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Geo-spatial Estimation and Forecasting of LULC Vulnerability Assessment of Mining Activity: A Case Study of Jharia Coal Field, India

Ajay Kumar* **and Amit Kumar Gorai**

Department of Mining Engineering, National Institute of Technology, Rourkela, India

***Corresponding author:** Ajay Kumar, Department of Mining Engineering, National Institute of Technology, Rourkela, India, Tel: +91 8797666963; E-mail: ajay3789@gmail.com

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Abstract

Coal is natural deposit minerals and vestibules effect in environment due to operation of mine. Preliminary phase is reconnaissance survey for extraction of coal ores and after that, next operation is happen. In addition, Mining has considered as an eco-unfriendly in natural action but in recent scenarios of Indian coal mines production is very hugs rate with undisciplined nature accompanied by large volumes of hazardous solid, liquid and gaseous material during various mining and related activities. Global aided for the eco-system of mining, associated activities in mining complexes, minimization prevention and extenuation of these encroachments. There are applying geospatial approaches for most important classified classes related to mining activity of land use land cover (LULC) estimation from landsat of four-year data. Vulnerability assessment of classified classes and forecasting of spatial data in future likes features agricultural land, forest, vegetation, mine plantation, scrub land, open cast mine, abandoned mine pit, overburden dump, settlement and water body respectively. It has focused on spatial feature change due to mining activities and mainly use to a case study of Jharia coalfield (JCF), Jharkhand.

Keywords: Land use land cover; JCF; Landsat data; GIS

Introduction

Major block of coal is a notified and development area blocks of Dhanbad district in Jharkhand state, India. It has played a very important role in the economy and development of Dhanbad city and famous for ample coal resources, used to make coke. The coal fields are covering with produces bituminous coal suitable for coke and most of India coal comes from Dhanbad lies in the near of damodar river valley and badakar river. However, its surface and subsurface coal fire is the major problem here like many coal-producing countries as China, Australia, Canada, etc., coal fire results from man-made activities, accident, forest fire, lighting strike etc., [1,2]. Jharia coalfield (JCF) are experiencing an environmental and social decline characterized by acceleration in degradation of the natural resources, expansion of agricultural area, rapid population growth, and deterioration in the quality of life. Coal are the major fossil fuel use in power generation and for producing more and more coal for mining activities increasing day by day [3,4]. Coal mining activities are leads to environmental changes largely such as degradation in quality of air, water, soil, changes in landform, land use land cover (LULC) and vegetation distribution. They has wide spread, accelerated and significant processes been driven by human actions but also produce changes that influence humans [5,6]. The patterns are one of the important parameters, which depict this change [7] and change detection in land use and land cover can be performed on a temporal scale such as a decade to assess landscape change cause due to anthropogenic activities on the land [8]. The satellite remote sensing data is helps in quantification of LULC patterns and determines their changes with time [9-13]. A Geographical information system (GIS) has used as an effective tool for managed secondary data necessary to analyses and documents the spatial changes [14,15]. Mapping of vegetation in mountain areas based on remote sensing is obstructs by atmospheric and topographic distortions. There are various methods for correction of atmospheric and topographic to minimize effects and principle lead to a better land cover classification [16,17]. Only a limited number of atmospheric and topographic combinations have being tests with the effect on class accuracy in different illumination conditions applied to researched extensively not yet. Moreover, ecologically sensitive environments research is challenging due to heterogeneous relief and high altitude, quantifying changes in vegetation photosynthetic activity using remote sensing can provide essential information regarding trends in vegetation cover. It is linking with anthropogenic impacts [18-22], managing the impacts of land use change is essential for ecosystem services to secure human well-being, a task often complicated by landscape-scale spatial dynamics [23]. The process of a dynamics multisite interaction for a change in the supply or use of an ecosystem service at one site affects that service at a second site [24,25]. A high value ecosystem has faced large-scale human induced land use cover change (LUCC), but they are quantitative data to time lacking. A combination of ancillary data and satellite imagery has interpreted to construct dynamics of LUCC for the last century [26-28]. An intensity analysis is a top-down hierarchical accounting framework to differences among categories, such as changes in land categories over time. Some aspects of interpretation are straightforward, while other aspects require deeper thought [29-31]. A challenging of analysis and monitoring in mountainous terrain of LUCC due to field based research. Landscape has increases in fragmentation the period under analysis, revealing a heterogenization trend, the adoption of similar human practices in the last decades and different levels of climatic, agricultural, demographic, political and socioeconomic change detected [32-34]. The ecological richness of the region, which coincides with heightened human population pressure, necessitates the monitoring of land change as input for improving land use planning with focus on conserving biodiversity [35,36]. Sensors on landsat satellites have been collecting images of the earth's surface for nearly 40 years and valuable for characterizing and detecting changes in the land cover and land use of the world [37-39]. For evaluating land cover conditions change in response to potential land use or climate driving variables, or the impact of land changes for carbon balance and other ecosystem processes [40-42]. The recent free availability of landsat historical data provides new potentials for LUCC studies and multi-temporal studies require a previous radiometric and geometric homogenization of input images to better identify true changes [43]. Topographic normalization is one of the key steps to create consistent and radiometric resolution stability of multi-temporal time series since, a terrain shadows change throughout time. The functions of the LULC is formal statistical survey methods a very complex, time consuming and wealthy. Moreover, land surveys is long and complicated in some areas likewise, as mentioned earlier, now modern LULC patterns requires a support updating of the existing land use maps of the area. Remote sensing applications has applied to low and high resolution imaginary data, multi temporal and multi spectral synoptic coverage for any area of interest. They are use of available data in a desires area at any given duration with executions for verification and review of the land use patterns [44]. They are download of acquisition data in form of pixel, enormous flexibility and applied in GIS application exposes a logically and an easy with the function to use multi-disciplinary data for interpretations. Moreover, it is use to beneficiary with a time comfort and minimization cost, although provides services and information for mapping a range of LULC at a variety of geo spatial and multi temporal scales [45]. They have applied for a validation of the used LULC map against some ground reference data set and divergences between the two data sets interpreted of debug errors, moreover reduces the error in image classification [46]. They have used of calculation in LULC analysis derived by combining several maximum likelihood classifications with a modal classification algorithm based on remote sensing data.

A statistical analysis of the land cover change reveals clear tendencies of land cover change distribution [47] with in at JCF, India. Thus, regions with higher imperviousness show higher mean land cover change with less variance (operation of mines), compared to regions with a bigger amount of impacts of mines operation. The methods used present an advanced application and combination of remote sensing data and GIS, with a large area and high quality data set. There are many features of spatial information easily get in proper manner into for a particular non-hazards situation.

Research Methodology

This research article is aims the status of LULC classification accuracy assessment and forecasting. It has done an investigates statistical relationships between LUCC, Landsat series imagery, where the conversion of development leads to dynamic processes, acting on the spatial aggregation of various LUCC types and impact of mining activities on the environment [48,49]. The natural and human factors both are appoint to explain the important changes of natural vegetation at JCF, mainly driven by the expansion of coalmines. Land use change has significant, widespread and long-lasting impacts on ecosystem services the ecological attributes and functions that contribute to human well-being. For example, tropical deforestation negatively influences climate regulation open cast mining and nature-based recreation. For long-term human is well-being securing ecosystem services requiring on effective land management and the task need to knowledge of the pathways through which land use change impacts the supply of ecosystem services and their use by human beneficiaries. It is parting of some activity in mining operation at open cast and land use change of modification and corroborated. They are part of their environment, act upon human necessitate and urbanization, changes environmental quality and cultural experiences. This understands of how land use change impacts ecosystem services often used to inform land management decisions [50,51]. The impacts of LUCC on ecosystem services are spatially dynamic and dependent on environmental and socio-economic landscape context and degradation of land cover as an ecosystem variable, our cognition of land cover and dynamics in poor [52,53]. Surveying is the significance of LULC and predicting the effects of LUCC in particularly limited by the dearth of accurate land cover data. Such data, especially in map form are averse to popular belief in some quarters, land the most important natural resources, which comprises of soil, water and the associated fauna and flora, thus involving the total ecosystem [54]. Land use has the intended employment of land management strategy placed on the land cover by land managers or human agents to exploit the land cover and reflects human activities such as industrial zones, residential zones, agricultural fields, grazing, logging and mining among many others [55,56].

Location of case study area and physical geography

JCF area a part of Dhanbad, Jharkhand, India and lies between 23°37'3" N to 24°4' N latitude and 86°45'21"E to 86°50'31" longitude. It is linking with a transportation road to NH_2 and approximately 260 km west of Kolkata and total covers area of about 393 sq. km and neighbor district are Asansol, Bokaro, Giridih, Jamtara (Figure 1). It has divided into three natural divisions,

- North and North-West portions consisting of the hilly,
- Highland containing coal mines and most of the coal mines,
- Remains highland and plains lying to south of the damodar river consisting of agriculture lands.

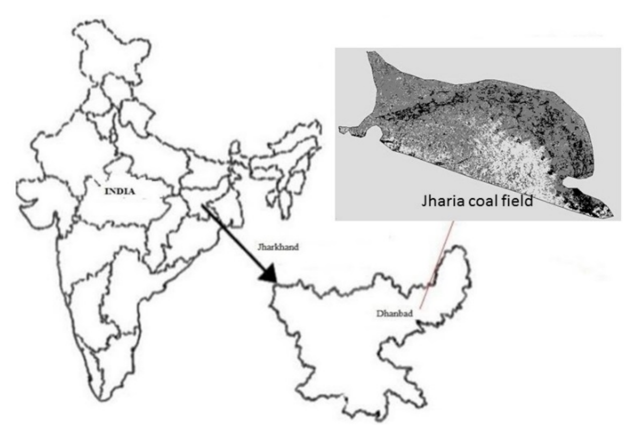

Figure 1: Location for Case Study of JCF, India.

Geospatial methodology and materials

Geospatial protocol is vital role for LULC studies and analysis of mining environment at JCF, Jharkhand. Moreover, it is two main themes, for identifying the time sequential changes in LULC patterns shown in Figure 2. Preliminary methodology adapted to preprocessing, digitization of toposheet at 1: 50,000 scales obtain from Survey of India to serve as the base maps. They are putting in satellite imaginary data to the GIS user interface, digitization of all other relevant maps and data likes geological, structural, topographic, land-use, registration and geo-referencing of all data sets [57].

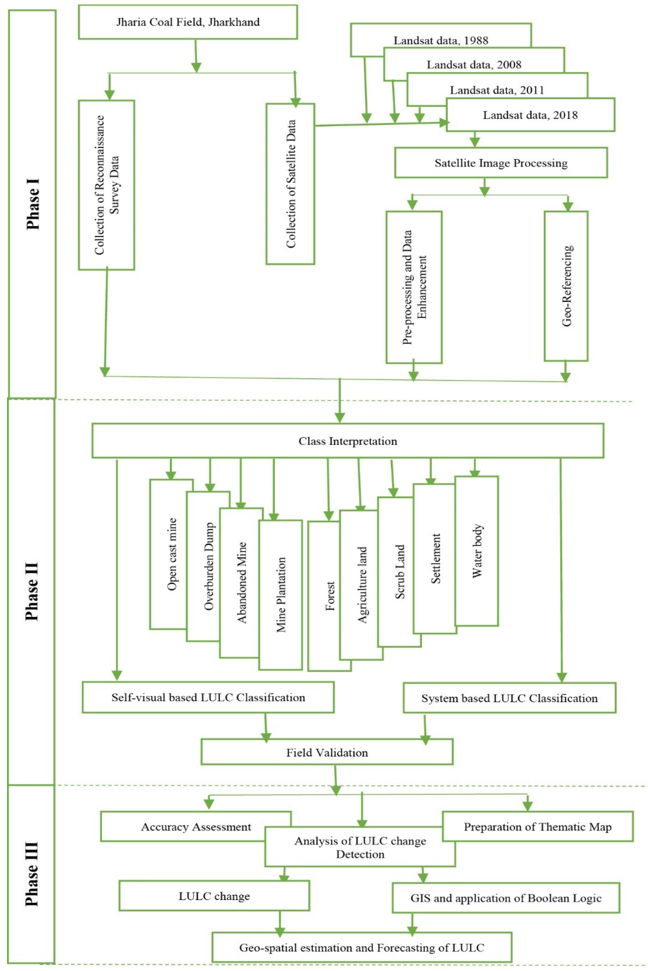

Figure 2: Methodology of geo-spatial estimation and forecasting of LULC.

Secondary Processing has involved application of various GIS functions and advanced digital image processing techniques including contrast manipulation, edge enhancement, color compositing, density-slicing, color-coding, ratio image generation, principal component analysis, overlay and logical operations etc., [58,59]. Thus, it is use to process of LULC due to operation of mines with change predication.

Data accusation and validation protocol

The underlying are raster data of landsat series of 1988, 2008, 2011, 2018 scenes of spatial resolution (30 m). They have geometrically corrected with ground control points that evenly distributed in space and the root mean square error within a pixel and atmospheric correction performed through the FLAASH module, available in the ENVI 4.0 software. The atmospheric correction removed the influence of aerosols that affect reflectance values primarily in the short wavelength regions of the electromagnetic spectrum. An investigating of spatial features from ground truth to raster data pixel wise identification and validation of visual interpretation with satellite data with real world [60]. Some characteristics are fully involve in LULC for classification of classes defines are following characteristics as (define as tone) an intensity of electromagnetic radiation reflected/emitted by the terrain; (define as texture) the frequency of tonal change on an image; (define as shape) the geometric arrangements of the image features; (define as size) the dimension of the image features; (define as pattern) the spatial arrangement of objects; (define as shadows) interpretation capability depending on the situation [61,62]. They are reflecting less light with contact with a dark tone object and an identification of objects within the shadow difficult. (defines as association) as a features with respect to other objects or features helps to narrow down the possible option of classes to features, (define as site or location) helps to identify the occurrence of a particular object [63]. There are an area of low reflectance appears as dark grey tones, while higher reflectance areas as light tones in a black and white photograph. It does carry out of prone information of LULC and overview idea of future discrimination.

LUCC and spatial clustering features change

Land cover refers to the material present in the particular terrain e.g., agricultural land, forest, vegetation, mine plantation, scrub land, open cast mine, abandoned mine pit, overburden dump, settlement and water body from land transformations. Although land use has generally inferred based on the cover, yet both the terms LULC been closely related are interchangeable [64,65]. Land refers to man activities on land utilitarian in nature, whereas land cover denotes to mining activity and visual interpretation technique for the detection, identification, delineation and characterization of LUCC types occurring in the physiological study area. The remote sensing images are analyzing and utilizing a variety of observable elements of a spectrum like size, shape, shadow, tone or color, texture, repetition of pattern, site, association and resolution [66]. In the interpretation of the data, the false color composite paper prints has checked with the help of light table. A classification scheme is being finalization after careful scrutiny of the satellite data and the ancillary information gathered during the course of field surveys. Efforts has made to visit the study area several area times to verify the classification of LUCC features delineated and depicted in the satellite imageries. After careful scrutiny of final map preparation [67,68]. The base map has prepared using survey of India topographical sheets in 1:50,000 scale and important land features like roads, rivers, railway lines etc., has marked on the base maps. The details of the satellite imageries have transferred on the tracing films using simple light table. The final maps contained borders, legends and titles. Since the verification of the LULC features physically on the ground, as depicted on satellite imageries of earlier dates not possible. The rate of change in the various LULC categories are varying very fast and apart from mining, industrial development, a large part of forests alarmingly damaged by other anthropogenic activities, which is legal and illegal firewood and timber collection overgrazing by cattle, extension of urban area. It has based on image signatures; supervised classification and final estimation of LULC coverage of the existing study area has recorded from the year of 1988 to 2018.

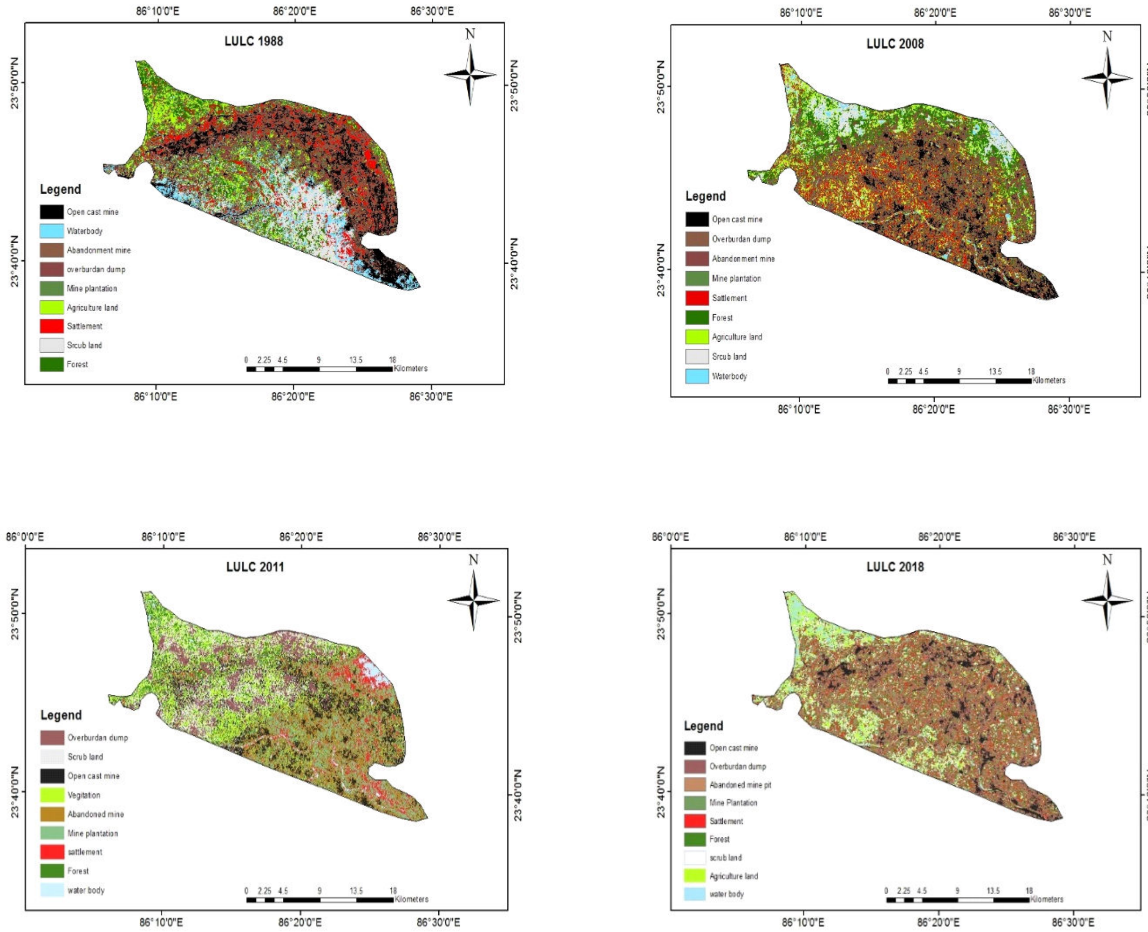

Figure 3: LULC of Landsat Data series of year 1988, 2008, 2011 and 2018.

Spatial Boolean logic for an accuracy assessment of raster data

Spatial Boolean logic matrix for accuracy assessment [69] towards change in spatial matrix detection row implies the 'i' types at time at time t1 and column implies the 'j' types at time t_2 or condition usually not only does i=j, but the indicates sets of spatial features classes at t_1 and t_2 are identical. The matrix has proceeding according equation (1) and (2) in the change of spatial features classes and deals with the areas which were type K_i at time t_1, and category K_j at t_2. If types 1 to i correspond to types 1 to j, then for each types, the area that has remained unchanged given by the diagonal elements shown in Table 1. Now indicates of process types K_1, the area unchanged is given by $RK_{1,1,}$ the area of K_1 which has become K_2 is given by the element $RK_{1,2}$, and the area of K_1 that has become K_n is given by Loss (K_1). Other way, the area that is gain, of land cover K_1 is the sum of all off-diagonal elements in the column K_1, an area lost from one cover type is gain by another. The application of Boolean logic in accuracy assessment matrix deals a Boolean mapping of the LULC in the study area.

An accuracy assessment is important part of classification of geospatial data set and most of appropriate application use to confusion matrix principle [70,71]. It has used mainly to get basic details of thematic map accuracy and for the comparison of accuracies between them. It has occurred more considerably information in the confusion matrix application after applied into comparison shown in Table 2 and Figure 3.

$$Decrease(K_1) = \sum_n^j RK_{1,n} - RK_{1,1} \qquad (1)$$

$$Increases(K_1) = \sum_n^i RK_{n,1} - RK_{1,1} \qquad (2)$$

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	Time (ti) {1988,2008, 2011,2018}									
Time (ti) {1988,2008, 2011, 2018}		**OCM**	**OBD**	**AM**	**MP**	**F**	**AL**	**SL**	**S**	**WB**
	OCM	$R_{OCM \rightarrow OCM}$	$R_{OCM \rightarrow OBD}$	$R_{OCM \rightarrow AM}$	$R_{OCM \rightarrow MP}$	$R_{OCM \rightarrow F}$	$R_{OCM \rightarrow AL}$	$R_{OCM \rightarrow SL}$	$R_{OCM \rightarrow S}$	$R_{OCM \rightarrow WB}$
	OBD	$R_{OBD \rightarrow OCM}$	$R_{OBD \rightarrow OBD}$	$R_{OBD \rightarrow AM}$	$R_{OBD \rightarrow MP}$	$R_{OBD \rightarrow F}$	$R_{OBD \rightarrow AL}$	$R_{OBD \rightarrow SL}$	$R_{OBD \rightarrow S}$	$R_{OBD \rightarrow WB}$
	AM	$R_{AM \rightarrow OCM}$	$R_{AM \rightarrow OBD}$	$R_{AM \rightarrow AM}$	$R_{AM \rightarrow MP}$	$R_{AM \rightarrow F}$	$R_{AM \rightarrow AL}$	$R_{AM \rightarrow SL}$	$R_{AM \rightarrow S}$	$R_{AM \rightarrow WB}$
	MP	$R_{MP \rightarrow OCM}$	$R_{MP \rightarrow OBD}$	$R_{MP \rightarrow AM}$	$R_{MP \rightarrow MP}$	$R_{MP \rightarrow F}$	$R_{MP \rightarrow AL}$	$R_{MP \rightarrow SL}$	$R_{MP \rightarrow S}$	$R_{MP \rightarrow WB}$
	F	$R_{F \rightarrow OCM}$	$R_{F \rightarrow OBD}$	$R_{F \rightarrow AM}$	$R_{F \rightarrow MP}$	$R_{F \rightarrow F}$	$R_{F \rightarrow AL}$	$R_{F \rightarrow SL}$	$R_{F \rightarrow S}$	$R_{F \rightarrow WB}$
	AL	$R_{AL \rightarrow OCM}$	$R_{AL \rightarrow OBD}$	$R_{AL \rightarrow AM}$	$R_{AL \rightarrow MP}$	$R_{AL \rightarrow F}$	$R_{AL \rightarrow AL}$	$R_{AL \rightarrow SL}$	$R_{AL \rightarrow S}$	$R_{AL \rightarrow WB}$
	SL	$R_{SL \rightarrow OCM}$	$R_{SL \rightarrow OBD}$	$R_{SL \rightarrow AM}$	$R_{SL \rightarrow MP}$	$R_{SL \rightarrow F}$	$R_{SL \rightarrow AL}$	$R_{SL \rightarrow SL}$	$R_{SL \rightarrow S}$	$R_{SL \rightarrow WB}$
	S	$R_{S \rightarrow OCM}$	$R_{S \rightarrow OBD}$	$R_{S \rightarrow AM}$	$R_{S \rightarrow MP}$	$R_{S \rightarrow F}$	$R_{S \rightarrow AL}$	$R_{S \rightarrow SL}$	$R_{S \rightarrow S}$	$R_{S \rightarrow WB}$
	WB	$R_{WB \rightarrow OCM}$	$R_{WB \rightarrow OBD}$	$R_{WB \rightarrow AM}$	$R_{WB \rightarrow MP}$	$R_{WB \rightarrow F}$	$R_{WB \rightarrow AL}$	$R_{WB \rightarrow SL}$	$R_{WB \rightarrow S}$	$R_{WB \rightarrow WB}$

Table 1: Model of Boolean logic of an accuracy assessment.

Further, it has enhanced the value of the classification for the user and possible to use the matrix to help optimize the thematic map for a particular user [72]. Thus, the confusion matrix useful for information on the actual costs of errors and other side the value of the map to optimize a classification for general application in estimation of accuracy assessment shown in Table 3. They have applied confusion matrix and obtained overall classification accuracy 80-90% and according to case of LULC, classification for remote sensing data accuracy has considered strong [73].

Trend time of LULC change classes

Operation of mines has used of trend analysis from LULC change of classes as agricultural land, forest, vegetation, mine plantation, scrub land, open cast mine, abandoned mine pit, overburden dump, settlement and water body with correlation co-efficient value (R^2) value likes for year 1988-2018 and 2028 [74]. A trend line is most reliable when its correlation co-efficient value (R^2) is at or near 1. Regression analysis is widely used for prediction and forecasting. The equation for linear regression trend is as follows:

$$Y_i = MX_i + M_o + \epsilon_i \qquad (3)$$

Where, Y_i is the number to be calculated, X_i is the dependent variable, in this case it is the year, M is the slope of the line and M_o is the Y-axis intercept of the line and ϵ_i is the random error with mean zero. After that the least squares regression line is obtained by finding the values of M and M_o values that will minimize the sum of the squared vertical distances (Δ) from all points to the line.

Confusion Matrix (1988)	**Open cast mine**	**Overburden Dump**	**Abandoned Mine**	**Mine Plantation**	**Forest**	**Agriculture land**	**Scrub Land**	**Settlement**	**Water body**	**X_{i+}**
Open cast mine	62	2	0	1	4	0	1	1	0	71
Overburden Dump	0	28	0	0	3	1	0	0	1	33
Abandoned Mine	1	2	23	0	0	2	0	0	2	30
Mine Plantation	3	0	1	19	1	0	2	2	0	28
Forest	0	1	0	0	78	1	0	0	0	80
Agriculture land	3	4	0	0	1	67	0	0	0	75
Scrub Land	1	0	1	0	1	0	69	0	1	73
Settlement	1	0	0	0	0	1	0	39	1	42
Water body	0	0	0	1	0	0	0	0	13	14
X_{+i}	71	37	25	21	88	72	72	42	18	446
Confusion Matrix (2008)	**Open cast mine**	**Overburden Dump**	**Abandoned Mine**	**Mine Plantation**	**Forest**	**Agriculture land**	**Scrub Land**	**Settlement**	**Water body**	**X_{i+}**
Open cast mine	72	1	1	2	2	0	1	1	0	80

Overburden Dump	3	27	0	0	0	1	0	0	1	32
Abandoned Mine	0	1	28	2	2	0	2	0	0	35
Mine Plantation	0	2	0	18	0	0	0	0	1	21
Forest	2	0	1	0	76	2	2	0	2	85
Vegetation	1	0	1	0	1	65	0	0	3	71
Scrub Land	2	1	0	1	0	0	63	0	0	67
Settlement	0	0	0	0	0	0	0	45	1	46
Water body	0	0	0	0	1	2	0	0	11	14
X_{+i}	80	32	31	23	82	70	68	46	19	451
Confusion matrix (2011)	**Open cast mine**	**Overburden Dump**	**Abandoned Mine**	**Mine Plantation**	**Forest**	**Agriculture land**	**Scrub Land**	**Settlement**	**Water body**	**X_{i+}**
Open cast mine	69	1	1	0	0	0	4	1	1	77
Overburden Dump	2	28	0	0	0	3	0	0	1	34
Abandoned Mine	0	1	25	3	1	0	1	0	0	31
Mine Plantation	1	0	1	31	0	1	3	0	0	37
Forest	0	1	0	1	61	2	0	1	1	67
Agriculture land	2	1	1	2	0	55	1	0	2	64
Scrub Land	0	1	3	1	3	2	57	0	1	68
Settlement	0	0	0	1	0	0	0	48	1	50
Water body	0	0	0	0	1	1	1	0	12	15
X_{+i}	74	33	31	39	66	64	67	50	19	443
Confusion matrix (2018)	**Open cast mine**	**Overburden Dump**	**Abandoned Mine**	**Mine Plantation**	**Forest**	**Agriculture land**	**Scrub Land**	**Settlement**	**Water body**	**X_{i+}**
Open cast mine	70	5	1	4	4	0	2	1	0	87
Overburden Dump	0	29	0	0	2	0	1	0	0	32
Abandoned Mine	1	0	35	0	0	1	0	0	0	37
Mine Plantation	0	0	0	20	2	0	1	0	0	23
Forest	0	1	2	0	89	0	0	0	1	93
Agriculture land	2	0	0	2	0	70	1	1	1	77
Scrub Land	0	1	1	0	1	1	68	0	0	72
Settlement	1	0	0	0	0	1	0	47	0	49
Water body	0	0	0	0	0	0	0	0	15	15
X_{+i}	74	36	39	26	98	73	73	49	17	485

Table 2: Confusion matrix of year 1998, 2008, 2011 and 2018.

$$\Delta = \Sigma d^2 = \Sigma(Y_i - \hat{Y}_i)^2 = \Sigma(Y_i - MX_i - M_o - \epsilon_i)^2 \qquad (4)$$

The solutions are found by solving the equations (3) and (4), $\frac{\partial \Delta}{\partial M_o} = 0$ and $\frac{\partial \Delta}{\partial M_i} = 0$

The fitted least squares regression line $\hat{Y}_i = \widehat{M} X_i + \widehat{M}_o \qquad (5)$

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$$\widehat{M} = \frac{S_{xy}}{S_{xx}} \text{ and } \widehat{M}_o = \bar{Y} - \widehat{M}\bar{X}S_{xy} = \Sigma XY - \frac{\Sigma X \Sigma Y}{n}$$

$$= \Sigma(X_i - \bar{X})(Y_i - \bar{Y})$$

$$S_{xx} = \Sigma XX - \frac{\Sigma X \Sigma X}{n} = \Sigma(X_i - \bar{X})(X_i - \bar{X})$$

The sum of squares, Total sum of squares (SST)=Regression sum of squares (SSR)+Error sum of squares (SSE)

$$SST = \Sigma(Y_i - \bar{Y})^2;\ SSR = \Sigma(\hat{Y}_i - \bar{Y})^2;\ SSE = \Sigma(Y_i - \hat{Y})^2$$

Finally, it can carry out coefficient of correlation from the regression goodness of fit (R^2).

$$R^2 = \frac{SSR}{SST},\ 0 \le R^2 \le 1 \qquad (6)$$

Year	1988						2011					
Class	Producer Accuracy (%)	User Accuracy (%)	Overall accuracy	Kappa	commission error	omission error	Producer Accuracy (%)	User Accuracy (%)	Overall accuracy	Kappa	commission error	omission error
Open cast mine	87.3	87.3	89.2	0.875	12.7	12.7	89.6	93.2	87.1	0.852	6.8	10.4
Overburden Dump	84.8	75.7			24.3	15.2	82.4	84.8			15.2	17.6
Abandoned Mine	76.7	92			8	23.3	80.6	80.6			19.4	19.4
Mine Plantation	67.9	90.5			9.5	32.1	83.8	79.5			20.5	16.2
Forest	97.5	88.6			11.4	2.5	91	92.4			7.6	9
Agriculture land	89.3	93.1			6.9	10.7	85.9	85.9			14.1	14.1
Scrub Land	94.5	95.8			4.2	5.5	83.8	85.1			14.9	16.2
Settlement	92.9	92.9			7.1	7.1	96	96			4	4
Water body	92.9	72.2			27.8	7.1	80	63.2			36.8	20
Year	**2008**						**2018**					
Class	**Producer Accuracy (%)**	**User Accuracy (%)**	**Overall accuracy**	**Kappa**	**commission error**	**omission error**	**Producer Accuracy (%)**	**User Accuracy (%)**	**Overall accuracy**	**Kappa**	**commission error**	**omission error**
Open cast mine	90	87.3	89.8	0.882	12.7	10	80.5	94.6	93.1	0.9	5.4	19.5
Overburden Dump	84.4	84.4			15.6	15.6	90.6	80.6			19.4	9.4
Abandoned Mine	80	90.3			9.7	20	94.6	89.7			10.3	5.4
Mine Plantation	85.7	78.3			21.7	14.3	87	76.9			23.1	13
Forest	89.4	92.7			7.3	10.6	95.7	90.8			9.2	4.3
Agriculture land	91.5	92.9			7.1	8.5	90.9	95.9			4.1	9.1
Scrub Land	94	92.6			7.4	6	94.4	93.2			6.8	5.6
Settlement	97.8	97.8			2.2	2.2	95.9	95.9			4.1	4.1
Water body	78.6	57.9			42.1	21.4	100	88.2			11.8	0

Table 3: Accuracy report of LULU time series data.

Citation: Kumar A, Gorai AK (2018) Geo-spatial Estimation and Forecasting of LULC Vulnerability Assessment of Mining Activity: A Case Study of Jharia Coal Field, India. J Remote Sens GIS 7: 253. doi:10.4172/2469-4134.1000253

Results and Discussion

Satellites data studies depicted that impact of coalmine has both expands increases and decreases. Due to the mining operation of the area have been changed agricultural land, forest, vegetation, mine plantation, scrub land, open cast mine, abandoned mine pit, overburden dump, settlement and water body which have depends on geospatial analysis (Figure 4).

Comparison of spatial feature change of satellite image

There is trend time change pattern of spatial feature in agricultural land, forest, vegetation, mine plantation, scrub land, open cast mine, abandoned mine pit, overburden dump, settlement and water body likes in year wise as classified classes from 1988-2018 respectively [75,76]. In addition, it is deal of comparison between two spatial features change and represented into spatial picture change in year 1988 between 2008 shown in Figures 4 and 5, 2008 between 2011 shown in Figure 6, 2011 between 2018 shown in Figure 7 and 1988 between 2018 shown in Figure 8.

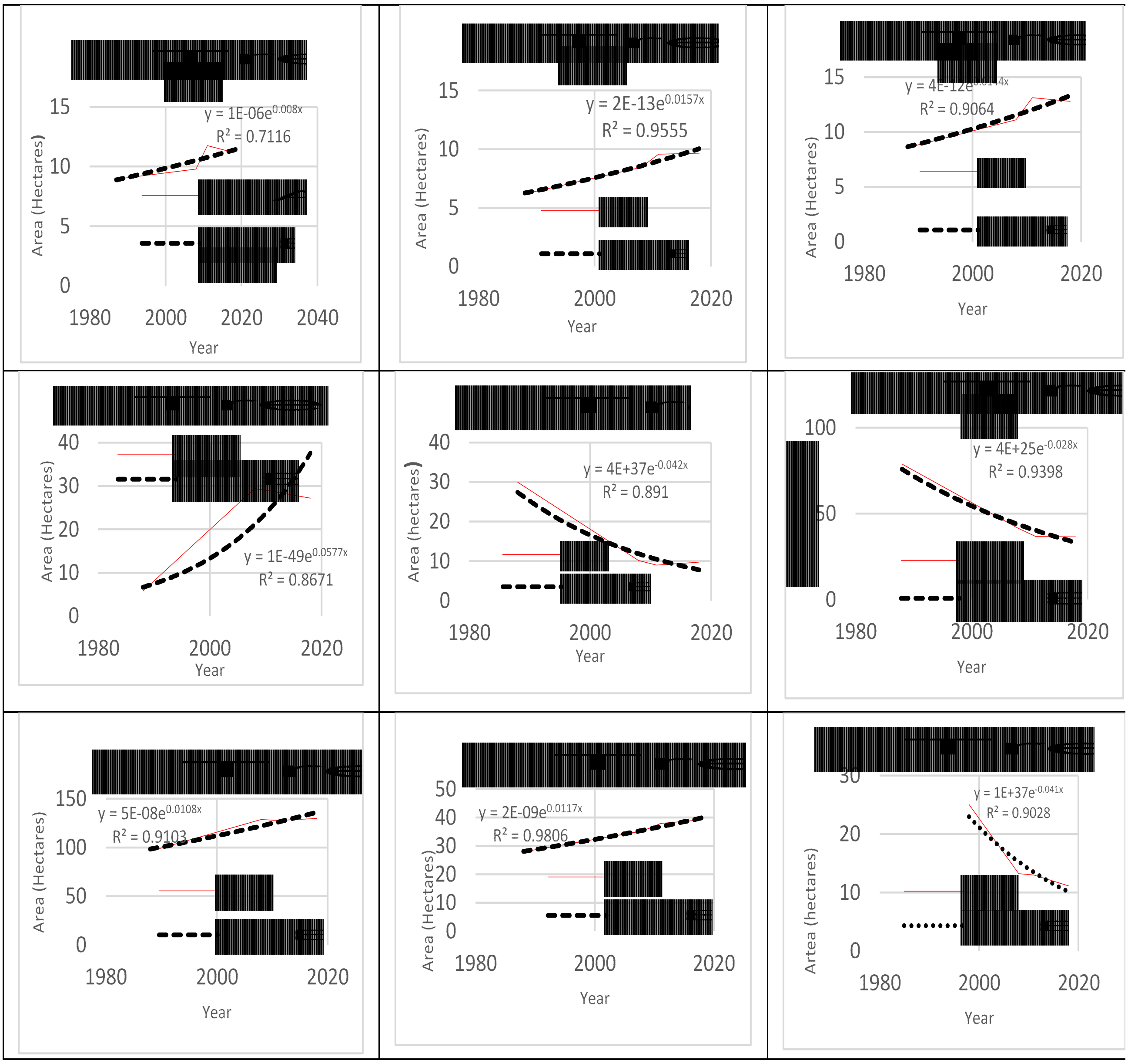

Figure 4: Trend time graph for next forecasting classes change of open cast mine, overburden dump, abandoned mine pit, mine plantation, forest, agricultural land, scrub land, settlement and water body.

Citation: Kumar A, Gorai AK (2018) Geo-spatial Estimation and Forecasting of LULC Vulnerability Assessment of Mining Activity: A Case Study of Jharia Coal Field, India. J Remote Sens GIS 7: 253. doi:10.4172/2469-4134.1000253

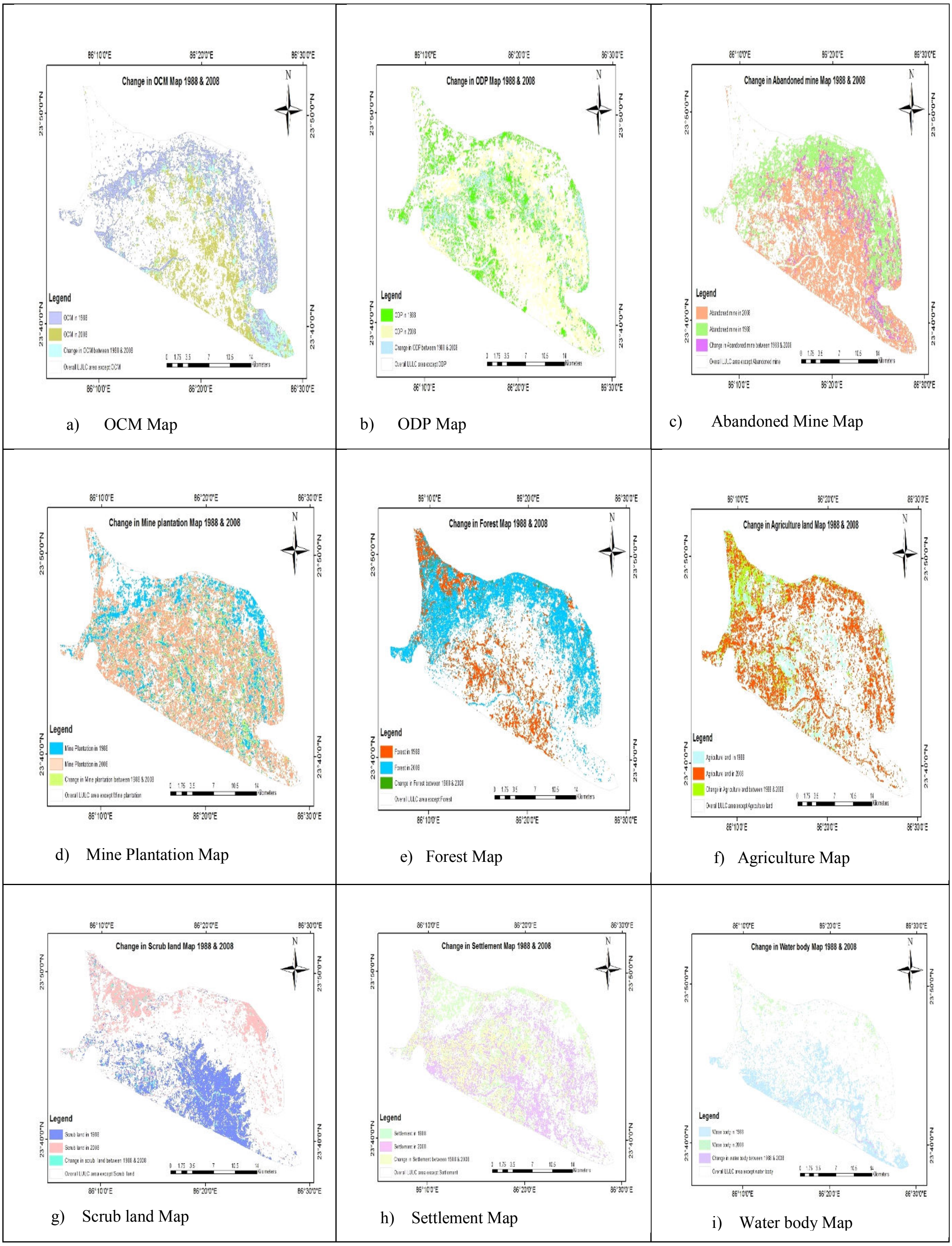

Figure 5: Change in year 1988 between 2008 of spatial feature classes Map likes a) OCM, b) ODP, c) Abandoned Mine, d) Mine Plantation, e) Forest, f) Agriculture, g) Scrub land, h) Settlement and i) Water body Respectively.

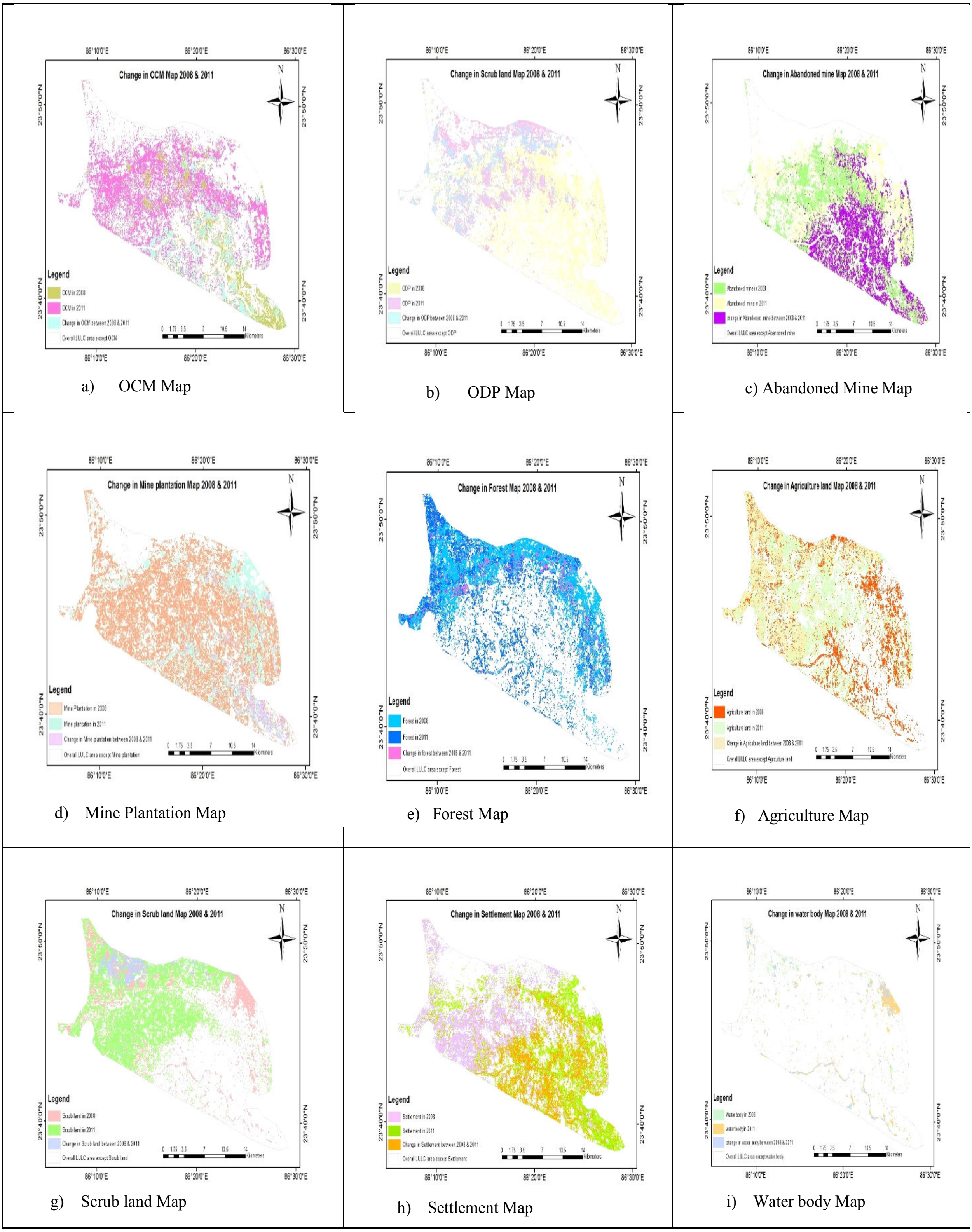

Figure 6: Change in year (2008 between 2011) of spatial feature classes Map likes a) OCM, b) ODP, c) Abandoned Mine, d) Mine Plantation, e) Forest, f) Agriculture, g) Scrub land, h) Settlement & i) Water body Respectively.

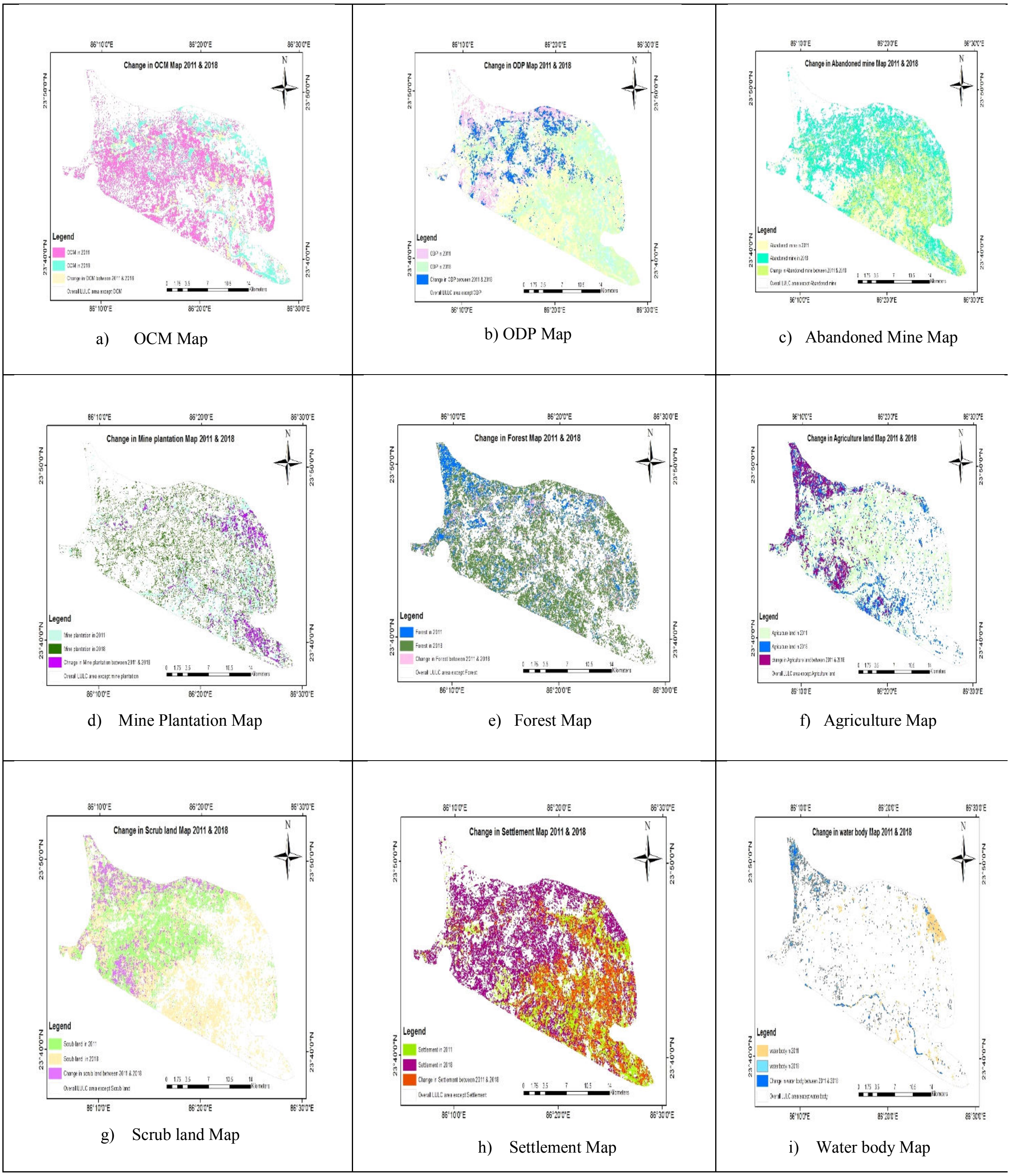

Figure 7: Change in year (2011 between 2018) of spatial feature classes Map likes a) OCM, b) ODP, c) Abandoned Mine, d) Mine Plantation, e) Forest, f) Agriculture, g) Scrub land, h) Settlement and i) Water body Respectively.

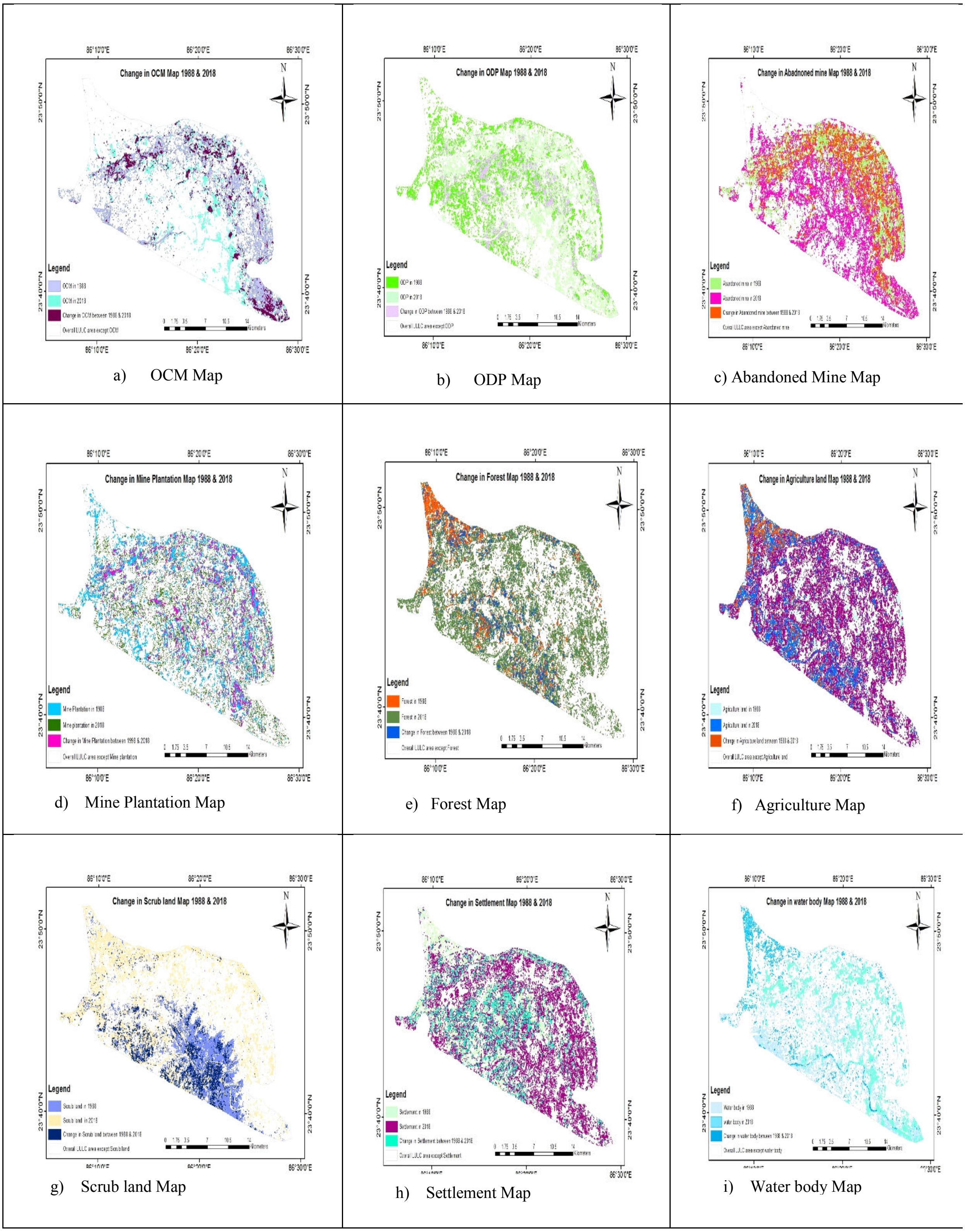

Figure 8: Change in year (1988 between 2018) of spatial feature classes Map likes a) OCM, b) ODP, c) Abandoned Mine, d) Mine Plantation, e) Forest, f) Agriculture, g) Scrub land, h) Settlement and i) Water body Respectively.

Estimation and Forecasting of LULC

According to actual map of consistent area of LULC classes from 1988, 2008, 2011 and 2018 carried out of spatial feature area in hectares and applying average moving method for forecasting of next year of corresponding change in hectares shown in Table 4. There are obtained result of predicating year 2028 using 3MA, with MAPE error is less and acceptable for comparable with trend time change graph shown in Figure 4.

Change Estimation and Forecasting of LULC 2028							
Year	LULC classified classes	Area (Hectare)	3 Year Moving Average (3MA)	Forecast Error	|Forecast Error|	Mean Square Error (MSE)	Mean Absolute Percentage Error (MAPE)
	Open cast mine	8.98					
	Overburden Dump	6.21					
	Abandoned Mine	8.59					
	Mine Plantation	5.78					
	Forest	29.97					
	Agriculture land	78.94					
	Scrub Land	96.23					
	Settlement	27.97					
1988	Water body	24.98					
	Open cast mine	9.78					
	Overburden Dump	8.45					
	Abandoned Mine	11.1					
	Mine Plantation	29.41					
	Forest	10.13					
	Agriculture land	41.56					
	Scrub Land	128.78					
	Settlement	35.23					
2008	Water body	13.21					
	Open cast mine	11.74					
	Overburden Dump	9.58					
	Abandoned Mine	13.12					
	Mine Plantation	28.78					
	Forest	8.97					
	Agriculture land	36.76					
	Scrub Land	127.79					
	Settlement	37.94					
2011	Water body	12.97					
	Open cast mine	11.18	10.17	1.01	1.01	1.03	9.06
	Overburden Dump	9.67	8.08	1.59	1.59	2.53	16.44
2018	Abandoned Mine	12.78	10.94	1.84	1.84	3.4	14.42

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	Mine Plantation	27.19	21.32	5.87	5.87	34.42	21.58
	Forest	9.76	16.36	-6.6	6.6	43.52	67.59
	Agriculture land	36.98	52.42	-15.44	15.44	238.39	41.75
	Scrub Land	129.76	117.6	12.16	12.16	147.87	9.37
	Settlement	39.23	33.71	5.52	5.52	30.43	14.06
	Water body	11.1	17.05	-5.95	5.95	35.44	53.63
	Open cast mine		10.9		1.01	1.03	9.06
	Overburden Dump		9.23		1.59	2.53	16.44
	Abandoned Mine		12.33		1.84	3.4	14.42
	Mine Plantation		28.46		5.87	34.42	21.58
	Forest		9.62		6.6	43.52	67.59
	Agriculture land		38.43		15.44	238.39	41.75
	Scrub Land		128.78		12.16	147.87	9.37
	Settlement		37.47		5.52	30.43	14.06
2028*	**Water body**		12.43		5.95	35.44	53.63

Table 4: Estimation and Forecasting of LULC. *Shows predicated year obtained after statistical evaluation of each year of mean gap has approx. 10 year.

The moving-average method provides an efficient protocol for obtaining a value for forecasting stationary time series. The technique has applied as simply an arithmetic average as time passes, with some lag-length determined optimally by an underlying cycle present in the area (hectares). Thus, moving averages method has developed based on an average of weighted three year observations.

Arithmetic formula for evaluation and forecasting

$$M_t \equiv \hat{Y}_{t+1} \quad (1)$$

$$et = Y_t - \hat{Y}_{t+1} \quad (2)$$

Where, Mt ϵ (a moving average at time t, which is the forecast value at time t+1),

Y_t ϵ (Observation at time t), e_t ϵ (Forecast error).

Using the evaluation process of forecasting classify classes area (hectares) with respect to error occurred in mean absolute percentage in year 2028 likes open cast mine (10.90 hectares, 9.06%), overburden dump (9.23 hectares, 16.44%), abandoned mine (12.33 hectares, 14.42%), mine plantation (28.46 hectares, 21.58%), forest (9.62 hectares, 67.59%), agriculture land (38.43 hectares, 41.75%), scrub land (128.78 hectares, 9.37%), settlement(37.47 hectares, 14.06%), and water body (12.43 hectares, 53.63%).

Conclusion

LULC change due to operational mining are versatile effect on other part of area are classify like agricultural land, forest, vegetation, mine plantation, scrub land, open cast mine, abandoned mine pit, overburden dump, settlement and water body. There are deals of effecting classes and probable future trend time of spatial feature in change of 2028 year shown in Table 4. Therefore, this is particularly important with regard to the mapping of very large areas and monitoring of change, where accuracy assessment remains a challenging task with considerable scope for further development [77]. It is proofing for gain support for research on classification accuracy assessment than classification projects, yet the value of such projects will be valuable in the poor quality of the accuracy assessment and reporting. It is deal with environment effect as well as operational mining area monitoring and delineation report. Furthermore, the research has open challenges into for future work modeling regarding details of networking of transporting routes and cognition free route services.

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