Summer 2017

Land Use and Land-Cover Change Detection and Its Effect on Bengal Tiger Mortality for Central India

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LAND USE AND LAND-COVER CHANGE DETECTION AND ITS EFFECT ON BENGAL TIGER MORTALITY FOR CENTRAL INDIA

A Master's Thesis

Presented to

The Graduate College of

Missouri State University

In Partial Fulfillment

Of the Requirements for the Degree

Master of Science, Geography, Geology and Planning

By

Tania Banerjee

August 2017

LAND USE AND LAND-COVER CHANGE DETECTION AND ITS EFFECT ON BENGAL TIGER MORTALITY FOR CENTRAL INDIA

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ABSTRACT

This research investigates land use/land cover change in central India and it's impacts on the tiger population. Central India is situated on the Deccan plateau with tropical climate patterns and includes two large states: Maharashtra and Madhya Pradesh. Central India has the largest tiger reserves in India. The land cover of this area is dominated by forest, agricultural land, and urban settlement. After the Green Revolution in the 1970s, the central India has undergone tremendous changes in land use/land cover. Time-series Landsat satellite imageries were processed and classified in a GIS environment to identify these land use/land cover changes. The relationships between tiger mortality and influential factors (e.g., urban settlement expansion, forest change and expanded agricultural land) are revealed with a repeated measure Poisson regression model. The results of the research showed that agriculture is having an effect on tiger mortality. More agricultural land leads to deforestation and encroachment of forest area finally resulting into increase in death of tigers.

KEYWORDS: land use and land cover change (LULLC), central India, supervised classification, tiger mortality, Poisson regression.

This abstract is approved as to form and content

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ACKNOWLEDGEMENTS

I would express my sincere gratitude to the Missouri State University and Department of Geography, Geology and Planning for giving me this opportunity to write this thesis. To my committee, Dr. Jun Luo, Dr. Sean Maher and Dr. Xin Miao, I am grateful for your assistance and suggestion throughout my research. To Dr. Jun Luo, a special thanks and appreciation for his knowledge of GIS and his patience in my journey to finish my research. To Dr. Sean Maher, hearty thanks for helping me with his statistics skills. To Dr. Xin Miao, for his profound knowledge of remote sensing. A special thanks to all my friends and family for helping me in completing me this thesis.

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INTRODUCTION

India is a country with a vast diversity of geography and culture. As a developing country, India has experienced rapid growth after independence in 1947. It is the second most populous country, and most of population live in rural areas. The rapid growth has caused considerable changes in the country. The Ministry of Environment and Forest has monitored many shifts in the climate, land use change, forest degradation and agriculture.

After independence of India in 1947, there was urgent demand to supply food to the fast-growing population. Green Revolution was initiated in 1950s. It was land-use and land-cover change (LULCC) detection showed that due to the Green Revolution, there was a significant decline of forest in India. These changes reflect the greatest environmental concerns of human populations today, including climate change, biodiversity loss and the pollution of water, soils, and air (Ellis, 2007). The deforestation contributed to the decline in tiger population after the 1970s and since tiger was declared as the endangered species in 1970 by International Union for Conservation of Nature (IUCN). India has the largest tiger population in the world according to the census in 2016. The Wildlife Protection Act, 1972 is an Act of the Parliament of India enacted for protection of plants and animal species. Similarly, Project Tiger is a tiger conservation program launched in 1973 by the Government of India.

Of the original nine subspecies of tigers, three have become extinct in the last 80 years; an average of one every 20 years. It has been predicted all tigers may become extinct in the wild within the next decade (Tiger in Crisis, n.d.). Bengal tigers (*Panthera tigris tigris*) are the most numerous tiger subspecies with its remaining wild populations estimated at around 2,500 (Tiger in Crisis, n.d.). They are primarily found in parts of India, Nepal, Bhutan and Bangladesh. Bengal tigers are sometimes called Indian tigers and account for over half of all tigers remaining in the wild.

Land-use and land-cover change (LULCC) is a general term for the human modification of Earth's terrestrial surface (Ellis, 2007). Though humans have been modifying land to obtain food and other essentials for thousands of years, and intensities of LULCC are far greater than ever, driving unprecedented changes in ecosystems and environmental processes at local, regional, and global scales (Ellis, 2007). Natural scientists define land use in terms of syndromes of human activities such as agriculture, forestry and building construction that alter land surface processes including biogeochemistry, hydrology, and biodiversity (Ellis, 2007). Maps and measurements of land cover can be derived directly from remotely sensed data by a variety of analytical procedures, including statistical methods and visual interpretation. Maps of LULCC are produced from remotely sensed data by inferring land use from land cover. Application of remotely sensed data has made it possible to study the changes in LULCC in less time, at lower cost and with better accuracy if used in association with Geographical Information System (GIS) that provide a suitable platform for data analysis, update, and retrieval.

BACKGROUND

Numerous studies have been done to investigate the changes of land use/cover and habitat shrinkage and fragmentation throughout the world (Wikramanayake et al., 1998), and their effects on wildlife. The technology of using satellite remote sensing, digital image processing, and GIS are widely used in these researches over years. Techniques like image fusion (Gharbia et al., 2014), supervised, and unsupervised classification yield better results for LULCC detection. Satellite-based remote sensing by its ability to provide synoptic information of land use and land cover at a time and location has revolutionized the study of land use and land cover (Roy and Roy, 2010).

Land Covers

Forest and Wildlife. According to the widely-used United Nations Food and Agriculture Organization, forests covered an area of four billion hectares (15 million square miles) or approximately 30 percent of the world's land area in 2006. Forests play a significant role in the global carbon cycle as both carbon source and sinks, and have the potential to form a critical component in efforts to combat global climate change. Forests are not only a resource for human exploitation but also support wildlife. Only a small fraction of the forest that once covered the world remains. In India, deforestation is increasing greatly and the Protected Areas (PAs) are the cornerstone for the conservation of endangered species, but individual PAs may be too small to harbor a stable and resilient population of wide-ranging large carnivores (Dutta et al. 2015).

The tiger (*Panthera tigris*) is a flagship species that can help garner support for conservation across all sectors, and their conservation is a global priority (Dutta et.al, 2015). Tigers typify the challenges faced by many large carnivore species worldwide: small isolated populations in fragmented and shrinking habitat, illegal trade of their body parts, poaching, and conflict with humans. Like many other large carnivore species, breeding populations of tigers are confined to small PAs that are insufficient for their long-term survival (Dutta et.al. 2015). Continued habitat loss and fragmentation is one of the major causes for the decline. Many of the remaining habitat fragments are too small, isolated, or degraded to hold viable populations of tigers and their prey (Kinnaird et al. 2003, Lynam et al. 2006).

Urban Settlement. Urbanization is a population shift from rural to urban areas. It is an inevitable process due to economic development and rapid population growth. Urban growth, particularly the movement of residential and commercial land use to rural areas at the periphery of metropolitan areas, has been long considered a sign of regional economic vitality. Its benefits increasingly are compared against ecosystem impacts, including a decrease of air and water quality because of smoke from vehicles and factories, a decline of farmland and forests provide spaces for the vast population, socioeconomic effects of economic disparities because the rich becomes richer, and the poor becomes poorer, and facilities costs. Dryland degradation or desertification is also due to population growth which contribute to increased pressure on natural resources through overgrazing, over-cultivation, and over-harvesting of woodlands. These activities, in turn, lead to deforestation, soil erosion, and poor land management which result in further environmental degradation and desertification (Abdi et al., 2012). Remote sensing and GIS are effective means for extracting and processing various resolutions of spatial information for monitoring urban growth. Villages are at the boundaries of the PAs and occur throughout the landscape. Now as the shift of people to urban have increased, the cities have started expanding and including the villages in them. As a result, the PAs in the central part of India are now surrounded by big cities, several townships, urban centers and numerous villages These surrounding settlements are encroaching the PAs from all possible sides thereby causing shrinkage of the habitat. Therefore, wildlife in the forest can enter the cities and nearby habitation because they aren't getting enough resources to survive and get killed and even the humans are entering the PAs for resources and killing wildlife either as poaching or for protection.

Agriculture. According to American Heritage Dictionary, agriculture can be defined as the science, art, and business of cultivating the soil, producing crops, and raising livestock. Agricultural intensification, defined as higher levels of inputs and increased output (in quantity or value) of cultivated or reared products per unit area and time, permitted the doubling of the world's food production from 1961 to 1996 with only a 10 percent increase in arable land globally (Lambin et al., 2001). Agriculture has expanded into forests, savannas, and steppes in all parts of the world to meet the demand for food and fiber. Agricultural expansion has shifted between regions over time; this followed the general development of civilizations, economies, and increasing populations. Two recent studies estimated historical changes in permanent cropland at a global scale during the last 300 years by spatializing historical cropland inventory data based on a global land-cover classification derived from remote sensing, which used a hindcasting approach, or based on historical population density data. (Lambin et al., 2003).

The Green Revolution was an agricultural revolution in India in 1950s. During the period 1950–1991, areas of barren and uncultivable land, cultivable wasteland, land not available for cultivation and fallow lands showed a steady decline. There was greater use of such land for agricultural and non-agricultural uses. The area under permanent pasture and other grazing lands also decreased. The introduction of high-yielding varieties of crops additional irrigation facilities, and a high input flow through fertilizer and pesticides ushered in the Green Revolution in India. This radical change in land use raised India from a food importing country to a self-sufficient, as well as food-exporting, nation. It stimulated infrastructure and rural development, increased the prosperity of villages, and improved the quality of life. This transformation also showed side effects regarding regional imbalance, social inequality and the second-generation problem of soil degradation (Challa et al., 2004). Regional imbalance such as few states in India has more agricultural production, and few states still need to import from others. More and more forest was taken under cultivable land. This period showed a tremendous decrease in forest cover of the country leading to noticeable LULCC by the environmentalist. The government of India, therefore started paying more attention towards the concern.

Effects of Land Cover Changes

Changes in land use and land cover date to prehistory and are the direct and indirect consequence of human actions to secure essential resources. This first may have occurred with the burning of areas to enhance the availability of wild game, and accelerated dramatically with the birth of agriculture, resulting in the extensive clearing and management of Earth's terrestrial surface that continues today. More recently, industrialization has encouraged the concentration of human populations within urban areas, the depopulation of the countryside, and the intensification of agriculture in the most productive lands and the abandonment of marginal lands. All of these causes and their consequences are observable simultaneously around the world today (Ellis et al., 2013).

Environmental Change. LULCC has negative impacts on the environment. The steady increase in global temperatures and accompanying climate changes in the past 150 years is simply an expression of natural variability, or they are a direct result of human activities. The most common problem that cities in central India faces is a continuous increase in temperature. Studies have shown that there is a striking difference in temperatures in urban and surrounding rural areas. (Katpatal et al., 2008).

Though LULCC certainly plays a indirectly role in greenhouse gas emissions, the complexity and dynamic interplay of land use processes favoring net accumulation versus net release of carbon dioxide and other greenhouse gasses makes it a poorly constrained component of our global budgets for these gasses, which is an active area of current research (Ellis, 2007). The ecological imbalance is another effect of LULCC. Biodiversity is often reduced dramatically by LULCC. When land is transformed from a primary forest to a farm, the loss of forest species within deforested areas is immediate and complete. Even when unaccompanied by distinct changes in land cover, similar effects are observed whenever relatively undisturbed areas are transformed to more intensive uses, including livestock grazing, selective tree harvest, and even fire prevention. The habitat suitability of forests and other ecosystems surrounding those under intensive use are also affected by the fragmenting of existing habitats into smaller pieces, which exposes forest edges to external influences and decreases core habitat areas. Smaller habitat areas support fewer species, and for species requiring an undisturbed core habitat, fragmentation can cause local and even global extinction.

Cultural Change. Human activity endangers tropical forests in different parts of the world (Weber et.al, 2007). The conflicting interests of nature conservation on the one hand, and the livelihood of farmers living at the woods margins on the other clash noticeably (Weber et.al, 2007). Cultural changes can be classified as a reduction of income from tourism and loss of cultural values and livelihood.

Tourism has always been a great source of income for people living near such areas. It has been supported because of the high proportion of revenue from this industry. Tourism depends on the land use and land cover. Tourists enjoy the natural beauty more. Therefore, the change in land cover sometimes causes the tourism of the areas to decrease. This reduction in travel can lead to loss of income from this industry.

Loss of cultural values and livelihood is a major issue caused by LULCC. From a socio-economic point of view, this means not only a loss of ecosystem services but also the decline of livelihoods and cultural values and a subsequent reduction of income from tourism (Brink and Eva, 2009). This is because the land cover changes the whole area sometimes to become barren which ultimately causes people to leave that place and immigrate to newer sites. Immigrating to new places causes the refugees to adapt to the existing pattern of the new area and thus lose their culture.

METHODOLOGY

Study Area

The landscape of central India is within the biogeographic zone of the Deccan plateau and is dominated by tropical dry deciduous and tropical moist deciduous forest (Champion and Seth 1968). The study areas are Kanha tiger reserve, Pench tiger reserve, Tadoba –Andheri tiger reserve, Bor wildlife reserve, Nagzira-Navegaon wildlife reserve, Melghat wildlife sanctuary, Umred wildlife sanctuary, Tipeshwar wildlife sanctuary, Achanakmar wildlife sanctuary, Narsinghgarh, Bandhavgarh and Panpatha wildlife sanctuary, Panna national park, Ratapani tiger reserve, Satpura national park, Nauradehi wildlife sanctuary, Sanjay- Dubri national park, Dewas range in central India. Figure 1 shows the study area in the India and tiger reserve. The area of interest (AOI) is marked in red and it covers most of the PAs. Figure 2 gives more details about the AOI and the location of the 19 forest patches. According to the Wildlife Protection Society of India in 1991, the elevation ranges from 284 m to 950 m above main sea level. The total area of the forest is divided into the core area and buffer area.

The central Indian landscape supports about ~40% of the total tiger total population (Jhala et al. 2011). According to the tiger census report released on March 28, 2011, by the National Tiger Conservation Authority (NTCA), the tiger population estimation was 1,706, ranging from a minimum of 1,571 to a maximum of 1,875. The results include figures from 17 Indian states with a tiger existence. In 2008, the tiger population figure stood at 1,411 for entire India. The Tiger Census 2008 report had classified the forest for tiger habitat in India into 6 landscape complexes.They are (a)

Shivalik-Gangetic Plains, (b) Central Indian Landscape Complex (c) the Eastern Ghats, (d) the Western Ghats, (e) North-Eastern Hills and Brahmaputra Plains, and (f) Sunder bans.

Figure 3, figure 4 and figure 5 are images are taken from three major tiger reserves in year December 2015. Winters are the time when tigers are found in all the 19 patches and is the prime time for tourism.

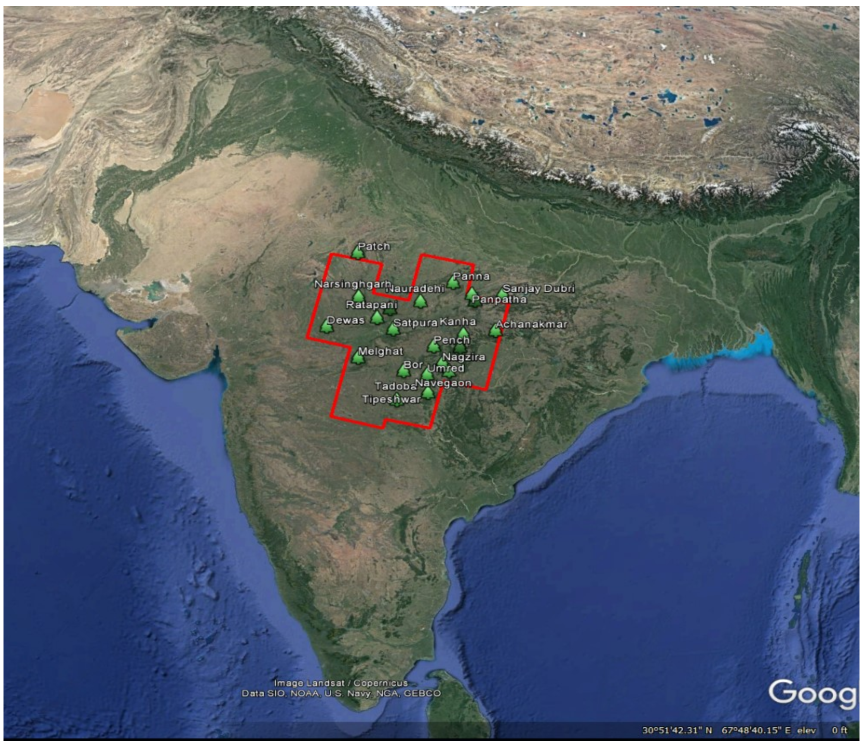

Figure 1: Study area in central India and tiger reserves.

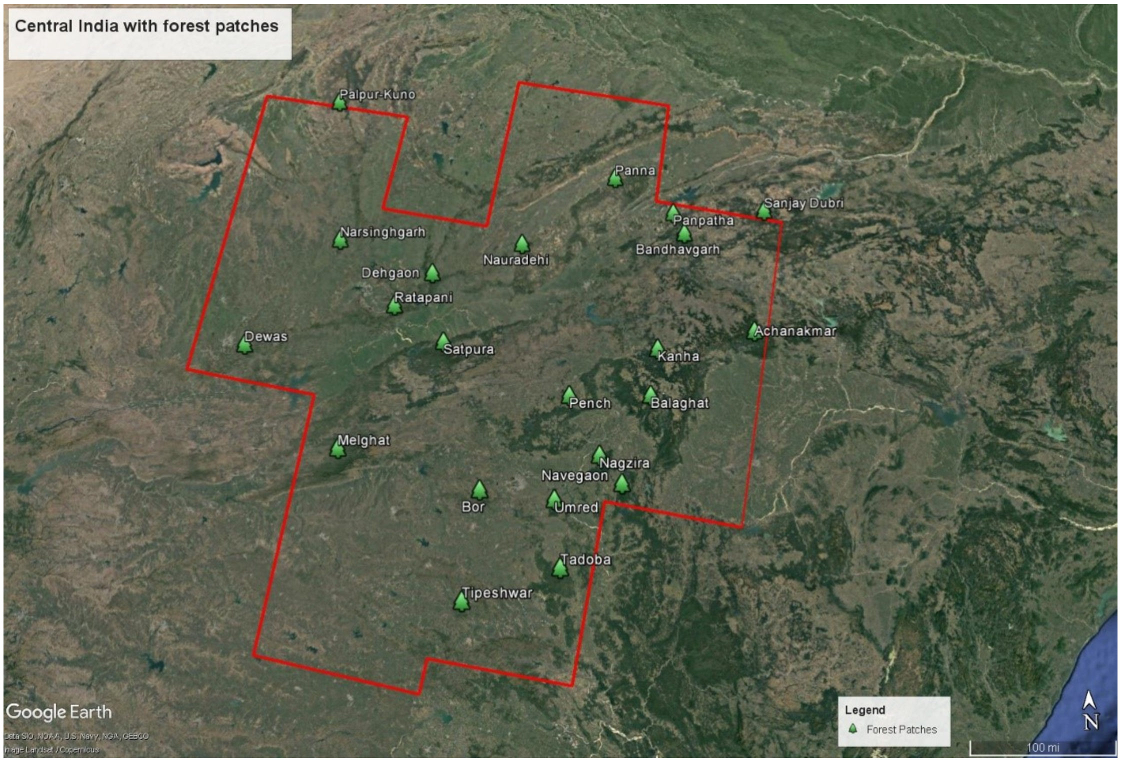

Figure 2: Central India with the forest patches Source: Google Earth Pro 7.1.5.

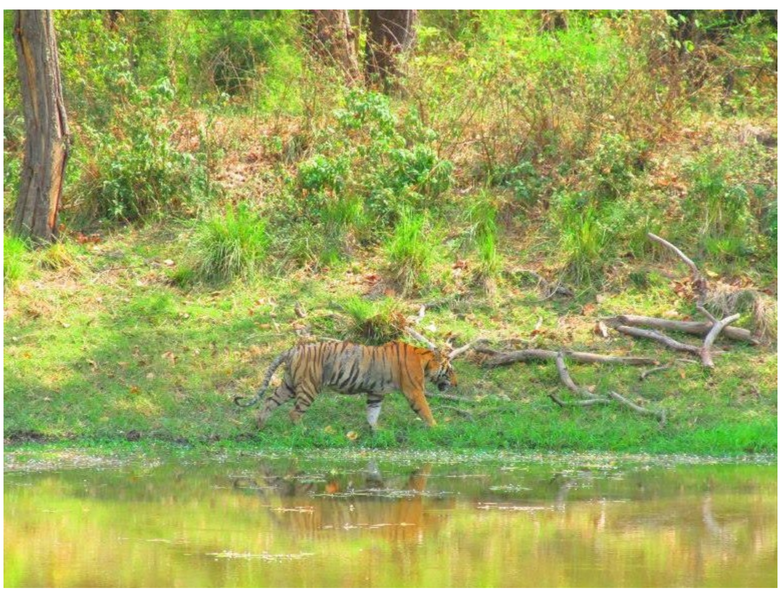

Figure 3: Kanha tiger reserve.

Figure 4: Tadoba tiger reserve.

Figure 5: Tadoba tiger reserve.

Image Used

Landsat images were collected from between 2009 and 2016 to find out LULCC. The images of the year 2009, 2011, 2013, 2014, 2015 and 2016 were downloaded from United States Geological Survey (USGS) Earth Explorer website, and for 2010, the image are taken from ArcGIS image server. Images of 2009 and 2011 were obtained from Landsat 5 Thematic Mapper (TM). As stated by an article of USGS Long Term Archive that very few images were acquired from November 2011 to May 2012 by Landsat 5 TM because the satellite began decommissioning activities in January 2013, and therefore, there were no images for 2012. Similarly, Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images after 2003 had a scan line corrector problem and, therefore, 2012 images were distorted. Remaining images of 2013, 2014, 2015 and 2016 were obtained from Landsat 8 Operational Land Imager (OLI).

Eleven Landsat scenes were to cover the study area with the 19 forest patches for each year. To avoid the cloud cover and better visibility, the images captured in the month of October, November, December, and January were used. Landsat TM 5 images consist of seven spectral bands with a spatial resolution of 30 meters for bands 1 to 5 and 7. Band 6 (thermal infrared) has a resolution of 120 meters, but resampled to 30-meter pixels. Enhanced Thematic Mapper plus Landsat 7 which has eight bands with a spatial resolution of 30 meters for bands 1 to 7. The resolution for band 8 (panchromatic) is 15 meters. Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) consists of nine spectral bands with a spatial resolution of 30 meters for bands 1 to 7 and 9. Band 8 is 15 meter, and thermal bands 10 and 11 are useful for more accurate surface temperature and are collected at 100 meters.

Data Processing

The process of LULCC begins with data processing. First, images taken from USGS were of spatial reference WGS 1984 UTM Zone 43N and 44N and map units was in meters. There is a metadata file (MTL.txt) in the Landsat image package. Landsat Metadata files contain beneficial information for the systematic searching and archiving practices of data and explain the essential characteristics of the Level-1 data products. Metadata describe individual parameters used during processing of the data, including the processing levels of each scene. Values important for enhancing Landsat data (such as conversion to reflectance and radiance) also are included in this file.MTL.txt files were used to mosaic the eleven images for each year. Mosaic is a tool for merging multiple existing raster datasets into an existing raster dataset. To get the existing dataset, create raster dataset tool was used.

There were two images taken from ArcGIS server imagery. The spatial reference was WGS84 with map units in degree. These imageries also have the collection of Landsat images in them, but they cannot be clipped. The good thing about these images is that there is no need to mosaic. Because the study area is central India, a shape file called area of interest (AOI) was made to define processing extent.

The next step was to create polygon feature classes for all the 19 forest patches. They were manually digitized in GIS environment. A buffer zone of 10 kilometers was created for each forest patch polygon to encompass the potential movements of tigers around habitat.

Supervised Image Classification

In supervised classification reference classes are used as additional information. This process safely determines which classes are the result of the classification. The following steps are the most common:

- Definition of the land use and land cover classes.
- Classification of suitable training areas.
- Execution of the true classification with the help of a suitable classification algorithm.
- Verification, evaluation, and inspection of the results ("Classification-Introduction to Remote Sensing," n.d.).

The user selects representative samples for each land cover class in the digital image. These sample land cover classes are called "training sites". In this research, for every land cover, seven or more samples were used. The area from which the sample is supposed to be taken is enlarged to get the correct land cover and polygons were drawn which served as a sample for the training set. The seven polygons of each land cover are merged into one class. The image classification software uses the training sites to identify the land cover classes in the entire image. Unlike the unsupervised classification method, sample sections of the known area with similar spectral reflectance were chosen as a signature set. These training sets were used to categories pixels of similar reflectance values into units that were labeled after areas of identifiable features, such as forest, urban, agricultural, water and so on. These samples are named accordingly as water, urban, forest, agriculture. In ArcGIS 10.4.1, there are two types of supervised classification methods. One is Interactive supervised classification, and other is Maximum likelihood classification.

In Maximum likelihood classification, the training samples are converted into a signature file (filename. gsg). The signatures generated from the training samples are then used to train the classifier to classify the spectral data into a thematic map (Lu and Weng, 2007). By default, all cells in the output raster will be classified, with each class having equal probability weights attached to their signatures. The input a priori probability file must be an ASCII file consisting of two columns. The values in the column represent class IDs and a priori probabilities for the respective classes. Valid values for class a priori probabilities must be greater than or equal to zero. If zero is specified as a probability, the class will not appear on the output raster. The sum of the specified a priori probabilities must be less than or equal to one (Maximum Likelihood Classification, n.d).

The interactive supervised classification is a quicker method. There is no requirement for the signature file; only training samples are created to obtain the result. In both the cases, the output is a raster file.

After the classification result is obtained, the tabulate area tool was used to calculate the area of those 19 patches with the buffer. This tool derived the area of all four land covers for each forest patch.

Accuracy Assessment

It is not easy to get the field data of all the 19 patches because of the vast area. Some are accessible easily, but some require permission to do research. Usually, acquiring permission includes a lot of government paperwork. Some areas have a local tribal government which make it harder to reach there. Therefore, accuracy assessment was used to find the user and producers accuracy. In the context of information extraction by image analysis, accuracy "measures the agreement between a standard assumed to be correct and a classified image of unknown quality". Accuracy assessment is performed by comparing the classification results by remote sensing analysis to a reference map based on a different information source ("Classification Accuracy Assessment" n.d.). In this case, the other source was Google Earth Pro 7.1.5. The Google Earth Pro 7.1.5 has the time slider option which gives the satellites of all the years. The accuracy of image classification is most often reported as a percentage correct. The *user's accuracy* is computed using the number of correctly classified pixels to the total number of pixels assigned to a category. It takes errors of the commission into account by telling the user that, for all areas identified as group X, a certain percentage are correct. The *producer's accuracy* informs the image analyst of the number of pixels correctly classified in a category as a percentage of the total number of pixels belonging to that category in the image. Producer's accuracy measures errors of omission.

After that, the confusion matrix was created, and overall accuracy and Kappa values were evaluated. Below given is the formula to calculate Kappa coefficient (K; Equation 1),

$$\frac{K=(N\sum_{i=1}^{r}X_{ij}-\sum_{i=1}^{r}(X_i*X_j)}{N^2-\sum_{i=1}^{r}(X_i*X_j)} \qquad \text{Equation 1}$$

Where N is the total number of same point and X is the element in row i and column j.

Statistical Analysis

Land use database for the nineteen forest patches for seven years was constructed with the image classification results, as shown in Table 1. The area of water doesn't have a direct effect on the tiger mortality. Therefore, it was not taken into consideration.

Table 1: Area of major land covers of 19 forest patches in terms km^2 and count of tiger mortality with the year.

Patches	Forest (km^2)	Urban (km^2)	Agriculture (km^2)	Tiger mortality	Year
Achanakmar	2099.6715	52.2468	1226.3985	0	2009
Panna	644.8581	341.9199	3832.6563	0	2009
Kanha and Pench	17418.7798	723.0528	12028.3434	15	2009
Tipeshwar	33.6387	65.8710	854.5851	0	2009
Palpur_Kuno	83.3138	430.4520	505.8396	0	2009
Panpatha and Bandhavgarh	861.1110	499.5594	1689.2172	4	2009
Navegaon	248.3712	92.8863	449.1279	0	2009
Narsinghgarh	163.4269	104.7798	446.706	0	2009
Nagzira	842.3176	123.9993	2181.6351	1	2009
Dehgaon	562.4974	727.6059	2170.7937	0	2009
Satpura	694.4508	508.2543	4053.8349	0	2009
Melghat	421.4403	136.7532	4060.2825	0	2009
Umred	122.0094	38.0574	644.3631	0	2009
Tadoba	2017.7630	313.7148	3670.1451	10	2009
Sanjay Dubri	398.6874	16.3593	269.8398	0	2009

Table 1: Continued

Patches	Forest (km^2)	Urban (km^2)	Agriculture (km^2)	Tiger mortality	Year
Nauradehi	20.6430	37.4508	579.9213	0	2009
Ratapani	144.7112	88.3899	546.5682	1	2009
Dewas	577.6749	82.4715	1067.4153	0	2009
Bor	86.3919	16.2864	583.4682	0	2009
Achanakmar	2672.3147	23.1444	682.4142	1	2010
Panna	787.9077	754.0661	3277.4634	0	2010
Kanha and Pench	16588.2884	690.7572	12875.5299	9	2010
Tipeshwar	27.6534	56.4806	870.6646	0	2010
Palpur_Kuno	75.0627	127.2174	817.2711	0	2010
Panpatha and Bandhavgarh	967.6539	506.4593	1575.283	2	2010
Navegaon	300.0666	88.2278	400.9998	0	2010
Narsinghgarh	147.7512	7.2108	517.2831	0	2010
Nagzira	977.2418	123.8024	2047.4004	0	2010
Dehgaon	509.3244	535.955	2418.5796	0	2010
Satpura	2458.9908	210.3413	2583.8523	0	2010
Melghat	2033.9937	144.7761	2428.7171	1	2010
Umred	120.6189	15.0939	666.6984	0	2010
Tadoba	3439.2543	177.5872	2393.3646	5	2010
Sanjay Dubri	373.0005	20.8945	290.8629	0	2010
Nauradehi	6.4206	39.6582	552.6252	0	2010

Table 1: Continued

Patches	Forest (km^2)	Urban (km^2)	Agriculture (km^2)	Tiger mortality	Year
Ratapani	237.3733	26.6548	515.4984	0	2010
Dewas	858.2913	18.6780	850.4272	0	2010
Bor	53.8956	2.6703	627.5439	0	2010
Achanakmar	1692.5130	167.7132	1518.0453	0	2011
Panna	541.8548	492.2100	3785.6730	0	2011
Kanha and Pench	13239.9279	1798.4880	15132.0909	2	2011
Tipeshwar	55.9476	54.8590	844.0036	1	2011
Palpur_Kuno	57.8760	252.6093	709.2009	0	2011
Panpatha and Bandhavgarh	752.1282	573.9158	1722.4133	3	2011
Navegaon	100.4139	160.2088	530.3004	0	2011
Narsinghgarh	100.4139	107.2088	507.3004	0	2011
Nagzira	554.5478	203.9141	2389.1584	0	2011
Dehgaon	428.8918	1336.518	1695.3069	0	2011
Satpura	675.3145	805.2190	3776.0503	1	2011
Melghat	400.7741	68.2561	4149.6576	0	2011
Umred	103.1418	42.0821	658.6446	0	2011
Tadoba	1542.1542	358.3424	4100.8173	6	2011
Sanjay Dubri	319.6719	28.4499	335.8629	0	2011
Nauradehi	99.0504	0	532.9575	1	2011
Ratapani	126.3585	80.6384	572.1171	0	2011

Table 1: Continued

Patches	Forest (km^2)	Urban (km^2)	Agriculture (km^2)	Tiger mortality	Year
Dewas	300.1611	88.3950	1338.5723	0	2011
Bor	56.0603	20.1187	610.8116	0	2011
Achanakmar	1861.8771	79.4776	1437.0364	0	2013
Panna	412.0397	500.8814	3905.9505	1	2013
Kanha and Pench	18013.2967	1798.3312	10362.8439	3	2013
Tipeshwar	44.5432	134.8358	774.8046	0	2013
Palpur_Kuno	99.4462	364.2426	555.4576	0	2013
Panpatha and Bandhavgarh	733.1316	493.0733	1840.1113	6	2013
Navegaon	112.2994	98.1504	580.1276	0	2013
Narsinghgarh	109.4367	192.3552	413.0452	0	2013
Nagzira	715.6033	199.4819	2232.2394	0	2013
Dehgaon	301.4529	883.1655	2276.177	0	2013
Satpura	873.5281	1383.6270	2999.7263	0	2013
Melghat	330.3754	276.8670	4010.7724	4	2013
Umred	100.0288	66.8754	637.1104	0	2013
Tadoba	943.1496	539.3097	4518.8679	7	2013
Sanjay Dubri	265.5475	98.7381	320.221	0	2013
Nauradehi	88.3728	9.2187	538.727	0	2013
Ratapani	254.916	253.4751	270.6619	0	2013
Dewas	508.3893	137.6657	1081.2904	0	2013

Table 1: Continued

Patches	Forest (km^2)	Urban (km^2)	Agriculture (km^2)	Tiger mortality	Year
Bor	50.2430	58.639	575.3466	0	2013
Achanakmar	1604.3526	60.6325	1710.2207	0	2014
Panna	791.5929	391.8330	3635.8925	1	2014
Kanha and Pench	13234.5707	839.5541	16067.0305	7	2014
Tipeshwar	43.7139	120.5316	790.7127	0	2014
Palpur_Kuno	57.5523	173.0500	788.9742	0	2014
Panpatha and Bandhavgarh	741.4541	500.2725	1807.8261	7	2014
Navegaon	101.5686	104.7601	583.7518	0	2014
Narsinghgarh	38.3348	93.0780	583.2702	0	2014
Nagzira	704.0769	157.9923	2285.8849	0	2014
Dehgaon	629.0397	1586.7801	794.8845	0	2014
Satpura	762.7990	894.6700	3598.5410	0	2014
Melghat	230.3242	333.3999	4055.2572	1	2014
Umred	151.5672	74.4264	578.2836	2	2014
Tadoba	1854.9733	459.3450	3687.1129	5	2014
Sanjay Dubri	436.4820	94.5027	152.8407	0	2014
Nauradehi	18.1061	239.8131	380.5604	0	2014
Ratapani	245.4957	196.4502	337.9180	0	2014
Dewas	186.3108	461.1150	1080.5549	0	2014
Bor	157.5954	102.3093	428.4702	0	2014

Table 1: Continued

Patches	Forest (km^2)	Urban (km^2)	Agriculture (km^2)	Tiger mortality	Year
Achanakmar	1534.4332	320.2722	1523.2974	0	2015
Panna	626.8328	767.1006	3425.4313	1	2015
Kanha and Pench	12230.0961	1068.8124	16872.2143	5	2015
Tipeshwar	10.1037	93.3300	850.7823	0	2015
Palpur_Kuno	28.5622	223.1701	768.2643	0	2015
Panpatha and Bandhavgarh	602.1775	509.2092	1938.2365	3	2015
Navegaon	125.9401	96.4825	567.7244	0	2015
Narsinghgarh	12.3435	40.2291	661.5845	1	2015
Nagzira	927.2924	220.0220	2000.3800	0	2015
Dehgaon	509.8700	1089.4854	1861.0131	0	2015
Satpura	573.3361	999.4575	3684.9574	2	2015
Melghat	1390.7907	831.0411	2396.823	0	2015
Umred	110.0963	173.3911	520.9869	0	2015
Tadoba	1619.2224	425.2905	3957.3788	11	2015
Sanjay Dubri	228.7892	55.6115	399.8635	1	2015
Nauradehi	55.3678	75.6342	507.1110	0	2015
Ratapani	149.2425	235.7259	394.8993	1	2015
Dewas	237.7339	237.9330	1251.3385	1	2015
Bor	77.6104	23.3271	585.7066	0	2015
Achanakmar	1426.3209	300.5163	1651.3913	0	2016

Table 1: Continued

Patches	Forest (km^2)	Urban (km^2)	Agriculture (km^2)	Tiger mortality	Year
Panna	510.9011	801.3158	3506.7893	2	2016
Kanha and Pench	10270.3034	1380.5916	18519.9155	24	2016
Tipeshwar	20.9133	77.0940	856.4196	0	2016
Palpur_Kuno	92.1323	263.9556	666.6246	0	2016
anpatha and Bandhavgarh	1015.9729	418.9041	1614.699	7	2016
Navegaon	172.3033	98.7053	519.1996	0	2016
Narsinghgarh	73.3527	222.3574	418.3194	1	2016
Nagzira	763.9463	231.9136	2151.7671	2	2016
Dehgaon	869.9445	600.8625	1989.7356	0	2016
Satpura	512.7563	780.0676	3963.9154	0	2016
Melghat	560.1825	595.3006	3462.6179	2	2016
Umred	154.6983	156.2193	493.7994	0	2016
Tadoba	1862.1179	888.8763	3250.2842	11	2016
Sanjay Dubri	422.8794	35.6114	226.1426	0	2016
Nauradehi	30.3527	42.3574	565.3194	0	2016
Ratapani	181.1781	135.0369	463.2175	0	2016
Dewas	290.8226	281.9780	1155.1277	0	2016
Bor	54.6411	24.7656	607.5471	1	2016

The research attempts to reveal the LULCC factors contributing to tiger mortality. A regression analysis was performed with the tiger mortality as dependent variable and forest, urban and agriculture land uses as predictor variables or independent variable. The patch and year are categorical variables.

To begin with the analysis, first, we need to standardize the mean as zero and variance as one for all the predictor variables. All the predictor variables were standardized to have a mean of zero and a variance of one. Poisson regression is an appropriate method to test for the relationship between a dependent variable measured in counts (i.e. tiger mortality) and a single or set of continuous variables. It's best used for rare events, as these tend to follow a Poisson distribution, as opposed to more frequent events which tend to follow a normal distribution (Zeilieis et.al., 2016). Poisson regression analysis was then performed. Because there were 7 events per patch Poisson regression for repeated measure is used.

RESULTS

Classification Results

In figures 6 to 9, supervised classification maps are built in ArcGIS 10.4.1 using the Landsat images and ArcGIS image server. Looking at the first two images of year 2009 and 2010 in figure 6, we find that forest area is not concentrated to the 19 patches instead it looks more scattered. This may be due to the pixel of agriculture and forest has fuzzy boundaries and the user gets confused while classifying. India is an agricultural country and masses in rural go for agriculture compared to the other employment. Due to the increasing population and limited land and resources for agriculture, forest land are turned into agricultural land and hence, deforestation keeps increasing.

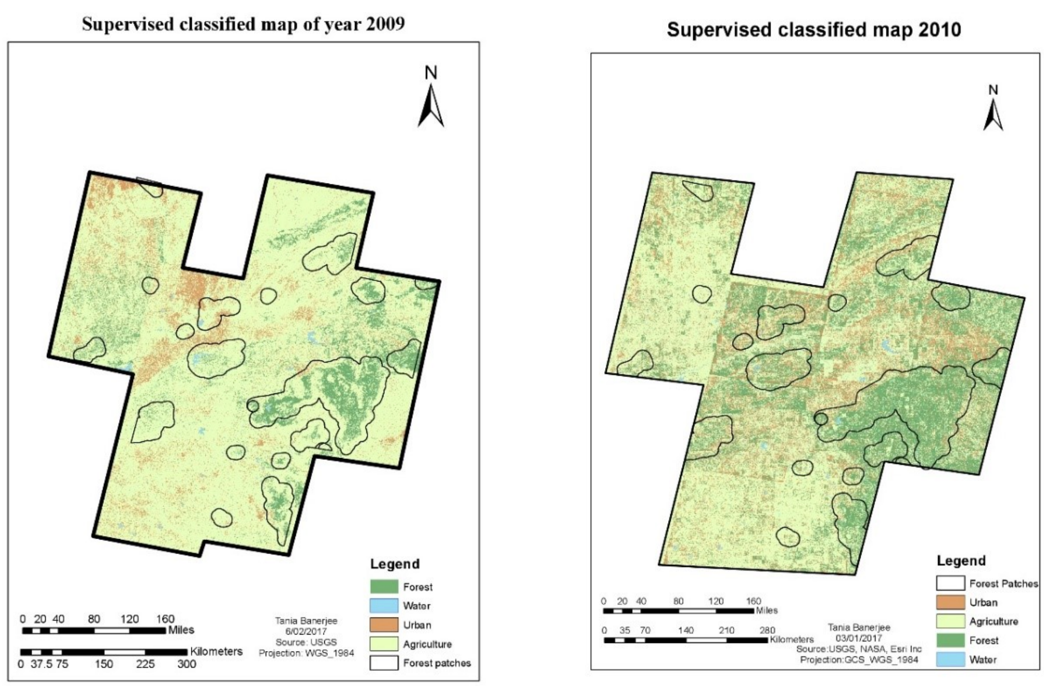

Figure 6: The classified maps of study area with the 19 patches from 2009-2010

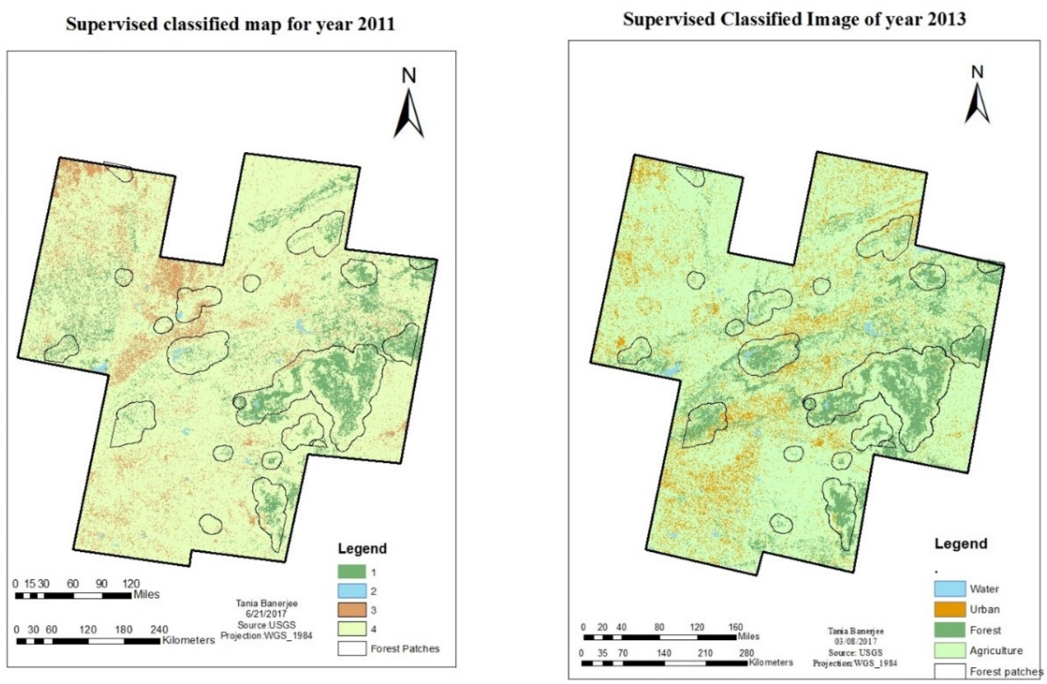

Figure 7: The classified maps of study area with the 19 patches from 2011-2013

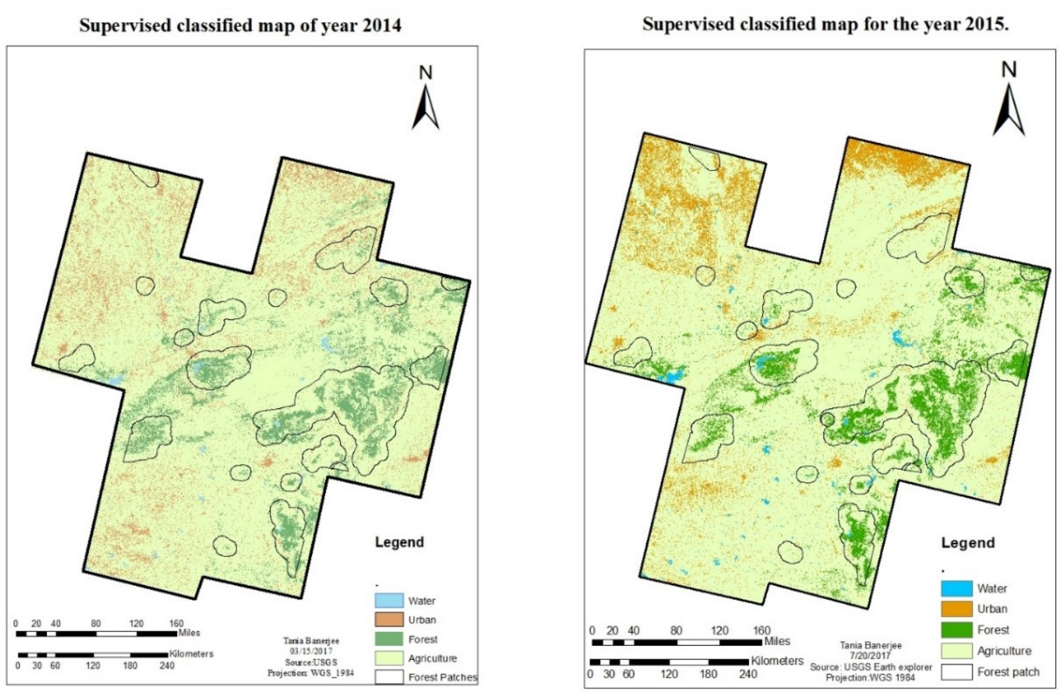

Figure 8: The classified maps of study area with the 19 patches from 2014-2015

Supervised classified map of the year 2016

Figure 9: The classified map of study area with the 19 patches from 2016

Considering the image of year 2011 in figure 7, there are more urban pixels in the southern part of study area. This is because of the cloud cover. Out of the eleven images, only two images had cloud cover which is misclassified as urban. But the fact that urban is increasing cannot be denied. Table 2 shows the area of four land covers in km^2 of the total study area. In table 2, the area of urban settlement can be observed from the visual interpretation of the classified images. Images of 2014, 2015 and 2016 in figures 7, 8 and 9 have urban settlement spreading near the forest. Even water, in form of rivers or lake, apparently has declined over the years. Because central India is dry compared to the rest of India. Overall inferences are that there has been decrease in forest and increase in urban and agriculture from 2009 to 2016.

To find the shrinkage in terms of numerical data, the area of land cover is determined. The area of the land cover may also include an area which is not designated forest or PAs or might not be a proper farm but may be a fertile land with some wild trees and canopies or unused pasture.

Table 2: The area of the land covers are calculated.

Years	Urban	Agriculture	Water	Forest
2009	112393.795	286930.227	1659.555	39352.936
2010	112767.985	276356.430	1759.191	49452.900
2011	113040.436	288823.509	3590.183	34882.365
2013	113492.195	292500.352	3989.966	30354.000
2014	115293.795	292730.767	2912.916	29398.765
2015	116101.245	294345.128	3327.251	26562.889
2016	116812.198	295767.033	2415.049	25342.234

From the figures 10, 11, 12 and 13 overall similar results are observed as of the map classification. There is a steep increase in agriculture and a steady decline in the forest. As per Central Intelligence Agency (CIA), estimated agriculture land is 60.5% which includes 52.8% arable land, 4.2% permanent crops and 3.5% permanent pasture. According to the estimates in the year 2011, only 23.1% is under forest cover. In the data obtained, the agricultural area has increased from 286930.228 km^2 to 295767.034 km^2 in eight years whereas the forest has declined from 39,352.93 km^2 to 25342.234 km^2

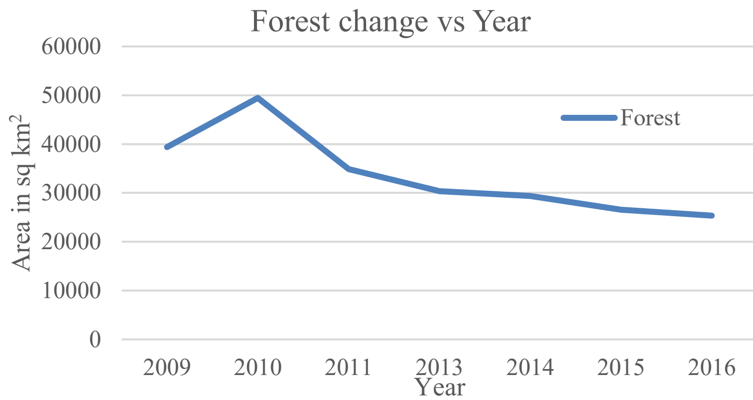

Figure 10: Graph is showing water in terms of area (km^2) vs. all Years.

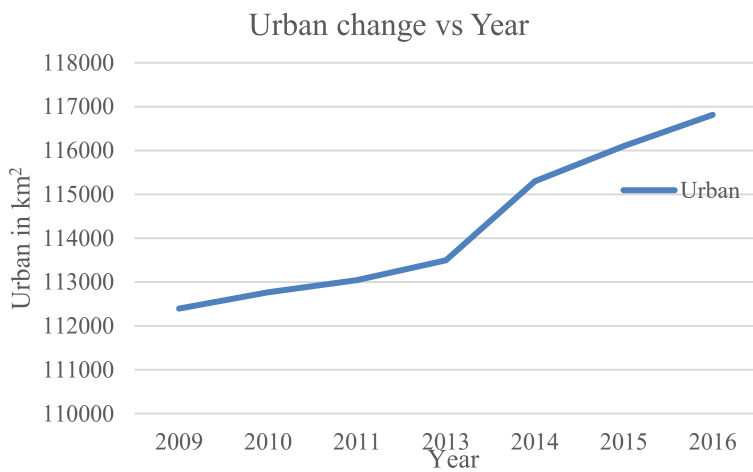

Figure11: Graph is showing urban in terms of area (km^2) vs. all Years.

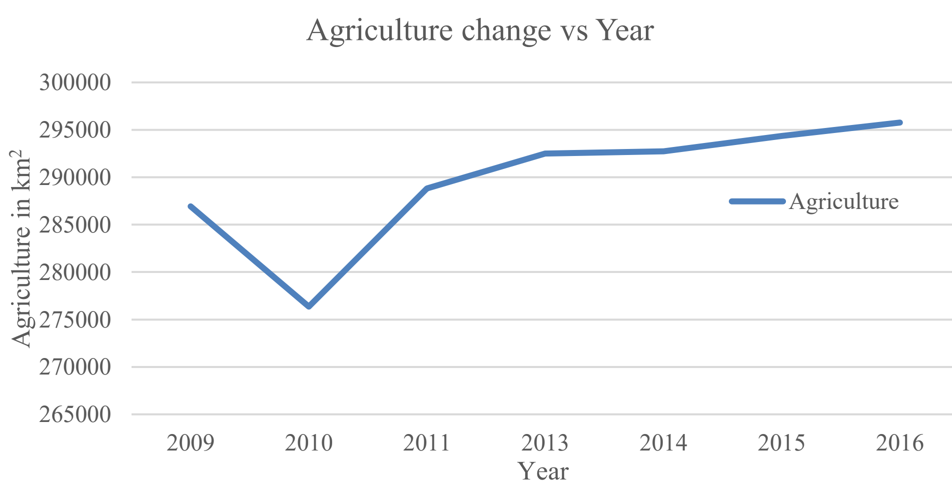

Figure 12: Graph is showing agriculture in terms of area (km^2) vs. all Years.

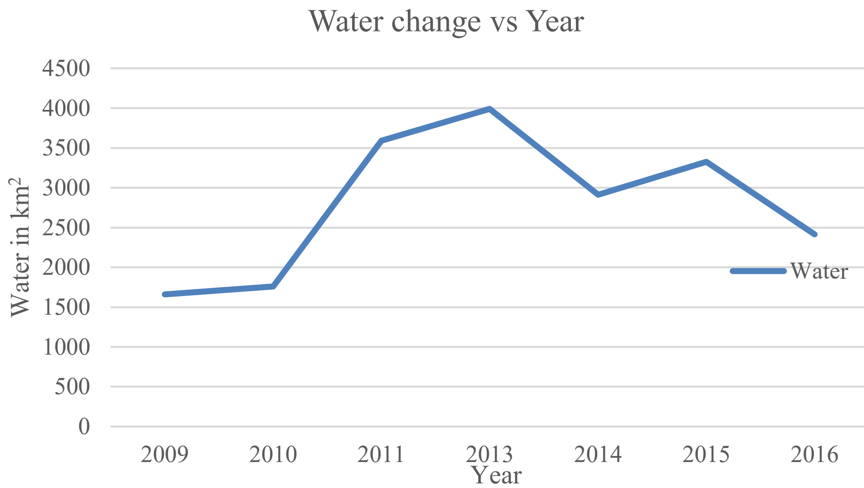

Figure 13: Graph is showing water in terms of area (km^2) vs. all Years.

Table 4 shows the land use conversion matric. Land use conversion matrix can be defined as to what other land use types the present land use type can be converted or not. In which regions, a specific conversion can occur and in which regions it is not allowed (Verburg, 2010). It is a common observation from the table that mostly the forest land got converted into different agriculture and urban.

Table 3 : Land use conversion matrix in terms of km^2

		2009				
		Urban (km^2)	Agriculture (km^2)	Water (km^2)	Forest (km^2)	Total (km^2)
2010	Urban (km^2)	112393.796	374.190	0	0	112767.986
	Agriculture (km^2)	0	276356.430	0	0	276356.430
	Water (km^2)	0	99.641	1659.550	0	1759.191
	Forest (km^2)	0	10099.960	0	39352.937	49452.897

Table 3: Continued

		Urban (km^2)	Agriculture (km^2)	Water (km^2)	Forest (km^2)	Total (km^2)
	Total (km^2)	112393.796	286930.221	1659.550	39352.937	440336.500
				2010		
		Urban (km^2)	Agriculture (km^2)	Water (km^2)	Forest (km^2)	Total (km^2)
2011	Urban (km^2)	112707.900	60.086	0	272.451	113040.437
	Agriculture (km^2)	0	276296.344	0	12527.166	288823.510
	Water (km^2)	0.00	0	1759.191	1830.993	3590.180
	Forest (km^2)	60.086	0	0	34822.279	34882.365
	Total (km^2)	112767.986	276356.430	1759.191	49452.889	440336.500
				2011		
		Urban (km^2)	Agriculture (km^2)	Water (km^2)	Forest (km^2)	Total (km^2)
2013	Urban (km^2)	110783.952	2256.485	0	451.759	113492.196
	Agriculture (km^2)	1956.723	286567.027	0	3976.603	292500.353
	Water (km^2)	0	0	3590.180	399.786	3989.970
	Forest (km^2)	299.765	0	0	30054.235	30354.000
	Total (km^2)	113040.440	288823.512	3590.180	34882.383	440336.500
				2013		
		Urban (km^2)	Agriculture (km^2)	Water (km^2)	Forest (km^2)	Total (km^2)
2014	Urban (km^2)	110076.880	3416.196	1077.053	723.667	115293.796
	Agriculture (km^2)	475.361	289084.539	0	3170.8677	292730.768

Table 3: Continued

	Water (km^2)	0	0	2912.917	0	2912.920
	Forest (km^2)	2939.955	0	0	26458.81	29398.765
	Total (km^2)	113492.196	292500.735	3,989.970	30353.344	440336.200
				2014		
		Urban (km^2)	Agriculture (km^2)	Water (km^2)	Forest (km^2)	Total (km^2)
2015	Urban (km^2)	115200.135	0	0	901.111	116101.246
	Agriculture (km^2)	0	292730.768	0	1614.360	294345.128
	Water (km^2)	0	0	2912.920	414.331	3327.251
	Forest (km^2)	93.661	0	0	26469.228	26562.889
	Total (km^2)	115293.796	292730.768	2,912.920	29399.030	440336.500
				2015		
		Urban (km^2)	Agriculture (km^2)	Water (km^2)	Forest (km^2)	Total (km^2)
2016	Urban (km^2)	116101.246	0	0	710.953	116812.199
	Agriculture (km^2)	0	294345.128	0	1421.906	295767.034
	Water (km^2)	0.00	0	2415.049	912.202	2415.049
	Forest (km^2)	0	0	0	23517.828	25342.234
	Total (km^2)	116101.246	294345.128	3327.251	26562.889	440336.500

Accuracy Assessment Results

The accuracy assessment table 4, has the confusion matrix. The class accuracies are determined by test pixel with the corresponding locations in the classified image. It is not always possible to get the field reference and in such cases the user select references that they have visually identified from the imagery. Usually the process is to take test pixel evenly distributed through the image and they should be distinct from the training samples pixel used for supervised classifications. Confusion matrices are widely accepted method for determining accuracy assessment for classification. The rule is to have ten times the number of pixels for each class or land cover, so there are four land covers. Therefore, 40 pixels for each land cover will give us total of 160 test pixels. But if any land cover is more than the other in that case more test pixels should be taken for the specific cover, and hence, the total remains same.

Table 4: Confusion matrix for the year 2009-2016.

	Reference			
Classified	Forest	Water	Urban	Agriculture
2009				
Forest	36	0	0	4
Water	0	28	0	0
Urban	1	0	30	4
Agriculture	3	0	3	52
2010				
Forest	26	0	1	24
Water	0	28	0	0

Table 4: Continued

Classified	Reference			
	Forest	Water	Urban	Agriculture
Urban	0	0	21	4
Agriculture	14	0	10	32
2011				
Forest	35	1	2	16
Water	0	26	0	0
Urban	0	0	29	0
Agriculture	5	1	1	49
2013				
Forest	32	0	0	7
Water	0	28	0	0
Urban	4	1	28	3
Agriculture	4	0	4	50
2014				
Forest	38	0	2	5
Water	0	28	0	0
Urban	2	0	28	0
Agriculture	0	0	2	55
2015				
Forest	34	0	2	6
Water	0	27	0	0

Table 4: Continued

Urban	1	0	28	0
Agriculture	5	1	2	54
2016				
Forest	35	0	0	12
Water	0	21	0	0
Urban	0	0	32	7
Agriculture	5	6	0	39

Table 5 has producer accuracy, user accuracy, and overall accuracy and Kappa statistics for each year. The overall accuracy value range 66.8% to 93.12%. In some cases, there has been confusion in the forest and agriculture signatures, and therefore, the accuracy of agriculture class is not as high as forest. Water has the highest accuracy among all land cover. Even in most of the cases, urban class has higher accuracy.

In 2010, the overall accuracy value was less because of the forest and agriculture exhibit similar signatures due to fuzzy boundaries and mixing of adjacent pixels between them (Hamdan and Myint, 2014). It is visually clear that the agricultural cover has increased over the years and forest has decreased considerably. Therefore, the computerized classification result is quite accurate.

Table 5: The accuracy assessment for the classification of the years from 2009-2016.

Classified	Producer's accuracy (%)	User Accuracy (%)
2009		
Forest	90.00	90.00
Water	100.00	100.00
Urban	90.62	85.29
Agriculture	86.67	89.65
Overall Accuracy 90.62%		
Kappa Statistics 0.88		
2010		
Forest	65.00	50.98
Water	100.00	100.00
Urban	65.63	100.00
Agriculture	53.33	57.14
Overall Accuracy 66.8%		
Kappa Statistics 0.64		
2011		
Forest	87.50	77.77
Water	92.86	100.00
Urban	90.62	93.55
Agriculture	81.66	85.96
Overall Accuracy 86.67%		
Kappa Statistics 0.89		

Table 5: Continued

Classified	Producer's accuracy (%)	User Accuracy (%)
2013		
Forest	80.00	82.05
Water	100.00	100.00
Urban	87.50	80.00
Agriculture	83.33	86.21
Overall Accuracy 86.2%		
Kappa Statistics 0.82		
2014		
Forest	95.00	84.44
Water	100.00	100
Urban	87.50	93.33
Agriculture	91.67	96.50
Overall Accuracy 93.12%		
Kappa Statistics 0.91		
2015		
Forest	85.00	80.95
Water	96.42	100.00
Urban	87.50	93.33
Agriculture	90	88.52
Overall Accuracy 89.37%		
Kappa Statistics 0.87		

Table 5: Continued

Classified	Producer's accuracy (%)	User Accuracy (%)
2016		
Forest	87.50	74.46
Water	75.00	100.00
Urban	100.00	82.05
Agriculture	65.00	78.00
Overall Accuracy 79.37%		
Kappa Statistics 0.75		

Poisson Regression

To separately find the shrinkage in the designated forest by the government and the protected wildlife like tigers, the 19 forest patches were considered and the research was narrowed down to the core and buffer zones of the PAs. Table 6 has the result of the summation of the areas (km^2) of all the 19 forest patches within the buffer zone. These all 19 patches are declared as the PAs by Government of India.

Forest in these regions is shrinking with the increasing year. The deforested area is either covered with urban or with agriculture. A buffer was taken to evaluate whether the wildlife inside these PAs have enough space for movement or whether these areas are occupied by human settlement and agriculture. Since these PAs are also tiger reserves, then LULCC might have influence in increasing tiger death. Therefore, the tiger mortality data was obtained from National Tiger Conservation Authority (NTCA) official database to investigate further which land cover has a more significant effect.

Table 6: Comparison of the total area of 19 forest patches over the years are shown below.

Year	Forest (km^2)	Urban (km^2)	Agriculture (km^2)
2009	27441.76	4400.11	40861.14
2010	32675.10	3569.68	36392.48
2011	21147.20	6639.15	44908.98
2013	25817.68	7568.41	39330.52
2014	21989.91	6884.52	43347.99
2015	21049.84	7485.53	44167.99
2016	19285.72	7336.43	46082.83

The data for the independent variables need to standardize by making their means zero and variance one. Z-scores are also known as standardized scores; they are scores (or data values) that have been given a common *standard*. This standard is a mean of zero and a standard deviation of 1 (Van den Berg, 2016). The reason may be that many variables do follow normal distributions. Due to the central limit theorem, this holds especially for test statistics. If a normally distributed variable is standardized, it will follow a *standard* normal distribution (Van den Berg, 2016). Below is the table 6 with the standard values.

Table 7: The standardized values of all the independent variables

Patch Name	Tiger Mortality	Year	Forest (Z-Score)	Urban (Z-Score)	Agriculture (Z-Score)
Achanakmar	0	2009	0.25548	-0.73529	-0.30797
Panna	0	2009	-0.19452	0.03168	0.50087
Kanha and Pench	15	2009	4.99396	1.04081	3.04436
Tipeshwar	0	2009	-0.38359	-0.69921	-0.42336
Palpur_Kuno	0	2009	-0.36822	0.26609	-0.53159
Panpatha and Bandhavgarh	4	2009	-0.12763	0.44907	-0.16433
Navegaon	0	2009	-0.31716	-0.62768	-0.54919
Narsinghgarh	0	2009	-0.34344	-0.59619	-0.54994
Nagzira	1	2009	-0.13345	-0.54531	-0.01151
Dehgaon	0	2009	-0.2200	1.05287	-0.01488
Satpura	0	2009	-0.17918	0.47209	0.56951
Melghat	0	2009	-0.26363	-0.51154	0.57151
Umred	0	2009	-0.35625	-0.77286	-0.4886
Tadoba	10	2009	0.23014	-0.04300	0.45044
Sanjay Dubri	0	2009	-0.27067	-0.83031	-0.60483
Nauradehi	0	2009	-0.38761	-0.77446	-0.50860
Ratapani	1	2009	-0.34923	-0.63959	-0.51895
Dewas	0	2009	-0.21531	-0.65526	-0.35731
Bor	0	2009	-0.36727	-0.83050	-0.50750
Achanakmar	1	2010	0.43261	-0.81234	-0.47679
Panna	0	2010	-0.15028	1.12293	0.32857

Table 7: Continued

Patch Name	Tiger Mortality	Year	Forest (Z-Score)	Urban (Z-Score)	Agriculture (Z-Score)
Kanha and Pench	9	2010	4.73707	0.95530	3.30728
Tipeshwar	0	2010	-0.38544	-0.72408	-0.41837
Palpur_Kuno	0	2010	-0.37077	-0.53679	-0.43494
Panpatha and Bandhavgarh	2	2010	-0.09468	0.46734	-0.19969
Navegaon	0	2010	-0.30117	-0.64002	-0.56413
Narsinghgarh	0	2010	-0.34829	-0.85453	-0.52804
Nagzira	0	2010	-0.09171	-0.54583	-0.05317
Dehgaon	0	2010	-0.23645	0.54543	0.06202
Satpura	0	2010	0.36662	-0.31670	0.11331
Melghat	1	2010	0.23516	-0.49030	0.06517
Umred	0	2010	-0.35668	-0.83366	-0.48167
Tadoba	5	2010	0.66983	-0.40342	0.05420
Sanjay Dubri	0	2010	-0.27861	-0.81830	-0.59831
Nauradehi	0	2010	-0.37963	-0.76862	-0.51707
Ratapani	0	2010	-0.32057	-0.80305	-0.52859
Dewas	0	2010	-0.12851	-0.82417	-0.42465
Bor	0	2010	-0.37732	-0.86655	-0.49382
Achanakmar	0	2011	0.12953	-0.42956	-0.21746
Panna	0	2011	-0.22639	0.42961	0.48629
Kanha and Pench	2	2011	3.70136	3.88825	4.0076

Table 7 : Continued

Patch Name	Tiger Mortality	Year	Forest (Z-Score)	Urban (Z-Score)	Agriculture (Z-Score)
Tipeshwar	1	2011	-0.37669	-0.72837	-0.42664
Palpur_Kuno	0	2011	-0.37609	-0.20478	-0.46848
Panpatha and Bandhavgarh	3	2011	-0.16134	0.64594	-0.15403
Navegaon	0	2011	-0.36293	-0.44943	-0.52400
Narsinghgarh	0	2011	-0.36293	-0.58976	-0.53114
Nagzira	0	2011	-0.22246	-0.33372	0.05289
Dehgaon	0	2011	-0.26133	2.66509	-0.16244
Satpura	1	2011	-0.18510	1.25836	0.48330
Melghat	0	2011	-0.27002	-0.6929	0.59925
Umred	0	2011	-0.36209	-0.7622	-0.48417
Tadoba	6	2011	0.08303	0.07517	0.58409
Sanjay Dubri	0	2011	-0.29511	-0.79829	-0.58434
Nauradehi	1	2011	-0.36335	-0.87362	-0.52317
Ratapani	0	2011	-0.35491	-0.66011	-0.51102
Dewas	0	2011	-0.30115	-0.63958	-0.27315
Bor	0	2011	-0.37665	-0.82035	-0.49901
Achanakmar	0	2013	0.18192	-0.66319	-0.24260
Panna	1	2013	-0.26654	0.45257	0.52362
Kanha and Pench	3	2013	5.17785	3.88784	2.52748
Tipeshwar	0	2013	-0.38021	-0.51661	-0.44812

Table 7: Continued

Patch Name	Tiger Mortality	Year	Forest (Z-Score)	Urban (Z-Score)	Agriculture (Z-Score)
Palpur_Kuno	0	2013	-0.36323	0.09079	-0.51619
Panpatha and Bandhavgarh	6	2013	-0.16722	0.43189	-0.11750
Navegaon	0	2013	-0.35925	-0.61375	-0.50853
Narsinghgarh	0	2013	-0.36014	-0.36432	-0.56039
Nagzira	0	2013	-0.17264	-0.34545	0.00419
Dehgaon	0	2013	-0.30075	1.46474	0.01783
Satpura	0	2013	-0.12379	2.78982	0.24238
Melghat	4	2013	-0.2918	-0.14056	0.55615
Umred	0	2013	-0.36305	-0.69655	-0.49085
Tadoba	7	2013	-0.10226	0.55431	0.71383
Sanjay Dubri	0	2013	-0.31185	-0.61219	-0.58919
Nauradehi	0	2013	-0.36666	-0.84921	-0.52138
Ratapani	0	2013	-0.31514	-0.20249	-0.60458
Dewas	0	2013	-0.23674	-0.50912	-0.35300
Bor	0	2013	-0.37845	-0.71836	-0.51002
Achanakmar	0	2014	0.10227	-0.71308	-0.15782
Panna	1	2014	-0.14914	0.16384	0.43981
Kanha and Pench	7	2014	3.69971	1.34927	4.29775
Tipeshwar	0	2014	-0.38047	-0.55449	-0.44318
Palpur_Kuno	0	2014	-0.37619	-0.41543	-0.44372

Table 7: Continued

Patch Name	Tiger Mortality	Year	Forest (Z-Score)	Urban (Z-Score)	Agriculture (Z-Score)
Panpatha and Bandhavgarh	7	2014	-0.16465	0.45096	-0.12752
Navegaon	0	2014	-0.36257	-0.59625	-0.50741
Narsinghgarh	0	2014	-0.38213	-0.62718	-0.50756
Nagzira	0	2014	-0.17621	-0.4553	0.02084
Dehgaon	0	2014	-0.19942	3.32771	-0.44189
Satpura	0	2014	-0.15804	1.4952	0.42822
Melghat	1	2014	-0.32275	0.00913	0.56996
Umred	2	2014	-0.34711	-0.67656	-0.50911
Tadoba	5	2014	0.17979	0.34259	0.45570
Sanjay Dubri	0	2014	-0.25898	-0.6234	-0.64114
Nauradehi	0	2014	-0.38839	-0.23867	-0.57047
Ratapani	0	2014	-0.31805	-0.35348	-0.5837
Dewas	0	2014	-0.33636	0.34728	-0.35323
Bor	0	2014	-0.34524	-0.60274	-0.5556
Achanakmar	0	2015	0.08064	-0.02563	-0.21583
Panna	1	2015	-0.20010	1.15744	0.37449
Kanha and Pench	5	2015	3.38900	1.95628	4.54763
Tipeshwar	0	2015	-0.39087	-0.62651	-0.42454
Palpur_Kuno	0	2015	-0.38516	-0.28273	-0.45015
Panpatha and Bandhavgarh	3	2015	-0.20773	0.47462	-0.08705

Table 7: Continued

Patch Name	Tiger Mortality	Year	Forest (Z-Score)	Urban (Z-Score)	Agriculture (Z-Score)
Navegaon	0	2015	-0.35504	-0.61816	-0.51238
Narsinghgarh	1	2015	-0.39017	-0.76711	-0.48325
Nagzira	0	2015	-0.10716	-0.29107	-0.06777
Dehgaon	0	2015	-0.23628	2.01102	-0.11102
Satpura	2	2015	-0.21665	1.77265	0.45503
Melghat	0	2015	0.03621	1.32673	0.05527
Umred	0	2015	-0.35994	-0.41453	-0.52689
Tadoba	11	2015	0.10686	0.25242	0.53958
Sanjay Dubri	1	2015	-0.32322	-0.72638	-0.56448
Nauradehi	0	2015	-0.37686	-0.67336	-0.53119
Ratapani	1	2015	-0.34783	-0.24949	-0.56602
Dewas	1	2015	-0.32046	-0.24364	-0.30023
Bor	0	2015	-0.36998	-0.81186	-0.50680
Achanakmar	0	2016	0.04720	-0.07794	-0.17607
Panna	2	2016	-0.23596	1.24803	0.39974
Kanha and Pench	24	2016	2.78280	2.78178	5.05899
Tipeshwar	0	2016	-0.38752	-0.6695	-0.42279
Palpur_Kuno	0	2016	-0.36549	-0.17474	-0.48169
Panpatha and Bandhavgarh	7	2016	-0.07973	0.23552	-0.18746
Navegaon	0	2016	-0.34069	-0.61228	-0.52744

Table 7: Continued

Patch Name	Tiger Mortality	Year	Forest (Z-Score)	Urban (Z-Score)	Agriculture (Z-Score)
Narsinghgarh	1	2016	-0.3713	-0.28488	-0.55875
Nagzira	2	2016	-0.15769	-0.25958	-0.02078
Dehgaon	0	2016	-0.1249	0.71729	-0.07107
Satpura	0	2016	-0.23539	1.19177	0.54161
Melghat	2	2016	-0.22072	0.70256	0.38603
Umred	0	2016	-0.34614	-0.46000	-0.53533
Tadoba	11	2016	0.18200	1.47986	0.32014
Sanjay Dubri	0	2016	-0.26319	-0.77933	-0.61839
Nauradehi	0	2016	-0.38460	-0.76147	-0.51313
Ratapani	0	2016	-0.33795	-0.51608	-0.54482
Dewas	0	2016	-0.30403	-0.12703	-0.33009
Bor	1	2016	-0.37709	-0.80805	-0.50002

The tiger mortality data obtained is the count of the tigers died in that year. To find the mathematical model for establishing a relationship between tiger morality and land cover affecting it, Poisson regression was applied. Because each patch has a value for seven years, therefore, repeated measure Poisson regression was considered. Poisson regression is regular general linear model wherein the dependent (Y) variable is an observed count that follows the Poisson distribution. Thus, the possible values of Y are the nonnegative integers: 0, 1, 2, 3, and so on. It is assumed that large counts are rare. Hence, Poisson regression is like logistic regression, which also has a discrete response variable ("Poisson Regression", n.d). Using R and R-Studio (RStudio-Open source and enterprise-ready professional software for R, n.d), the combinations of all the independent variables on dependent variable were obtained.

Table 8, shows that there are in total seven models developed to test for significant effects. The first model is the combination between all the three variables together. All the models have the categorical variables such as 'Patch name' and 'Year' included with them in the combination. By doing hypothesis testing and taking confident interval of 95% and α values of 0.05. If P value ≤0.05 then the variable id significant and P value > 0.05 is insignificant. The *P*-values from the table show that the agriculture is 0.000123 and therefore, significant. The next three models have the combinations of only two variables such as forest and urban, urban and agriculture, agriculture and forest. Similarly, in these combinations, P value of agriculture is less than 0.05. The last three models have only one variable predicting the categorical variables. In the model 5, model 6 the variable forest and urban are not at all significant whereas again model 7 has only agriculture which has P value of 0.0097 and hence, significant.

Table 8: Statistical analysis table for the combinations of the independent variables.

Model	Independent variable	Estimates	Standard error	Z value	*P* value
Forest + Urban + Agriculture + (1 | PatchName) + (1 | Year)	Forest	0.4606	0.1823	2.526	0.0115
	Urban	-0.2126	1338.0	-1.589	0.1121
	Agriculture	0.6855	0.1785	3.840	0.0001
	Intercept	-1.1741	0.3906	-3.006	0.0026

Table 8: Continued

Model	Independent variable	Estimates	Standard error	Z value	*P* value
	Forest	0.4305	0.1795	2.300	0.0164
Forest+ Agriculture +(1|PatchName) +(1|Year)	Agriculture	0.6506	0.1745	3.728	0.0001
	Intercept	-1.1562	0.3799	-3.043	0.0023
	Urban	-0.2039	0.1365	-1.493	0.1353
Urban+Agriculture +(1|PatchName) +(1|Year),	Agriculture	0.4085	0.1664	2.455	0.0140
	Intercept	-1.1632	0.4218	-2.7570	0.00582
	Forest	-0.0330	0.1670	-0.1990	0.8420
Forest+Urban +(1|PatchName) +(1|Year)	Urban	-0.2245	0.13503	-1.6630	0.0963
	Intercept	-1.2660	0.5050	-2.5050	0.0122
Forest +(1|PatchName) +(1|Year)	Forest	-0.0221	0.1612	-0.1370	0.8909
	Intercept	-1.2100	0.4683	-2.5900	0.0096
Urban +(1|PatchName) +(1|Year)	Urban	-0.2231	0.1344	-1.6590	0.0971
	Intercept	-1.2627	0.1344	-2.5220	0.0117
Agriculture +(1|PatchName) +(1|Year)	Agriculture	0.4036	0.1564	2.5800	0.0099
	Intercept	-1.1254	0.3971	-2.8340	0.0046

Akaike Information Criterion (AIC)

Akaike's information criterion (AIC) compares the quality of a set of statistical models to each other. The AIC will take each model and rank them from best to worst. The "best" model will be the one that neither under-fits nor over-fits (Guthery et al, 2003). Below is the AICc table for the seven models above.

Akaike's Information Criterion is usually calculated with software. The basic formula is defined as:

$$AIC = -2(\text{log-likelihood}) + 2K \qquad \text{Equation 2}$$

Where:

- K is the number of model parameters (the number of variables in the model plus the intercept).
- Log-likelihood is a measure of model fit. The higher the number, the better the fit. This is usually obtained from statistical output.

$$w_i = \frac{\exp(-\Delta_i / 2)}{\sum_{r=1}^{R} \exp(-\Delta_i / 2)}$$

(Guthery et al, 2003) Equation 3

The ΔAIC is the relative difference between the best model (which has a ΔAIC of zero) and each other model in the set. The formula is:

$$\Delta AIC = AIC_i - \min AIC. \qquad \text{Equation 4}$$

Where:

- AIC_i is the score for the model i.
- min AIC is the score for the "best" model (Guthery et al, 2003).

The AICc Score of the first model with three combinations is 299.53 which is the least and best model. Model 1, 2 and 3 has the cumulative AICc 0.96 which indicate that 96% of the information lies in the first three models. If observed precisely, the first three model has a common variable which is agriculture and thus, AIC table indicate that the models which has agriculture is the better model compared to others.

Table 9: AIC tables for the seven models

Model	AICc	AICc Weight	Cumulative weight
Mod 1	292.53	0.48	0.48
Mod 2	293.05	0.37	0.86
Mod 3	296.51	0.07	0.93
Mod 7	296.74	0.06	0.98
Mod 6	300.28	0.01	0.99
Mod 4	302.40	0	1
Mod 5	303.21	0	1

CONCLUSION

The Bengal tiger, also known as the Royal Bengal Tiger or the Indian tiger, is the subspecies with the largest population. It is the national animal of India, a place where its image is part of the traditions and the culture ("Bengal Tiger - Tiger Facts and Information," 2016). The main threats to this species are: poaching and conflicts with humans over the territories. Poaching's aim is to illegally trade the products obtained from tigers, such as decorative objects or the active ingredient of "drugs" to cure various diseases, but which have no proven efficacy. Severely degraded by logging and invasion of humans in their territories, tiger habitat continues to decline. When tigers attack domestic animals or even humans, they unleash the wrath of people who in retaliation kill them ("Bengal Tiger - Tiger Facts and Information," 2016). But directly or indirectly tigers are related to the decreasing forest or increasing urban settlement and agriculture. Still the government or the forest official has not been able to find the unable to determine of tiger mortality. Therefore, there is more scope for further research in this area.

LULCC has been a major area of research for many years. Many scholars and researchers have been working on the different land cover such as forests, agriculture, urban lands and so on. Growing population, widespread poverty, limited employment opportunities in agricultural and industrial sector has resulted in heavy pressure on forests, primarily due to unsustainable extraction of fuel wood and over-grazing resulting in forest degradation. Hence, there should be stringent law to protect them (Joshi and Singh, 2003). Agriculture is the most important occupation for most of the Indian families. In India, agriculture contributes about sixteen percent (16%) of total GDP and ten percent (10%) of total exports. Over 60% of India's land area is arable making it the second largest country in terms of total arable land.

Using different classification techniques like fusion, band ratio, principle component analysis, supervised and unsupervised classification, the detection of land cover change has become easier. In India, land cover changes have significance because of the decline of the forests and their conversion into agriculture. Deforestation is one of the major causes to the environmental degradation which is affected by the agents like small farmers, ranches, loggers and plantation companies (Mondal, n.d.). Along with this, many wildlife species are also endangered such as tigers. Since it is an alarming situation, the Government of India has started making policies for forest and tiger preservation.

This study focuses on two sections. First, the LULCC over the years from 2009-2016 of forest, water, urban and agriculture of central India. Secondly, the effect of land change on the tiger's mortality. The classification result shows that there has been decrease in forest and increase in urban and agriculture. According to the results, the area of agriculture land is double in 2016 as compared to 2009. The accuracy of the land cover classifications in this research is quite high. The research was narrowed down to the 19 forest patches which concentrate on the tiger reserves and PAs. The observations from the repeated measure Poisson regression indicate that agriculture is an important land cover type that has effect on tiger mortality. If agriculture continues to increase, then forest shrinkage will increase leading to confinement to the movement of tigers. As a result, these big cats will interfere with the human habitation and get killed by the people.

This research of LULCC has many limitations and constraints. The images obtained were having 0.5 to 1 percent of cloud cover. All the images are taken from the winter months of India but still they had some or few percent of cloud or haze. This caused some of the clouds to be classified in urban or water. Secondly, if high resolution images were obtained, the classification result would have been more accurate. Because there wouldn't have been any confusion by the user to provide training samples for classification. For determining the forest patches used in the research there were no shape files available online. Therefore, these shape files were made by digitizing the borders of the forest using Google Earth Pro 7.1.5.

One of the objective of this study is to give suggestions to policy makers and environmentalists. Due to deforestation, the forest cover of India has fallen below the minimum recommended level. According to experts, forests should cover about one-third of the total area of country. But in India forests covers around 24% of the total area (Mehta, 2016). There are an estimated 300 million people living as shifting cultivators who practice slash and burn agriculture and are supposed to clear more than 5,000,000 ha of forests for shifting cultivation annually (Mondal, n.d.). There has been many non-governmental organization working in this field but none of them have got any support from the government. There have been laws made once in every five years but Government pays attention to them. There should be an education or awareness program for the tribes, forest dwellers and urban cities or township near the forest boundaries. They should be educated on how forests and their resources are inseparable from their life, how eco-cycle works and if deforestation continues then what they will face in the future. The boundaries of the forests should be protected strictly. There should be more security in the buffer zones so that there should be no provision for encroachment and trespassing, illegal settlement and habitation. According to Dutta et.al (2015), among those 19 forest patches, few are located quite close and therefore, tigers use existing forest corridors to move from one patch to another. But urban settlement and agriculture expansion has started destroying them too. The principle of sustainable development must be recognized and emphasis on Environmental Impact Assessment is needed. Because India is a developing country, it concentrates on the socio-economic development but it must be in coordination with environmental upgradation. Though the Environmental (Protection) Act is very ambitious and maintained different components of the environment in India, environment protection has been dominated more by socio-economic constraints and the priority of development.

The existing legal provisions are inadequate to control the enormous problems of environmental pollution of various types in the country. Therefore, the judiciary must play a more active and constructive role. Environmental law should be implemented effectively by adopting new instruments, mechanisms and procedures like environmental impact assessment and environmental audit.

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