolated patches and are virtually 'is-landed' by dense habitation and are connected to other tiger reserves by narrow wildlife corridors. The study area is comprised of the Pench-Satpuda-Melghat-Kanha wildlife corridor (Figure 1). The 2,133 km<sup>2</sup>, Satpuda Tiger Reserve forms a vital link for migrating populations of the 2,769 km<sup>2</sup>, Melghat Tiger Reserve located in the southwest and the 1,180 km<sup>2</sup> Pench Tiger Reserve in the southeast, which eventually connects to the 2,052 km<sup>2</sup> Kanha Tiger Reserve. In this way, the Pench-Satpuda-Melghat-Kanha wildlife corridor is very vital to the regional movement of wildlife in the area. At the same time, it is a matter of great challenge from the point of view of the wildlife conservation that rich coal, bauxite, and metallic deposits lie in and around this corridor. Then, the loss of the corridor is eventually inevitable unless this corridor, in its very critical nature, is preserved in its entirety to take cognisance of the preservation activity with regards to the movement of wildlife that occurs. The state lies between latitude of 21.6°N–26.30°N and longitude of 74°9'E–82°48'E.

In this study, we have used the Visible, Optical, and NIR (Near Infrared) band available at 30m and 60m for Landsat-7, Landsat-8, and Landsat-9 satellites respectively. The emerging technologies and algorithms were used for LULC changes. We have used the same dataset for calculation and determination of Carbon Stocks, LULC change detection from year 2000-2021, Area changes in each class from year 2000-2021 [Galodha and Gupta, 2021] [Prakash and Gupta, 1998].

## 3. METHODOLOGY

The Google Earth Engine (GEE) has petabytes of freely available datasets which collects the datasets from the United States Geo-

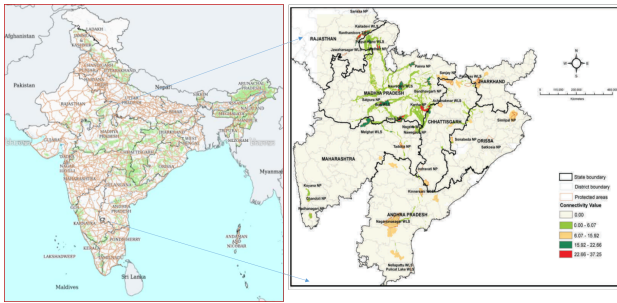


Figure 2: Study Area

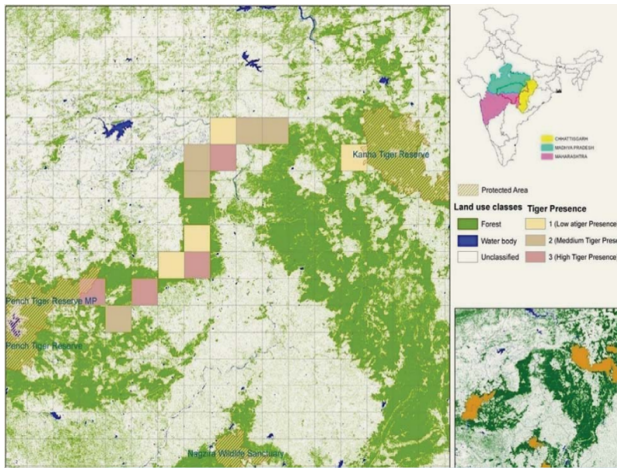


Figure 3: Land Use classes and Tiger presence.

logical Survey (USGS), European Space Agency (ESA), The National Aeronautics and Space Administration (NASA) and similar ones. This research work uses various datasets available in GEE such as Landsat-7,8,9, MODIS (TERRA/AQUA). For the computation of LULC across the years of 2000-2021 we are using the described Landsat series which are cloud cover masked and represent a Time-Series stack. Landsat-8 was used for NDVI vegetation cover determination, LULC was further used for change detection, classification in Landcover categories, Night-light intensity mapping was carried out using MODIS (TERRA/AQUA) satellite sensor. The Fishnet model raster's were created for mapping corridor portions. These buffer portions either as a buffer proximity and/or a Fishnet design was used to identify the Landscape connectivity using the circuitscape model design. Thus, finally collating all these aforementioned steps, wildlife corridor maps were generated to measure and monitor the changes across 2000-2021 period [Galodha and Gupta, 2021] [Sharma et al., 2013].

The digital number (DN) image can be converted to top of atmosphere (TOA) reflectance, which can be further used to compute surface reflectance (SR). The SR image is cloud masked and monitored for those images with cloud cover with less than 10% cover. The SR is used to determine normalized difference vegetation index (NDVI) using NIR and RED band of the images. SR reflectance data is readily available from GEE datasets derived from Land Surface Reflectance Code (LaSRC) where the coastal band is used for aerosol inversion, and Landsat, MODIS data for auxiliary atmospheric and atmospheric correction performed with radiative transfer model [Galodha and Gupta, 2021] [Srivastava and Tyagi, 2016]. Quality assessment band (BQA), can be used to retrieve cloud coverage masking, which includes cloud

shadowing for which a function was created in GEE [Tian et al., 2014]. To calculate the changes of vegetation cover Landsat series helped in checking the vegetation cover. The NDVI equation is mentioned as:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

where

*RED* = Red Band (Band 4)

*NIR* = Near Infrared Band (Band 5)

*NDVI* = Normalized Difference Vegetation Index (NDVI) [Galodha and Gupta, 2021]

### 3.1 Landuse Landcover

Landuse classification for the given study area can be carried out mainly into 4 classes i.e. Agriculture, Forest, Urban-city, and Waterbody. There are two methods to carry out classification i.e. unsupervised (without the presence of class labels) and supervised (with the presence of class labels). General steps to carry out a supervised based classification are (developers.google.com/earth-engine/guides/classification):

- Store training data, store class labels, identify specific properties of each class label as a numeric value to define part of predictors.
- Combine all these labels with the specific property as a feature collection.
- Identify or create a classifier, hyper-tune its parameters.
- Train the classifier with set parameters with defined training data.
- Classify image or feature collection with defined labels.
- Validate with test dataset, create error-matrix.
- Compute the overall accuracy and classified map.
- Iterate the process after tuning the hyper-parameters until desired overall accuracy isn't obtained.

With property storing class labels and properties storing predictor variables, training data is considered a feature collection. Class labels need to be continuous, starting from 0 and stored as integers. When it is necessary to convert class values to continuous integers, use remap() function. The prediction labels have to be numeric values. To use the available classification techniques from the GEE platform we use the Random Forest (RF) classifier and the Classification And Regression Trees (CART) algorithm which is a classification algorithm for building a decision tree (DT) based on Gini's impurity index as splitting criterion. CART is a binary tree build by splitting node into two child nodes repeatedly [Galodha and Gupta, 2021].

Validation, testing, and/or training dataset can be made from multiple sources. Preparation of training dataset can be intensely carried out in GEE, with the help of geometry drawing tool (point, polygon, multi-polygon) iteratively, a predefined training dataset can be imported from a GEE as an asset. A classifier can be defined from one of the constructor tabs as an ee.Classifier and can be trained using the classifier.train() option. The current research uses a Classification and Regression Trees (CART) classifier and Random Forest classifier (RF) [of International Economic et al., 2003] to easily predict more than two classes.

In this generalised methodology design as described and put above to summarize the understandings we can list them down into a set of laid down objectives. The main objectives of the study were as follows [Galodha and Gupta, 2021]:

- Monitor and assess the habitat use of tigers and other carnivores in the Satpuda-Melghat-Kanha-Pench corridor (SMKPC).
- Wildlife corridor distribution of tiger prey species, extent of human disturbance and connectivity between two existing source populations, i.e. Kanha, Satpuda and Pench Tiger Reserves.
- Identify critical areas within SMKPC for immediate as well as long-term conservation measures.

#### 4. WORKFLOW

The entire workflow can be segregated into 3 phases starting

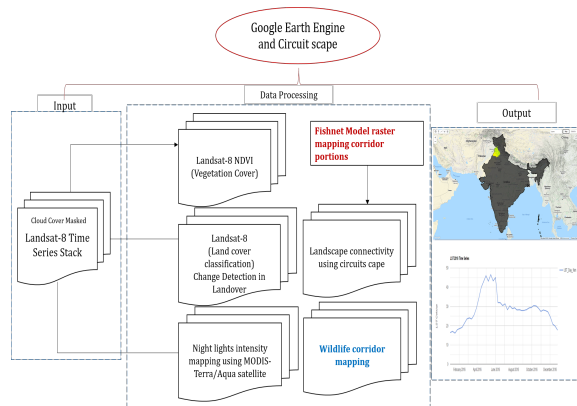


Figure 4: Workflow

with input where we have Landsat-7,8,9 a time series data is generated, which is layer stacked. The cloud-cover must be at less than 10% cloud-cover. In the data processing section, here I am showing single snippets using Landsat 8 imagery. I am determining the vegetation cover (VC) with normalized difference vegetation index (NDVI). For the Landuse Landcover classification we are using the Random Forest classifier (RF) and Decision Tree (DT) supervised classification algorithm. Here, we have assigned new class categories for existing reference class for each class-category. Following this, we determine the pixel-sum and pixel-area. For each category we assign Landuse-Landcover as a change measure determined with respect to the pixel level classification. We determine the LULC change measure as a function of every 5-years duration shift.

Overlaying the changes in  $CO_2$  as a measure of carbon stocks was measured and monitored for the changes across the years since 2000 onwards to 2021. The median values were taken for the study area and  $CO_2$  variation was monitored for the entire duration month and year wise. The median amount of  $CO_2$  is in the median representation of the forest cover, measured as a unit of kilograms per meter squares. With the help of pixel-area and pixel-sum of each class category after a set duration from 2000 onwards up until 2021, we determine the category classes area each for water, dense forest, moderate forest and bare soil. The property end represents the yearly modifications from 2000 up-to 2021 which is in comparison to the area changes for each class category. The Table 1,2 represents the area category variation.

Table 1: Area changes across different categories

	2000	2005	2010
Water	227.078	240.106	201.831
Dense forest	1383.808	2128.334	673.535
Moderate forest	13945.167	13239.23	13239.23
Bare soil	8103.506	9808.388	12007.398

Table 2: Area changes across different categories

	2015	2021
Water	230.387	290.523
Dense forest	6092.985	1684.714
Moderate forest	14428.655	18103.351
Bare soil	5,369.97	6043.407

The Satpuda-Maikal landscape (SML) measures 118, 113 $km^2$  out of which 40, 837 $km^2$  (34.6%) is forest cover (Forest Survey of India, 2011). [Thatte et al., 2018].

All the aforementioned factors were covered as part of our

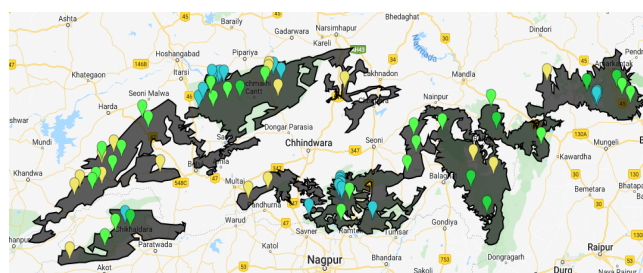


Figure 5: Reference points, for training and validation

proposed research using available Landsat series datasets due to their large scale availability. The description of the work process followed is as mentioned. The study consists of two primary steps: Landuse change analysis based on the GEE platform, and the area change evaluation of each class was based on QGIS. For the classification part, we carried out spectral indices method with the use of 4 parameters: MDNWI, AVI, BSI, and SSI. Here, AVI, BSI, and SSI were recommended in (Loi et al., 2017). The other spectral bands were ignored to be used to avoid the exceeding computation for the GEE. I identified six Landuse types: water body, dense forest, moderate forest, and bare soil. We didn't try to collect too many reference points since it can effect the objectivity and characterize the final response of the classification. As part of the classification as discussed earlier we employed the Random Forest (RF) algorithm as the Landuse classification classifier. The RF classifier is well known for its efficiency and accuracy, even with higher influence of substantial data noise. We trained the RF classifier using 70% of the reference data, and 30% for model validation. Finally, we employed the producer's accuracy, user's accuracy, and kappa coefficient to examine the accuracy achieved for the classification results. To visualize the output response, a chart was created to visualize the area of each class under the ambit of classification map [Xiao et al., 2011].

#### 5. RESULTS AND DISCUSSION

For the results section, as part of the classification result of the classifier we are dealing with various class categories to differentiate the outcomes between classification maps which are thus, generated [Galodha and Gupta, 2021]. The classification map will then add 1 value for every pixel to differentiate the first class (water) from the area outside the region of interest. Because it is necessary to assign the value of the classification class from 0 on GEE, otherwise, it will cause a misunderstanding. This step

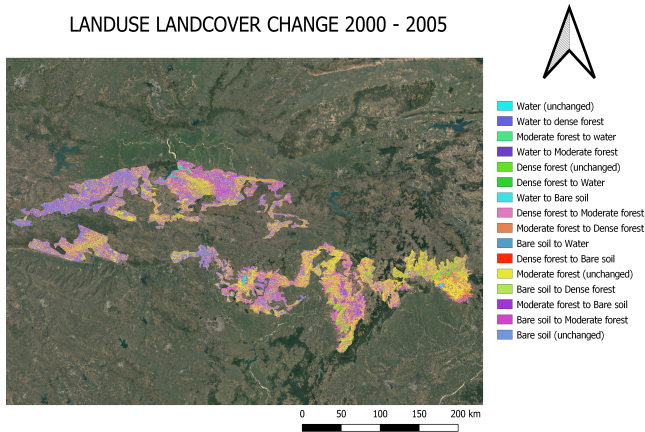


Figure 6: LULC Change 2000 - 2005

was done at the end of the process. The image after the available value can be turned into an added value with the long type data format, thus the need arises to be converted to integer data to be able to export to Google Drive. The workflow on the GEE is shown in figure 6 that gives a broad description to define the area selection boundary, create a time selection filter and a cloud masked filter for cloud masking at cloud cover less than 10%. The image collection was selected and the region of interest (ROI) was clipped with spectral indices used to carry out the LULC and change area monitoring. The reference points and polygons creates a training and test set with (70% and 30% limits). The classification map after being exported will be downloaded to calculate and visualize the change in an area using the Land cover change feature of the SCP (Semi-automatic classification plugin) plugin on QGIS. The Vegetation cover (NDVI), Landcover classification using Random Forest Classification (RF) which is derived from Landsat imagery. The landcover classification had an overall accuracy of 90.17% [Galodha and Gupta, 2021]. One can use the tools explore changes vegetation cover, land cover changes, and change detection of landcover categories. Selection of images as part of image collection can be carried out as individual scenes which can be overlaid on the map layer [Jhala et al., 2015].

Figure 7 describes the workflow of the methods that have been used for creating the thematic Landcover maps, for the accuracy assessment part 70% of the reference data is used for training and 30% of the result top left corner signifies images for Landsat 8 image collection visualized as true color composite [Galodha and Gupta, 2021]. The legend mentions the changes in predominant class category features. Attached Figure 8 measures and identifies the LULC change between the years 2005-2010. Attached Figure 9 measures and identifies the LULC change between the years 2010-2015. Attached Figure 10 measures and identifies the LULC change between the years 2015-2021.

In Figure 11 here, a change detection map is created that measures the changing landscape across different category features.

Figure 13 shows the Energy Map of India (2021) as provided by Visualisation of Earth Observation Data and Archival system (VEDAS), Space Application Center (SAC), Indian Space Research Organization (ISRO). This tool map signifies the presence of coal mines and coal conventional power plants which surrounds the study area of Satpuda-Maikal landscape. The figure clearly depicts that the entire landscape is subject to coal deposits and thus many Liquefied Natural Gas (LNG) and Liquefied Petroleum Gas (LPG) terminals are visibly available in this

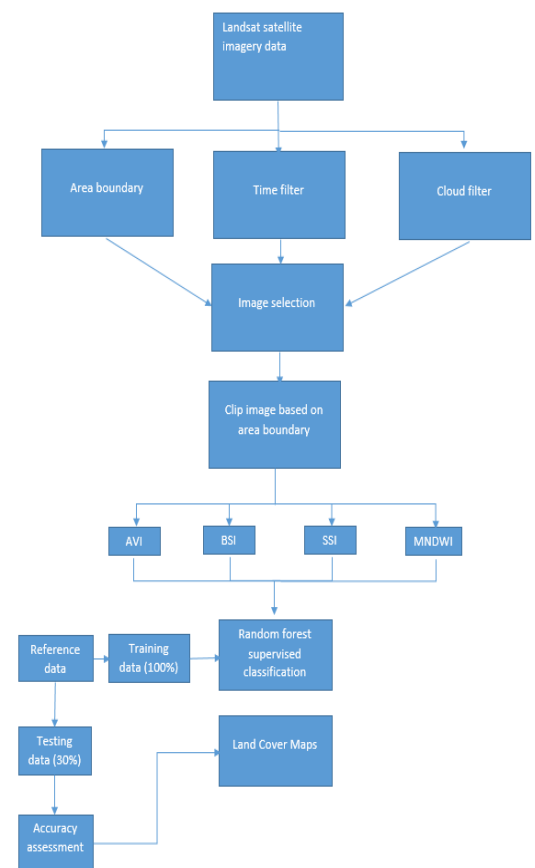


Figure 7: Descriptive workflow on GEE

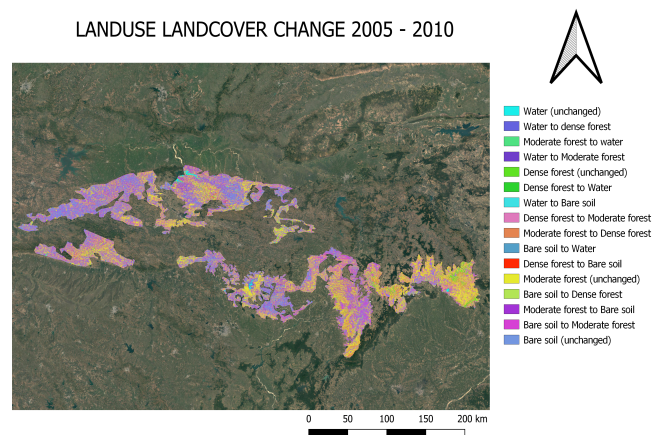


Figure 8: LULC Change 2005 - 2010

range. The coal reserves and coal blocks in the study area clearly represent the massive energy sector coal fields have turned into. Most of the Natural gas pipelines (NGP) and Petroleum products pipelines (PPP) passes through the sensitive area surrounding the protected forest cover landscape.

Figure 14, talks about the Potential habitat connectivity for tiger movement between tiger reserves and Maharashtra- Madhya Pradesh corridor as depicted by CIRCUITS-CAPE model that helps to monitor the change in the tiger movements and their habitat ac-

LANDUSE LANDCOVER CHANGE 2010 - 2015

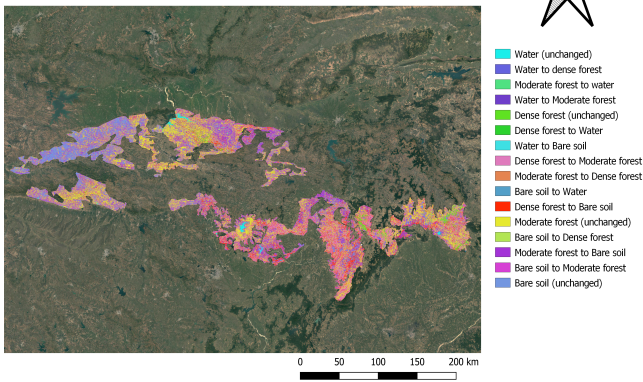


Figure 9: LULC Change 2010 - 2015

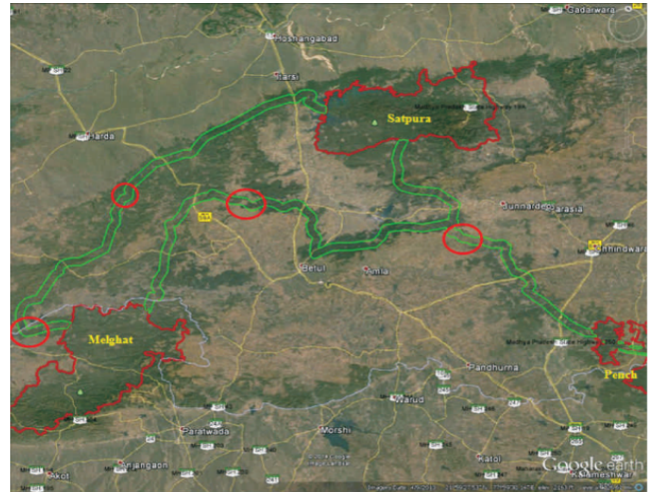


Figure 12: Satpuda Melghat and Pench corridor

LANDUSE LANDCOVER CHANGE 2015 - 2021

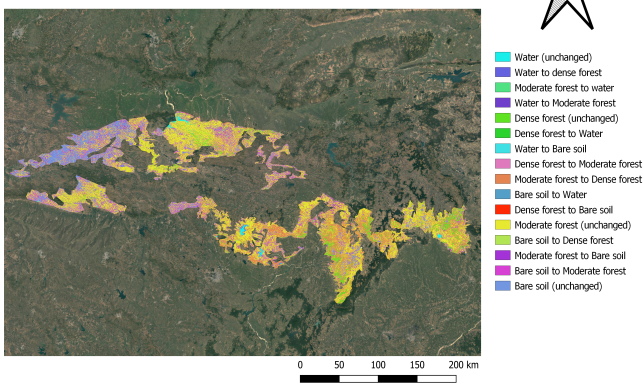


Figure 10: LULC Change 2015 - 2021

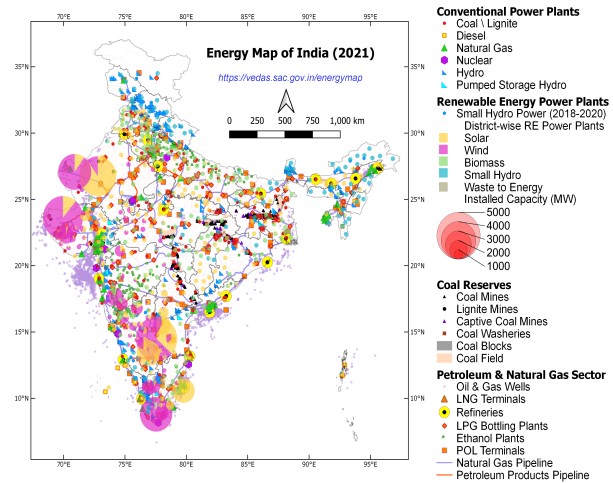


Figure 13: Energy Map of India (2021)

LANDUSE LANDCOVER CHANGE 2000 - 2021

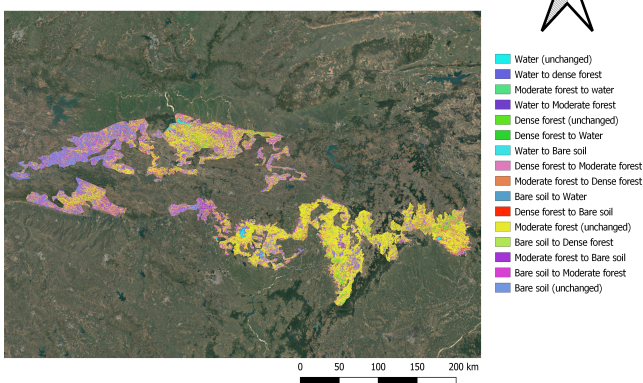


Figure 11: Change Detection LULC 2000 - 2021

## 6. CONCLUSION

In this paper we have tried to highlight through our research that, several species globally are facing threats due to anthropogenic impacts, similar to the tigers in our study area. Landscapes with high conservation value, especially in the tropics, have been changing rapidly due to increasing human population and exploitation of natural resource leading to conversion and degradation of habitat. Our results highlight the urgent need for informed development plans that consider biodiversity and connected wildlife populations in addition to human development goals. With habitats of most large mammals getting increasingly fragmented, our approach of combining landscape genetics with forward-time simulations to estimate extinction probability and loss of connectivity provides a valuable tool for conservation management. Such an approach can help identify populations vulnerable to landscape change, improving conservation and management of populations, species and landscapes to ensure long-term persistence.

According to the concept of least cost-least resistance path. The dataset was taken as per the Tiger Census data available with the Wildlife Institute of India, WII Dehradun from the period 2000-2021 [Thatte et al., 2018].

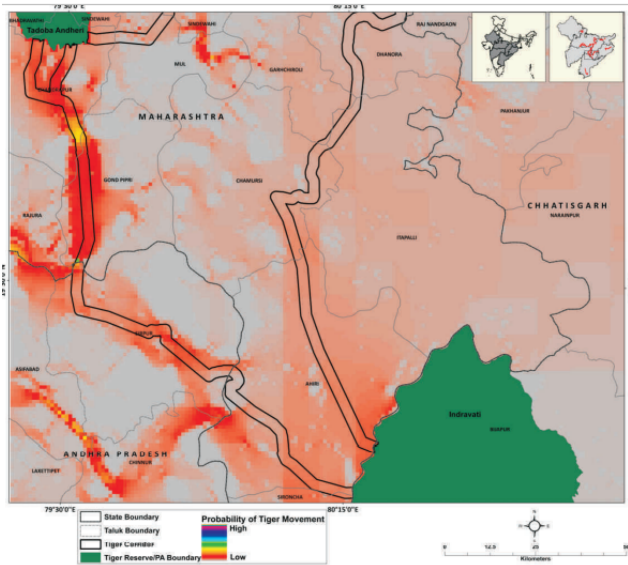


Figure 14: Potential Habitat connectivity

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